A STUDY ON FINANCIAL DISTRESS PREDICTION AMONG SELECTED COMPANIES WITH SPECIAL REFERENCE TO FINANCIAL, MARKET AND MACRO ECONOMIC VARIABLES

A Thesis

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in

MANAGEMENT

By

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DECLARATION

I hereby declare that the thesis entitled, "**A STUDY ON FINANCIAL DISTRESS PREDICTION AMONG SELECTED COMPANIES WITH SPECIAL REFERENCE TO FINANCIAL, MARKET AND MACRO ECONOMIC VARIABLES"** submitted to Lovely Professional University in partial fulfillment of the requirements of the degree of Doctor of Philosophy in Management is my original work and that the thesis has not formed the basis for the award of any Degree, Diploma, Associateship, Fellowship or any other similar titles.

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CERTIFICATE

This is to certify that the thesis entitled, "**A STUDY ON FINANCIAL DISTRESS PREDICTION AMONG SELECTED COMPANIES WITH SPECIAL REFERENCE TO FINANCIAL, MARKET AND MACRO ECONOMIC VARIABLES"** submitted by Rohit Bansal for the award of Doctor of Philosophy in Management is a record of research work done under my guidance and supervision during the period 2014- 2022 and the thesis has not formed the basis for the award to the scholar of any Degree, Diploma, Associateship, Fellowship or any other similar titles. Also certified that the thesis represents an independent work on the part of the candidate.

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ABSTRACT

A timely prediction of financial distress is a significant problem in the present economic environment, given the impact of the global financial crisis on world business over the past decade. The global financial crisis has exposed the severe weaknesses in the risk models used to handle credit risk and available models on distress prediction lack in terms of their accuracy. The study contributes to the financial distress prediction literature by conducting empirical studies and surveys. In this research, efforts have been made to study trends & patterns amongst financial distressed companies in India and to develop a predictive model for these companies. It has further analyzed the opinion of financial institutions about financial distress of Indian companies. It will be helpful to different regulators, lenders and investors in their decision-making process.

Regarding financial distress, this study examined the various types of trends and patterns that have emerged among publicly traded companies over the last fifteen years. It was found that the number of cases referred to the Board for Industrial and Financial Reconstruction (BIFR) has surged after the global financial crisis. Due to the strain on multiple firms' balance sheets, there has been a significant surge in the number of listed firms referred under IBC law. The global slowdown that began in 2008 has reduced listed companies' interest coverage ratios as well as their net profit margins. However, with the RBI's series of repo rate cuts beginning in 2015, companies not undertaking new investments, resulting in companies going slow on new borrowings, and many corporate deleveraging with outstanding debt and further improvements in earnings, there has been an improvement in listed firms' debt-servicing ability. While indicators such as debt-equity, debt- market capitalization has improved, but interest coverage ratio, net profit margin & current ratio, in particular, demonstrate that the risk of unsustainable business debt remains significant, as many firms have difficulty servicing existing debt, posing concerns to lenders. This emphasizes the importance of keeping a close eye on the business environment.

Various patterns were investigated among listed companies referred to BIFR and IBC with different characteristics such as sector, ownership structure, firm life cycle, and size. Maximum number of listed companies in both BIFR and under IBC were from major industrialised states of India. Textiles, steel, paper, pharmaceuticals, chemicals, sugar, packaging, consumer durables, FMCG, edible oil sector, capital goods, trading, infrastructure, construction and mining & mineral products have been identified as important sectors that have experienced financial distress in the last decade. Most firms that experienced financial distress have either widely held or family-owned ownership and were in the maturity stage of their life cycle. Small businesses have suffered more than larger ones due to economic slowdown.

Using logistic regression, the study framed new financial distress prediction models for listed firms in India. The present study has tested market and macroeconomic variables in addition to accounting variables to enhance predicative power of the models. Models using logistic regression have been estimated on the estimation samples and tested on the holdout samples for up to three years prior to financial distress. The analysis found that the predictive capacity of the models is diminishing with the increase in the time period of financial distress using financial variables.

For firms referred to BIFR, compared to models based only on ‘accounting ratios’, combining ‘accounting and market variables’ in a single model resulted in a negligible improvement in overall performance. Whereas for IBC firms, combining accounting and market variables in a single model resulted in a considerable improvement in overall performance, measured by predicted accuracy and goodness-of-fit of the models. The results of incorporating market variables into an accounting-based model revealed that market variables contain a significant amount of information not included in financial statement ratios that is relevant to estimating the likelihood of financial distress. As a result, incorporating market variables into an accounting-based model can greatly improve the model's predictive potential. It was investigated whether macroeconomic indicators supplement distress prediction models. The results found incorporating macroeconomic indicators does not improve the estimation of likelihood of financial distress.

Survey results show, the factors causing financial distress could be both internal and external. Further most important internal reasons were fund diversion, intentionally default, technology obsolescence resulting in outdated products, increase in production cost, investment in multiple projects at the same time, improper research & development, diversion of working capital loans and incompetent management. There was lack of proper equity capital infusion in the companies and the repayment of loan was refinanced rather made through cash flows of the company. Wrong managerial decisions in different functional fields, as well as unethical management actions such as siphoning off firm funds for own gain at the expense of the firm. Most important external reasons were product competitiveness, delay in statutory approvals, high cost of borrowing, policy paralysis, rupee devaluation, infrastructure bottlenecks, rising raw material prices, shifts in customer preferences. Frequent changes in government policy and reluctance on the part of the government and government-controlled entities to issue payments on time have a cascade effect on other enterprises that rely on them. Financial distress is also a result of restrictions on bulk purchases, the government's excessive tax policies, and the slowdown in the global economy. The warning sign for financial distress, begins with default of interest payment, additional fund requirement without expansion or modernization, inconsistencies in cash credit/overdraft accounts, delay of submission of statement with various statutory agencies like SEBI or publication of financial statements with a lag, unable to submit a stock statement on time, avoiding to calls made by bank officials, hindrances in project execution, substitution of collateral, adversely qualified accounting statements, sudden decrease in production and downtrend in sales & profits margin. Further, disturbance in the working capital cycle, investment in non-core assets, inadequate reserves, fake sales growth of companies, and promoters misusing unlisted private entities or subsidiaries for sales purposes were found as leading indicators of financial distress. Most of the experts believe that IBC law will effectively deal with the stress assets of Indian companies in a more effective manner. Prior to IBC, there was no effective method for recovering from distressed businesses on time like DRT was ineffective, whereas in the case of BIFR, the businesses continue to exist even after despite being defaulters. It was very challenging for the financial institutions to recover outstanding dues from the companies like in CDR, as most of the firms were not putting fresh equity in their businesses. IBC law also has made significant behavioural changes in management of the companies and now management willing to internal settle the various outstanding dues with financial institutions to stay away from NCLT and will further assist financial institutions for faster recovery for their loans. There are serious concerns about the role of rating agencies in assisting in the earlier detection of distress. Reasons given by different respondents on this issue include the fact that rating agencies are not familiar with the companies' day-to-day operations, a lack of access to accurate information such as manipulated accounting data of the businesses, and a reliance on the information provided by the companies. Further, it is possible to have a conflict of interest if the analyst rating an instrument has an ownership stake in the issuing firm. Thus, there is a need to change the approach taken by rating agencies.

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S.NO.	DESCRIPTION	ABBREVIATION
1.	Sick Industrial Companies Act	SICA
2.	Board for Industrial and Financial Reconstruction	BIFR
3.	Insolvency and Bankruptcy Code	IBC
4.	Receiver Operating Characteristics	ROC
5.	International Monetary Fund	IMF
6.	Gross Domestic Product	GDP
7.	Reserve Bank of India	RBI
8.	Interest Coverage Ratio	ICR
9.	Net Profit Margin	NP
10.	Current Ratio	CR
11.	Debt to Marketcapilization	DMCAP
12.	Debt to Equity Ratio	DE
13.	(Adjusted Gross Profit + Interest) / Sales * 100	PBIDTM
14.	Net Sales to Total Assets Ratio	NSTA
15.	(Adjusted Net Profit + Depreciation) / Sales * 100	CPM
16.	Cash Flow from Operations/ Interest	CFOINT
17.	Excess Returns	ER
18.	Market Value to Shareholder Funds	MVSF

S.NO.	DESCRIPTION	ABBREVIATION
19.	Standard Deviation	STDEV
20.	Non-performing Assets	NPA
21.	Exchange Rate	EX
22.	Area Under Curve	AUC
23.	Standard Error	SE
24.	Financial Distress	FD
25.	Hosmer and Lemeshow	HL

Chapter – 1

OVERVIEW

1.1 INTRODUCTION

Financial distress is a major issue for the global economy, and after the global financial crisis of 2007; the issue has become more critical, which is resulting in a lot of strain on the financial system worldwide **Jacobsen and Kloster (2005); Cirmizi, Klapper and Uttamchandani (2010); Bottazzi et al. (2011); Lesáková (2014); McNally (2017); Jabeur (2017); Peres and Antão (2017); Kovacova et al. (2018); du Jardin, Veganzones and Séverin (2019); Kashyap, Bansal and Nagale (2019); Camska and Klecka (2020)**. The financial strength of enterprises in an economy reflects the country's performance in comparison to rival economies **Lin (2009); Mommen and Jilberto (2017); Schönfeld, Kuděj and Smrčka (2018); Horváthová & Mokrišová (2018)**. Insolvency happens when a business experiences a persistent and significant loss, or its liabilities exceed its assets **Huang, Hsu and Wang (2007)**. Financial distress impedes the strong performance of the economy, which translates to the failure of a nation to keep up with the development of other nations **Delina and Packova (2013); Donato and Nieddu (2016)**. Failure can take many forms and be manifested at varying levels, each with its own set of implications for stakeholders, depending on the degree and nature of failure **Grice and Dugan (2001); Cielen, Peeters and Vanhoof (2004); Lee and Yeh (2004); Klieštik, Kočišová and Mišanková (2015); Shamsudin and Kamaluddin (2015); Sayari and Mugan (2017)**." Failures are increasing every year because of changing legal, political & economic scenario", **Kliestik, Vrbka and Rowland (2018)**. After the global financial crisis, businesses in India have been under a lot of stress. Growth in its debt has been related to a significant increase in firms' vulnerability to service interest obligations **Dhananjaya (2021)**. With the growth of the stock exchange and the growing trend in investors' participation, the risk of investor bankruptcy is a big challenge facing an inexperienced stock investor **Asgarnezhad and Soltani (2016)**.

Considering the debt, the most vulnerable portion of the businesses, the vulnerability of the Indian corporate sector to extreme structural shocks has increased further **Lindner and Jung (2014)**. Moreover, due to increasing competition and globalization, various companies are not able to withstand the situation & face difficulty in survival, resulting in default in scheduled repayment of their debt obligations **Jacobsen and Kloster (2005); Jenkins, Kane and Velury (2009)**; **Bottazzi et al. (2011); Tandon (2016); Gavurova et al. (2017); Kliestik, Vrbka and Rowland (2018)**. The number of firms facing financial distress in India is also increasing in the last two decades due to various structural & company-specific issues. The problem has increased further due to the slowdown in the global economy since the global financial crisis **Abraham and Omkarnath (2006); Kashyap, Bansal and Nagale (2019)**. Also, rising financial distress among Indian companies has a severe impact on the health of Indian banks, and stress in the banking sector is causing less cash to finance other projects, thus having an adverse effect on the domestic economy. Increased stress assets in the banking industry due to a drop in growth & expanding economic difficulty, coupled with wilful default, had a significant impact on banks' asset quality and this has severely impaired banks' ability to lend even to healthy businesses **Dhananjaya (2021)**. Distressed companies are, on average, more financially vulnerable, but they are also less competitive & profitable in all years preceding a default **Aziz and Dar (2006); Bottazzi et al. (2011); Sayari and Mugan (2017)**.

The amount of non-performing assets (NPAs) is the strongest indicator of the health of the country's banking system **Singh (2013); Sahoo (2015); Agarwala and Agarwala (2019).** Over the last few years, bad assets have become a serious issue for almost all the banks. In the post-crisis era, corporate distress has increased, and which has led to enormous debt exposure. Because of this, the banking sector has accumulated a significant amount of non-performing assets (NPA). It has been observed that the increase in non-performing assets is eroding bank profitability, as evidenced by the significant drop in bank profitability over the past few years **Gulati and Kumar (2016); Dubey, Kumari and Somaiya (2016); Bhaskaran et al. (2016); Mittal and Suneja (2017)**. The efficiency of an economy depends on its financial system's efficiency **Das and Ghosh (2007)**. A stable banking sector affects economic growth positively. The issue of NPAs affects not only the banks but also the entire economy **Barge (2012); Singh (2013); Mittal and Suneja (2017); Sengupta and Vardhan (2017)**. NPAs are now the most significant risk to the overall stability of the banks **Siraj and Pillai (2013); Singh (2013); Meher (2017); Mittal and Suneja (2017)**. A high level of NPAs specifies that a significant number of credit defaults and therefore erode the value of their assets **Dubey, Kumari and Somaiya (2016)**. Asset quality is one of the most relevant metrics for the evaluation of banking' overall financial performance. The quality of the asset represents the possibility for credit risk, which could further impact banking firms' valuations **Banerjee, Verma and Jaiswal (2018)**. Indian banks have recognized that non-performing assets have an adverse effect on banks' net worth, and profitability. Deterioration of the quality of banks' assets and subsequent rises in non-performing assets severely impact the financial intermediation mechanism **Sahoo (2015); Karunakar, Vasuki and Saravanan (2008); Digal and Kanungo (2015); Bardhan and Mukherjee (2016); Mittal and Suneja (2017)**. The resulting financial fragility has a negative impact on economic growth. Management of banks has invested a great deal of their time, energy, & money in managing their assets to minimize the peril associated with it on the economy. With ever-growing developments and bank credit procedures, the problem of credit defaults and their restoration is critical to banks' survival **Giesecke et al. (2011); Vikram and Gayathri (2018)**. As the crisis resulting from non-performing assets can shake not only the erring banks but also the whole country's economy **Pandey (2016)**. Therefore, it is vital for the government & RBI to take immediate steps to disperse this proverbial time bomb, which is almost ready to burst. Any more delay in the successful management of NPAs is bound to kill country's fiscal solidity, rendering it vulnerable to global payers' dictates. Moreover, the government should take additional measures to expedite the resolution of pending cases and reduce coercive lending to the priority sector. Therefore, the non-performing assets problem needs a great deal of effort; otherwise, non-performing assets would continue to destroy the competitiveness of financial institutions, which is unsuitable for the country's booming economy **Singh (2016)**.

Table 1.1 provides an overview of the gross NPAs of various scheduled commercial banks in India. As per the table, the amount of gross NPAs of different banks has increased substantially during the last few years, both due to high economic growth and rising stress in the economy. And there was a sharp increase in this segment after the year 2015 due to stricter regulatory guidelines with the dissolution of the Board for Industrial and Financial Reconstruction and the introduction of the Insolvency and Bankruptcy Code.

Table 1.1: Gross non performing assets in both Public and Private Sector Banks in India.

Year	**Banks**	**Gross non-performing assets (Amount in ₹ Million)**
2019	ALL SCHEDULED COMMERCIAL BANKS	9364737
2018	ALL SCHEDULED COMMERCIAL BANKS	10386838
2017	ALL SCHEDULED COMMERCIAL BANKS	7902680
2016	ALL SCHEDULED COMMERCIAL BANKS	6116074
2015	ALL SCHEDULED COMMERCIAL BANKS	3229161
2014	ALL SCHEDULED COMMERCIAL BANKS	2630152
2013	ALL SCHEDULED COMMERCIAL BANKS	1927688
2012	ALL SCHEDULED COMMERCIAL BANKS	1369683
2011	ALL SCHEDULED COMMERCIAL BANKS	939969
2010	ALL SCHEDULED COMMERCIAL BANKS	817181
2009	ALL SCHEDULED COMMERCIAL BANKS	699537
2008	ALL SCHEDULED COMMERCIAL BANKS	566060
2007	ALL SCHEDULED COMMERCIAL BANKS	505170
2006	ALL SCHEDULED COMMERCIAL BANKS	517531
2005	ALL SCHEDULED COMMERCIAL BANKS	573960

Source: Department of Banking Supervision, RBI.

Thomas and Vyas (2016) envisaged an early warning framework to avoid loan defaults and outlined all necessary corrective measures and strategic tools. The performance in the Indian banking system of various non-performing assets recovery networks is not satisfactory **Singh (2016)**. The fundamental cause of the poor recovery mechanism may be insufficient due diligence and ineffective legislation to counter defaults**.** Non-performing assets and their recovery are addressed only through a sound credit evaluation and recovery management system **Mittal and Suneja (2017)**. In a situation of excess liquidity and economic boom, banks continue to loan more, damaging asset quality, raising questions about their adverse selection & the possible risk that they will add to the non-performing assets **Dey (2018)**. For the banking industry, handling and regulating bad loans at the lowest level has become highly significant **Taj (2016)**. Since the 2008 global financial crisis, demand for goods and services has decreased, the supply of foreign funding has plummeted, investments have decreased, and payments have been limited, leading to insolvencies in the companies worldwide **Cirmizi, Klapper and Uttamchandani (2010)**.

1.2 DEFINITION OF FINANCIAL DISTRESS

Noticeably definitions of financial distress are more flexible due to their background of studies and availability of data. A broader definition of corporate default or financial distress makes modeling easier by increasing the sample size of distressed firms. Still, at the same time, it brings difficulties in interpreting the results of different dependent variables. This study investigates an ex-ante model for predicting financial distress by using the definition of distress based on its legal implications **Bansal and Singu (2017)**.

Different countries have different laws and policies to deal with financial distress. Each has different rules and legal regulations for timely detecting the firms facing financial distress**.** There are significant differences worldwide in legal processes due to legal norms, accounting systems, regulatory frameworks. For example, in the United Kingdom, the Insolvency Act, 1986 regulates the Insolvency framework related to company insolvency and winding up. Bankruptcy Code, a federal law, governs financial distress in the United States of America. Various laws have been enacted in India to address this issue regularly. Earlier the rules related to financially distressed cases were covered in the Companies Act, 1956 and the Sick Industrial Companies Act, 1985 **Bapat and Nagale (2014)**. "In India, a 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. Considering the fact that, in India, the number of companies experiencing financial distress has increased in recent times, and there is a rising trend of default in times of global slowdown, there have been various steps taken by the government to deal with this issue in India. Recently with the passage of the insolvency and bankruptcy code bill, a single law to deal with distressed firms is applicable in India. This law will ensure a time-bound process of winding up a distressed company" **Roychoudhury (2016)**. So, in this study, firms referred to both BIFR and IBC law will be taken as financially distressed companies based on the legal definition.

1.3 'SICK INDUSTRIAL COMPANIES ACT (SICA)', 1985

"In 1985, the government of India introduced the Sick Industrial Companies Act (SICA) for resolution of different companies facing financial distress **Sengupta, Sharma and Thomas (2016**). SICA was introduced to speed up the resolution of distressed companies in India, and it was an important law to deal with financial distress in India. The law was introduced in India to deal with timely detection of financial distress in companies or those which can face distress in the near future. SICA was introduced with the objective to assist the revival and reorganization of firms facing distress and liquidating them; in case there is not any possibility of reviving these firms so that to free capital locked in these firms, which will result in better deployment of resources to boost overall productivity" **Van Zwieten (2015)**. The board for industrial and financial reconstruction (BIFR) was formed to deal with various cases registered under SICA to speed up decision making for restructuring or liquidating the registered firms **Navulla, Golla and Sunitha (2016**). The purpose of BIFR was to cut down additional losses and value of sick company's assets by quickly approving the decisions concerning reorganization or winding up of various admitted cases. BIFR provides distressed company assistance in reviving and closing potentially non-viable units. In general, cases that apply to the BIFR were those in which borrowers have lost all hope of recovery. The SICA, under which BIFR functions, prohibits lending banks from taking legal action against enterprises **Barge (2012)**. Thus, many promoters are also in support of BIFR, as it shelters businesses against legal action by lenders. But somehow, SICA was not much effective in resolution for admitted cases **Van Zwieten (2015)**. SICA was neither helpful to creditors in faster recovery of dues nor quick restructuring of debtor firms and BIFR shelter misused by deceptive lenders**.**

1.4 'INSOLVENCY AND BANKRUPTCY CODE (IBC)', 2016

Given that the number of enterprises in financial hardship in India has increased in recent years, and there is an increasing pattern of default during times of global slowdown, the government has taken a variety of actions to address this issue in India. The Indian government's passage of the IBC (2016), was a key step in addressing the issue of financial distress **Vig (2019)**. The IBC was intended to settle the non-performing assets by developing a comprehensive mechanism to address conflicts between debtors and creditors and strengthen India's financial eco-system, reducing creditors' fears while ensuring companies continue to function. Insolvency law reforms are vital to improving India's corporate climate and credit markets. Banks in India have long been affected by the issue of non-performing assets, and many of its biggest companies face huge debts **Srivastava (2010); Kasilingam and Ramasundaram (2012)**. The fundamental purpose of the new law was to promote the resolution and liquidation of insolvencies in a timely manner and boost India's "free trade" index position. The code has become a game-changer to deal with enormous bad debt lying with the Indian banks.

IBC is one of the most significant economic changes that India has implemented. It is a remarkable case of a much-needed law that has seen rapid introduction & implementation. As a one-stop solution that tackles all bankruptcies in a time-limited & economically feasible environment, the legislation has dramatically contributed to

India’s achievement of the unprecedented 30-point jump in business rankings. The IBC turned out to be the sole regulation to deal with the matter related to restructuring and liquidation of distressed companies. By granting both creditors and debtors the ability to take legal action against one other, the law has significantly altered the power-sharing dynamic between creditors and borrowers. The measure will likely provide much-needed relief to India’s banking industry, which is beleaguered by at least Rs. 10.36 lakh crores in bad loans. Things are improved a lot with the implementation of the new Insolvency & Bankruptcy Code in 2016. It emerged as the exclusive law to deal with the issues associated with reorganization and liquidation of firms facing distress **Sengupta Sharma and Thomas (2016)**. IBC law lays the insolvency processes for individuals, companies, and partnership firms. “This law is a game-changer, allows for a time-bound and market-determined insolvency resolution mechanism. It focuses on smoothing the progress of matters pertaining to restructuring and liquidation of financially troubled companies. The IBC intends to provide insolvency resolution through insolvency professionals within eighty days for various admit cases. The code can be prompted even in the initial claim of the debtor’s failure to repay dues, and the entire activity should be finished in a time-bound manner. The characteristic of providing resolution within a stipulated time differentiates it from earlier laws and makes it more effective to deal with default businesses. The code allows 180 days for completing the entire process of insolvency resolution but allows additional 90 days in specific cases. Under this new bankruptcy law, financial creditor, operational creditor, or the company itself can file a petition in NCLT in case of insolvency situation. The petitioner can apply to NCLT, and it is admitted in case of sufficient evidence. The tribunal will appoint an insolvency professional in case of all admitted cases with it. The role of an insolvency professional is to run the business and gather all the pending claims to come across a solution—the law emphasis smoothing resolution of admitted cases of financially distressed firms. The feature of finding resolution within a specific time distinguishes it from prior regulations and makes it relatively more efficient to handle defaulting firms **Kaveri (2018)**. Since the law is a changeover, settlements before admission, and transformed non-performing assets (NPAs) into cash, the new law effectively makes firms more responsible and committed to service their outstanding obligations. Under the new IBC law, approximately Rs four lakh crore of NPAs has come into the system. The number of new NPAs that are being built has declined. A significant number of cases, including those relating to vast quantities of stressed properties, have been exposed to insolvency. Thus, it is helping in a big way to recover lock up capital in distressed companies and make debtor companies more accountable and serious for repayment of their dues. The motive was either to provide assistance to revive & re-establish or to liquidate companies (if revival not possible) undergoing financial distress, which can help unlock capital invested in these companies to make way for more efficient utilization of productive assets. The bank also would help resolve large accounts' non-performing assets if the newly enacted Insolvency and Bankruptcy law were implemented effectively. Under BIFR, promoters have free run and a free hand to drag things up to infinity. At the same time, the banks were forced to fight and run from pillar to post for remedies under an indefinite moratorium period. IBC, too, would have gone and suffered the same fate as SICA prosecutions; had the government not stood on a strict timeline. Lending is a risky practice involving public funds, and it must be handled with caution to guarantee that the country's financial system continues to function smoothly. The borrower must know that the default will not be tolerated, and if one is looking for a long inning in the field, it has no space. It ensures that the banking sector will redeploy the funds in lending operations, and the pressure on taxpayers to recapitalize banks would be smaller.

The analysis of financial distress is becoming more significant and vital, as even large businesses worldwide are struggling, contributing to social and economic problems for society. Financial distress in the industry has just become a sensitive issue in India. It is having a detrimental effect on industrial health and the economy. Additionally, it is a factor that has a detrimental influence on employment; the investors lose money, creditors lose future returns, and the business deteriorates. Governments, lenders and corporates should concentrate on averting distress to save the economy. An efficient early warning system for financial crisis prediction is vital for better corporate governance **Geng, Bose and Chen (2015)**. Financial distress forecasting is often essential for financial institutions to assess corporate and individual financial health **Kumar and Ganesalingam (2001)**; **Liang, Tsai and Wu (2015)**. Predicting failure using financial distress models is essential for most companies in their decision-making **Sun et al. (2014)**. There are growing numbers of businesses facing economic and financial challenges in current economic conditions, which sometimes leads to financial distress due to insufficiencies of current forecast models **Jabeur (2017)**. Considering the fact that, in India, the number of companies experiencing financial distress has increased in recent times. There is a rising trend of default in times of global slowdown. The existing methods to assess the sign of distress among companies have shortcomings that need further improvement **Bansal and Singu (2017)**.

As a result, developing an accurate prediction model for corporate financial distress has been an essential topic of research **Kim, Lee and Ahn (2019); du Jardin (2018); Veganzones and Séverin (2018)**. It is critical not only for the owners of companies but also for the other stakeholders **Geng, Bose and Chen (2015)**; **Antunes, Ribeiro and Pereira (2017); Kovacova et al. (2018); Veganzones and Séverin (2018)**. The prediction of bankruptcy is of concern to investors, creditors, lenders, and governments **Geng, Bose and Chen (2015)**; **Nanayakkara and Azeez (2015); Pereira, Basto and Silva (2016)**. **Wu, Gaunt and Gray (2010); Altman et al. (2020)** reviewed models of financial distress in the literature and concluded that they provide unique information on the probability of financial distress, but their output varies with time. Previous studies have not considered the combined effect of financial ratios, market and macroeconomic variables to predict financial distress in the Indian context in a comprehensive manner. Therefore, future studies should help identify companies at risk of facing potential financial distress in the future. This advance warning will help management take appropriate steps and decisions to avoid financial distress, which will help mitigate the cost associated with financial distress and resulting business failure. Lenders like banks could better control their risk exposure and potential future bad debts. It will also help banks track borrowers' financial profiles and identify sickness at the initial stages when a unit starts becoming weak.

Management of financial distress also improves productivity and development **Eklund, Levratto and Ramello (2020)**. Portfolio managers and investors could better assess the risk profile of their investments and diversify by avoiding investing in future potential failures **Lin (2009); Nanayakkara and Azeez (2015); Čámská (2016); Mahtani and Garg (2020); Altman et al. (2020)**; **Bansal and Singu (2017)**.

Corporate financial distress impacts many other associated agencies such as suppliers, consumers, financial institutions, government, etc **Čámská (2016); Jones, Johnstone and Wilson (2017)**. Stakeholders such as suppliers and customers would have better information about the company's financial soundness, which will help in their long-term exclusive engagements with those entities. There is a need to explore those issues to frame effective rules & policies dealing with these cases and the overall betterment of the financial system **Čámská (2016); Bansal and Singu (2017); Kliestik, Vrbka and Rowland (2018)**. Right now, the industries seeing the most significant number of distressed companies undergoing bankruptcy and restructuring procedures are the oil and gas, retail, healthcare, and maritime and shipping industries. Regarding the retail sector, the drivers of distress are the popularity of online shopping and the built-in costs associated with maintaining brick-and-mortar retail locations. Sustaining a large real estate footprint while consumer preferences shift to online shopping has negatively impacted sales. It has made it increasingly difficult for these brick-and-mortar retail companies to compete. The oil market downturn continues to be a driver of distress in the oil and gas industry. Along with turbulence in the commodity markets, it is also a driver of distress in the maritime and shipping industry. In contrast, oil prices have appeared to stabilize, therefore slowing the pace of restructuring of oil and gas companies.

1.5 NEED OF STUDY

Dhananjaya (2021) emphasized the issue of growing leverage, dropping productivity, and the contraction of investment growth in the corporate sector and suggested that the corporate balance sheets would deteriorate significantly in India. **Bakshi and Mitra (2020)** has concluded that "it took ten years on an average to wind up / liquidate a company in India compared to 1 to 6 years in other countries. Such lengthy timeframes are unfavourable to the interest of all stakeholders. The process should be time-bound, aimed at maximizing the chances of preserving value for the stakeholders as well as the economy as a whole". No firm, even during a time of prosperity, can be convinced of its prospects **Korol (2013)**. According to a study by **Jardi and Severin (2010)**, failure of a business is not an unexpected event; instead, it is the result of a failure path, which may consist of several phases, each characterized by specific signs of failure. Failure is not a sudden phenomenon, and if the warning signals are detected, managers will have more time for preparing and reacting in subsequent phases of the crisis.

Therefore, forecasting the default of companies is an area that has become quite significant in recent times. "Lenders in India can recover only 20% of their loans when businesses go bankrupt, and an average time of 4.3 years is taken for insolvency proceedings. This compares to a 70% recovery rate in developed countries and about 1.7 years of the average time for insolvency proceedings in developed economies. Currently, the Indian economy is reeling under mounting bad loan pressure" **Lindner and Jung (2014)**. Thus, lenders and investors, along with various regulators, require timely information on the default risk probability of the firm within lending and investment portfolios. Early warning of financial distress or business default has become an important research area for financial risk management **Altman, Sabato and Wilson (2010)**. Any prediction technique should provide a sign with an adequate time lag to allow for remedial actions. If the time is sufficient, then timely steps can be taken to correct the state of financial distress. Lenders like banks can restrict themselves from lending money to firms bound to fail or are expected to face distress in the near future. Investors can prevent capital loss by not investing in companies that are likely to face financial trouble. It will also help various firms willing to maintain long-term relationships with other companies and ready to deal with only those companies that will not witness any failure in the future, hence increasing the prolonged existence of their trade contacts **Bansal and Singu (2017).** The Indian economy has witnessed phenomenal growth in the past few years. There is plenty of amounts invested in the Indian stock market due to increasing corporate profits **Sridharan and Joshi (2018)**. Portfolio investors should have techniques for selecting financially sound firms for proper asset allocation. Investors usually do portfolio allocation based on different parameters like sector, ownership, firm life cycle stage, etc **Bruwer and Hamman (2005)**. Thus, it is vital to examine various patterns of financial distress companies in the listed universe **Pereira, Basto and da Silva (2016)**. This research emphasizes exploring different patterns among financially distressed companies on major stock exchanges in India, which will benefit regulators, lenders, and investors in their decision-making process. The outcome will also help policymakers to check the effectiveness of various laws dealing with financial distress in India and timely amend them to make them more effective.

1.6 OBJECTIVES AND SCOPE

The research contributes to the financial distress prediction works by conducting empirical studies and surveys. In this research, efforts have been made to study trends & patterns amongst financially distressed companies in India and develop a predictive model for these companies. The result of the study will be helpful to different regulators, lenders, and investors in their decision-making process. Therefore, the present study aims to achieve the following objectives:

1) To study the trends and patterns of financial distress in Indian companies.
2) To develop a predictive model of financial distress using financial variables.
3) To evaluate usefulness of market and macroeconomic variables for predicting financial distress.
4) To analyze the opinion of financial institutions about financial distress of Indian companies.

1.7 SOURCES OF DATA

The research is based on both primary and secondary information. The empirical study for objectives one, two, and three is based on secondary data. Primary data were gathered for the fourth objective by conducting a survey to solicit opinions from various financial institutions.

1.7.1 Data Sources

Secondary data for non-financial firms listed either on the Bombay stock exchange or the National stock exchange, registered under both the Board for Industrial and Financial Reconstruction (BIFR) and the Insolvency & Bankruptcy Code (IBC), 2016 has been taken as a sample for this particular study. The sample period has been taken from 2006 to 2020, so that the effect of the slowdown in the world economy during this period on the overall distress situation among various listed firms in India can be examined. The list of non-financial firms who have made reference to the BIFR has been taken from the BIFR database & data related to firms admitted to the Insolvency & Bankruptcy Code (IBC) has been taken from the Insolvency and Bankruptcy Board of India (IBBI) database and National Company Law Tribunal (NCLT). Financial data, market data, and company-specific information related to both financially distressed and healthy companies have been taken from the companies' annual statements and the Capitaline database. Data for various macroeconomic variables were obtained from the (RBI) database on the Indian Economy and the World Bank database. Data have been further analyzed by taking the percentage of firms found under a particular pattern to the total number of firms under the study.

1.8 RESEARCH METHODOLOGY

This section discusses sample selection procedure, financial, market, and macro-economic factors used as variables, sources of data, the definition of financial distress, and the statistical techniques employed in the study.

In this study, firms listed on (BSE) or (NSE) referred to BIFR or IBC have been taken as financially distressed companies. For a firm referred to BIFR, the year of financial distress will be the year in which it has been referred to BIFR. For a firm referred to IBC, the year of its financial distress will be the year when there is the first instance of default by the firm either to its creditor or supplier. Details for each firm's first instance of default have been taken from the order sheet of admitted cases issued by the National company law tribunal bench. To study financial distress trends and patterns, data related to financial, market, and company-specific information have been taken for all the listed companies and non-financial firms listed registered under both Board for industrial and financial reconstruction (BIFR) & Insolvency & Bankruptcy Code (IBC), 2016 on NSE and BSE for a period from 2006 to 2019, so that effect of slowdown in the world economy during this period on overall distress situation in among various listed firms in India can be examined. Only listed companies have been considered for the study due to the presence of market-based variables. Financial firms have been omitted because of these enterprises' unique characteristics about regulatory standards, financial reporting standards, and compliance requirements. Further percentage analysis has been used to do trends and patterns analysis of the firms under the study. Financial data and company-specific information related to distressed companies have been taken to analyze various patterns among them by state, sector, ownership, size, and firm life cycle stage. For trend analysis, information related to the number of companies, current ratio (CR), debt-to-equity ratio(DE), interest coverage ratio (ICR), debt to market capitalization ratio(DMCAP) & net profit margin(NP) has been taken for all the listed firms on NSE and BSE.

1.8.1 Financial Distress Predictive Model

Only those companies for which data of accounting and market variables are available within the period of study have been considered for the final model. A total of one hundred eighty-nine firms referred to BIFR & one hundred eighty-eight to IBC during this period. Each financial distress firm has been matched with a healthy company during the same period with the same asset size and industry by applying matched –pair selection technique **Altman (2000)**; **Agrawal and Maheshwari (2014)**. Data of both financial distress and healthy firms from the non-financial sector have been taken from 2006 onwards for the study. Separate predictive models of financial distress have been tested for both BIFR and IBC firms using financial, market & macroeconomic variables.

1.8.2 Variable Selection for Predictive Model

The objective is to develop distress prediction models for listed firms in India by identifying the accounting, market & macroeconomic variables, which are significant for predicting distress. Hence, it is vital to use data from reliable sources & apply appropriate methods to develop the model. The current research examined the market & macroeconomic data, as well as accounting variables, to develop models. According to **Tinoco and Wilson (2013)**, "market prices will operate as a supplement to the financial ratios by boosting the predictive potential of the general model, and not as competing or mutually exclusive alternatives that should be used in isolation." The reason is that market prices will discount financial statement data as well as other information which is not reflected in the financial data of the company, potentially making markets a more efficient processor of all available public information than accounting data alone and therefore increasing the overall accuracy of financial distress prediction model **Chen (2011); Bansal and Singu (2017)**. Macroeconomic variables are taken to capture the change in general business surroundings. To develop a predictive model for financial distress companies under both BIFR and IBC, a total of seventy variables, including accounting, market, and macroeconomic variables, were examined. The approach for selection has been focused on findings, theoretical ideas, and empirical reviews previously reported. Various variables that have proven helpful in earlier study in the mainstream literature for framing predictive models are also tested. The data has been cleaned and tracked strictly. The final choice for regressors using both univariate and multivariate methods has been conducted in specific experiments. The probability of incorrect results has been minimized by discarding or eliminating variables that have not proved their contribution to the success of the models in prior studies. Also, variables that have proven helpful in earlier studies in addressing the given model have been used. Variables that are strongly correlated that could give rise to multicollinearity problems or redundant variables are discarded. So, correlation analysis has been performed to determine highly correlated ratios. Linear regression was also used to calculate the variance inflation factor (VIF) of these ratios. This research agrees with past studies that a VIF of 10 is a decisive inflation factor.

Finally, eliminate the variables from the model that are contributing to the increase in the VIF **O'brien (2007)**.

1.8.3 Logistic Regression

It has been found that researchers prefer using "logistic models rather than discriminant analysis because logistic models do not require any assumptions about the distribution of predictors. A further advantage of logistic models is that they provide results in terms of probabilistic outcomes and do not require any score to be converted into probabilities, which can be an additional source of error. Logistic models assume that there is a certain probability that the firm will default for a firm with a given set of predictors. The dichotomous dependent variable takes 1 for a distressed firm or 0 for a healthy firm. Where x is the set of independent variables contributing to default and is the vector of unknown parameters. As the outcome of logistic regression is binary, y needs to be transformed so that the regression process can be used" **Ohlson (1980)**. The logit transformation gives the following:

$$\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \ldots\ldots + \beta_n x_n$$

$\beta_0 = \dfrac{\text{constant}}{\text{intercept}}$, $\beta_1 \rightarrow \beta_n$ = coefficients for n explanatory variables $x_1 \rightarrow x_n$.

$$P(Y) = \frac{1}{e^{-(\beta_0+\beta_1 x_1+\beta_2 x_2+\beta_3 x_3 \ldots\ldots\ldots\ldots\ldots + \beta_n x_n + \varepsilon_i)}}$$

$$\text{In}\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \ldots\ldots\ldots\ldots + \beta_n x_n$$

Where p = probability of financial distress, p / (1-p) = odd ratio

The outcome variable is binary in logistic regression, which results in a model that can predict the likelihood of an event. As with multiple linear regression, it is concerned with estimating model parameters, assessing model adequacy, and determining the relevance & meaning of computed parameters. Logistic regression is a statistical technique that utilizes a binary dependent variable, yi, to reflect the state of the business.

If the company is in "distress," the value 1 is assigned, otherwise 0 for “non-distress”. This regression technique is used to predict the likelihood that a company would be categorized, either in a healthy or distressed group. The study will use logistic regression to forecast financial distress for listed companies over one to three years. It will estimate the likelihood of a firm going distressed in year “d” based on accounting and non-accounting information from a previous year “d-x” in which “x” is one, two, or three years preceding the year “d”. In past studies, logistic regression is frequently described as a cross-sectional statistical method that results in a static model **Balcaen and Ooghe (2006)**. This study employs a seventy-thirty cross-validation method to estimate a static model on a sample and validate it on another independent sample: the entire dataset of one to three years before the year “d” is randomly divided into seventy percent cases and thirty percent cases: where seventy percent of cases are used to estimate models, and then the accuracy of those models is tested on the remaining thirty percent of cases.

1.8.4 Model Testing

The Chi-square test is for the goodness of fit for the model, which has the null hypothesis that intercepts, and all coefficients are zero. If the p-value is < 0.05, the null hypothesis can be rejected, which means the overall model is significant. To assess the goodness-of-fit of a model, various other measures are available. When assessing the goodness-of-fit of predictive models, this research further uses pseudo-R squares, Hosmer-Lemeshow test, classification tables, and the area under the curve.

1.8.4.1 The Pseudo-R-squares

Cox & Snell R Square and Nagelkerke R Square does not have corresponding R-squared value, which is used in the case of OLS regression. These values do not have the same interpretation for OLS regression and have only been used to make comparisons for different models. Nagelkerke R^2 is a further adjustment to Cox &

Snell R^2, as it does not attain a value of 1. So, it is *preferable* to report the value of Nagelkerke R^2. It is a measure of model ability to predict the dependent variable based on various independent variables. As the value increases, the stronger the fitness of the model. "The Hosmer-Lemeshow test (HL test) is a test of goodness of fit for the logistic regression model. A goodness-of-fit test determines how well an observed data set fits a set model" **Hosmer, Lemeshow and Sturdivant (2013)**. Like other fitness assessments, these smaller p values (generally below 5%) indicate that the model is a poor fit. But big p-values do not inherently suggest that the model suits well, but there is insufficient evidence to imply it is poor.

1.8.4.2 Classification Matrix for Model Accuracy

In previous studies, classification tables were used as a supplementary method to calculate the predictive distress accuracy of models. This research uses cross-validation of 70-30 to test the model. Data collected for one to three years before financial distress has been randomly divided into 70 percent and 30 percent cases. It is standard practice to use 70 percent of the cases to frame models before determining their accuracy in the remaining 30 percent cases. In a classification table, the outcome of crossing the initial variable and prediction variables, whose values are obtained from calculated logistic likelihood, can be expressed as effects of the fitted model. "The fitted model coefficients are used to classify the out-of-sample outcomes" **Hosmer, Lemeshow and Sturdivant (2013)**. For consistency of the classification model, i.e., the percentage of accurate model predictions, 0.5 is used as a cut-off in the projected classification table based on training and holdout samples. If the company's calculated probability of financial distress is > 0.5, the firm is expected to be financially distressed. Table 1.2 shows the cross-classification matrix of the outcome variable with dichotomized variable; if the estimated likelihood exceeds the cut-off point, then the computed variable is equal to one, or else it is equal to zero. If the estimated probability value is 0.5 or more, it will predict financial distress (as financial distress = 1) and healthy if it is lesser than 0.5 (as Healthy =0) **Bellovary, Giacomino and Akers (2007)**. The goodness-of-fit of a model is frequently evaluated using a classification table containing Type I and Type II errors. Table 1.2 summarises the two types of errors mentioned:

Table 1.2: Classification Matrix

Observed Predicted		
Classified	**Financial Distress firms**	**Healthy firms**
Financial Distress firms	Correctly predicted	Type -2 error
Healthy firms	Type -1 error	Correctly predicted

Source: Bellovary, Giacomino and Akers (2007)

The two types of errors are depicted in table 1.2. The classification of financial distress companies as healthy companies is a “Type I error,” whereas for healthy companies as financial Distress companies is a “Type II error”.

1.8.4.3 Area under the Receiver Operating Characteristics Curve

An alternative approach to calculating the predictive precision of a predictive model is a ROC curve, a plot of strike rate (sensitivity) versus false alarm rate (1-specificity) over all possible cut-off ranges. The steeper the ROC curves at the left and the greater the AUC, the higher a model’s predictive accuracy. The AUC reflects the possibility that a randomly selected failing company is more suspect of failure than a randomly chosen successful company. The ROC plot compares the likelihood of actual financial distress against the chance of mistakenly anticipated financial distress. This metric assesses the fitted model's ability to assign a higher likelihood to outcome y=1 than to outcome y=0. The Area under the ROC (AUROC) curve might have a value ranging from 0.5 to 1. An AUROC approaching to one implies that the model is more capable of distinguishing between the two outcomes **Hosmer, Lemeshow and Sturdivant (2013)**. There is a general principle; there is no discrimination in a model with an AUC of 0.5, satisfactory discrimination between 0.7 to 0.8, tremendous discrimination with 0.8 to 0.9, and outstanding discrimination with 0.9 or greater **Hosmer and Lemeshow (2000)**. If a model has perfect discriminating power, its AUC will be 1.

1.8.5 Survey Methodology

This survey aims to analyze the opinion of financial institutions on financial distress and related matters to financial distress as financial institutions are the most familiar with financial distress, which is one of the reasons for investigating their opinions. The risks faced by all the financial institutions have increased manifold. Banks are now confronted with innumerable challenges like worrying level of NPA, pressure of high profitability, managing better assets quality and, so on. A survey has been conducted to get valuable comments and suggestions to take financial institutions' opinions on prevailing financial distress. The survey findings would contribute significantly to gaining further insights related to prevailing financial distress in Indian companies and risk mechanisms, which will further help financial institutions frame policies and risk management practices.

A survey is an effective tool in recognizing different opinions and in gaining key perspectives from various stakeholders. Because this study is looking into the financial institutions' opinions, a semi-structured interview will be the most useful because the questions will be more likely to adhere to their view of what is happening in the actual world **Fetterman (2019)**. So semi-structured interview method has been opted to collect primary data from representatives of various financial institutions like banks and NBFC involved with different financially distressed firms. Respondents were Chief Manager, Assistant General Manager for various commercial banks and NBFCs in India dealing with various corporate loans. Data was collected through a field survey using a structured questionnaire facilitating face-to-face interviews with multiple bank officials and other persons dealing with financial distress firms. Out of fifty individuals contacted, only twenty-one have responded. The survey findings would contribute significantly to getting further insights into prevailing financial distress in Indian companies and risk mechanisms, which will further help financial institutions frame policies and risk management practices. There are four steps in data analysis, first, structuring the interview data; second, coding to classify the various categories; third, analyzing and fourth, summarizing and interpreting the data **Miles and Huberman (1984); Wolcott**

(1994); McIntosh and Morse (2015). The interviews are conducted through telephonic and face-to-face methods. The open-ended questions are used to gain rich and detailed descriptions of the phenomenon being studied. The interview questions in semi-structured interviews are based on prior information. Before the interview, questions are decided. **Kelly, Bourgeault and Dingwall (2010); Turner (2010); Kallio et al. (2016)**. This method proved suitable for analyzing respondents' opinions regarding the research themes **Kallio et al. (2016); Brown and Danaher (2019).** The investigator can ask respondents to comment on an opinion expressed during the interview by seeking even more details or a relevant example **Maxwell (2012); Kallio et al. (2016); Hershberger and Kavanaugh (2017); Brown and Danaher (2019)**. To check the face validity of the questionnaire, these items were presented to academicians and industry experts to examine whether the questions asked were appropriate. Some questions were deleted on experts' suggestions, some new items were added, and some were modified. The next step was pilot testing of the preliminary questionnaire. Pilot testing has been conducted to clarify responses **Bajpai (2011)**.

1.9 DESIGN OF STUDY

The rest of the thesis is organised into the sections:

Chapter One : pertains to introduction, need, objectives for the study, sources of data, research methodology for this study

Chapter Two : related to review of literature in this area of study

Chapter Three : deals in study of trends and patterns of financial distress in Indian companies.

Chapter Four : for developing a predictive model of financial distress using financial variables.

Chapter Five : evaluate the usefulness of market & macroeconomic variables in distress prediction

Chapter Six : analyze the opinion of financial institutions about financial distress of Indian companies.

Chapter Seven : relates to the summary, conclusion, and findings of the research.

Chapter – 2

REVIEW OF LITERATURE

2.1 INTRODUCTION

Any research cannot be accomplished without the assistance of past studies and other related work, which is available in the form of literature. The literature review aids in the identification of research gaps, as well as the prevention of duplication of work. Researchers can use this information to determine the best course of action for their research. Previous studies are discussed in detail in this part of the study, serving as a foundation for the current investigation.

2.2 PAST PATTERNS AMONG VARIOUS FIRMS

Hoshi, Kashyap and Scharfstein (1990) found that the probability of default increases for the companies with the high leverage ratio. The study further revealed that high debt limits investment and puts the firm's solvency in an alarming situation. **Bhaduri (2002)** found various factors impacting the capital structure choice of a firm, like size, growth, product features, and various characteristics of the industry. **Shirai (2004)** found that firms with a good track record in terms of profitability can quickly raise funding from the commercial paper market and reduce the level of loans post-Asian crises. **Moyen (2004)** companies under financing restraint are less cash flow-sensitive than companies with no financial restriction. **Martinez and Love (2005)** examined various patterns used by Indian firms for financing between 1994-2003; the result of the study found a stable debt-to- asset ratio but a slowdown in the nominal debt growth. It was found fall in the interest coverage ratio of the firms during Asian financial crises but improvement in the later years. There was a significant increase in borrowing from banks during these years, whereas the share of non-bank financing went down. The amount of debt taken by different firms increases with the firm's size and difficulty in raising debt by smaller firms. Young firms from the manufacturing sector have taken a lower level of debt from south India. **Saggar (2005)** analyzed the various patterns prevailing in investment and financing used by public companies in India. It was observed that the majority of Indian companies rely on external debt for different funding requirements. Still, there was a significant increase in funding from internal sources of finance in the subsequent years of the 1990s. Interestingly, there was a decrease in investment in inventory but an increase in the financial assets of the companies **Kashyap, Bansal and Nagale (2019)**. **Steyn Bruwer and Hamman (2005)** found that mature firms had more regular cash flow patterns, whereas firms in their growth phase had the highest investment outflow to achieve growth in revenues and assets. Start-up firms had the maximum inflow from financing activities. It was also found that cash flow patterns from operating, investing, and financing activities can be used to evaluate common characteristics of a company, as per the life cycle approach, which can further help to check its financial position. **Abraham and Omkarnath (2006)** analyzed kinds of trends and patterns about sickness in Indian large, medium, and small industrial units. The study revealed a larger share of the small-scale industry during the pre-reform period. In contrast, during the post-reform period, it was dominated by large and medium industrial units. A study found a decline in the amount recovered from sick units in the post-reform period, which proves the ineffectiveness of BIFR to revive and detect sick units at their initial stage. **Douma, George and Kabir (2006)** investigated how foreign ownership affects the performance of various companies in developing countries. The result showed the positive effect of foreign ownership on the firm. Still, the impact of foreign institutional ownership cannot be determined in a clear-cut manner, so there is a need to make a distinction between the influence of corporate & institutional ownership on business performance. **Nanda and Panda (2018)** investigated the impact of size on the profitability of Indian manufacturing firms. The result showed a positive influence of firm size on profitability in the steel sector and negative impact in case of electrical & electronics sector. Other attributes like retained earnings were found to have a negative impact on earnings in the steel sector but positive in the case of the electrical & electronics sector. In contrast, bank credit was found to have an adverse effect on the firm performance of both sectors. As per the study done by **Lins, Volpin and Wagner (2013)**, during economic downturns, family-controlled businesses cut their investment compared to other businesses**.** These investment decisions impact performance since corporations that cut investment, experience more significant stock price falls during the crisis. Further, when a family controls numerous enterprises in a group, and one of the firms in the family group is severely impacted by the crisis, the family cuts investment in the other relatively strong group firms. Overall, the study highlighted a conflict of interest as a justification for the lack of performance of family-controlled enterprises during the crises. **Koh et al. (2015)** found early-stage companies are more inclined to downsize their workforce, whereas mature companies are more likely to engage in asset restructuring. The impact of the life cycle is especially noticeable when it comes to financial restructuring methods such as dividend reductions or capital structure changes. **Kota and Singh (2016)** found that non-family businesses outperform family businesses in terms of profitability, size, market position, debt position in listed companies in India. Family successions can harm a company's performance in a variety of ways. For instance, they reduce the number and quality of the pool of potential successors. Professional managers are a self-selected group of highly motivated individuals, but family heirs may lack the skills and motivation to run the organization effectively. Furthermore, irrespective of the characteristics of family successors, companies under heir control may not perform; if the family company has a long tradition of fulfilling implicit agreements with stakeholders, such as employees or local associations, which are costly for the company but provide indirect benefits to the founding families **Pérez-González (2001)**.

Many studies find evidence in support of improving corporate performance under foreign ownership. **Binti, Zeni and Ameer (2010)** found that the probability of turnaround of financially distressed firms is dependent upon the degree of distress, liquidity, and size of the firms. **Dickinson (2011)** applied a cash flow pattern as a proxy to capture the life cycle of a firm and found it to be better than other life cycle proxies like age, size for knowing the future profitability of firms. **Sane and Thomas (2012)** examined borrowing patterns in Indian firms. It was found that firms with large sizes prefer the bond market route for financing, and those firms with a size of assets less than 1000 cr prefer banks for getting credit to have easy access. A significant portion of debt financing is routed through foreign investment in the Indian bond market. **Agrawal and Chatterjee (2015)** found companies under distress put a lot of stress on their stakeholders. A study conducted by **Shamsudin and Kamaluddin (2015)** looked at various cash flow patterns in publicly traded Malaysian companies from 2006 to 2013 to identify those most likely to experience financial distress. The study found that firms that cannot meet short-term obligations from operating cash flows can come under financial distress. Firms facing distress generally have negative cash flow from operating, investing, and financing activities and take funding from external sources of finance due to inadequate operating cash flows. The result showed a significant difference among cash flow patterns of both financial distress and sound firms. **López-Gutiérrez (2015)** examined the decisions related to investments among the firms facing financial trouble. It was found that firms in financial crisis consider only those opportunities, which would eventually assist them in preventing them from avoiding bankruptcy. In this dilemma, these firms usually miss other lucrative opportunities which can be otherwise more profitable for these firms.

Hintošová and Kubíková (2016) examined the impact of ownership by foreign entities on the performance of the companies. The result found that companies with foreign ownership of up to 65% perform better, but subsequent ownership increases negatively impact. As per the study done by **Udin, Khan and Javid (2017)**, foreign ownership is negatively associated with the likelihood of financial distress. It may be because foreign investors are much more profit-driven and have several motivations to supervise business management, decreasing the probability of financial difficulty. According to the agency theory, a dispersed ownership structure can strengthen corporate governance and decrease the probability of business failures. **Tandon (2016)** examined the companies' attributes behind the survival and death of firms in India. The study found that some of the inefficient firms with very small market shares survived with foreign affiliation. Also, the result revealed that some of the firms may have closed for tax evasion and external factors have more roles to play than internal factors to decide the fate of a business. **Ahamed and Mallick (2017)** studied the impact of restructured assets on bank risks in India. It was found restructured assets helped banks in reducing their level of risk by having lower loan provisions. **Sridharan and Joshi (2018)** explored the link connecting firm ownership patterns with its financial performance through different life cycle stages in BSE 500. The study found the performance of firms that are closely held superior to widely held and firms with a significant share of foreign promoters performing better across various stages of the life cycle.

2.3 ISSUES PERTAINING TO FINANCIAL DISTRESS

Gugloth and Kumar (2011) found that while small firms succumb to external issues such as a lack of infrastructure & funding and promotion difficulties, big & medium size firms succumb to internal issues such as mismanagement, access to raw materials & working capital. **Fatoki (2014)** identifies both internal and external factors as contributing to the failure of SMEs. Among the internal issues include a lack of managerial expertise, a lack of competence, inadequate skills development for employees, and a lack of positive customer service attitudes. Among the external obstacles are the lack of a logistical network and a significant warehousing cost, competitive pressure, increasing business costs, a lack of capital. **Navulla, Golla and Sunitha (2016)** examined the reasons behind industrial sickness from previous studies. According to the findings of the study, the key reasons for failure in Indian companies were a lack of capital, labour-related concerns, a lack of efficient management, technical developments, the availability of power, and globalisation. As per **Rafailov (2011)**, credit ratings are critical to the proper operation of bond markets. Credit rating agency failures exacerbated the adverse effects of the financial crisis, introducing more market risk. The agencies' faults can be attributed to a variety of factors, including business structures, ethical violations, and the absence or inefficient supervision of their services. We can take a variety of techniques to resolving these significant issues. The optimal strategy is to enhance regulatory processes while also limiting rating agencies' regulatory authority. According to the findings of **Jollineau, Tanlu and Winn (2014)**, credit ratings are at their highest when the borrower pays for the ratings. The report advocated a change to the "issuer pays" approach, which would remove the existing incentive for credit rating agencies to prejudice their decisions. Secondly, justification will be required, in case of any deviation of rating from the result of their quantitative assessment models, so eliminating the chance to influence credit scores. According to **Bose, Filomeni and Mallick (2021)**, troubled enterprises are able to perform better as compared to healthy enterprises because of increased credit availability and reduced costs of financing during the post-IBC era. Moreover, the research showed that gains resulting after the adoption of the IBC are more pronounced in the case of financially troubled enterprises that are bigger, young, & better collateralized than in the case of other firms.

2.4 FINANCIAL VARIABLES USED IN PREVIOUS STUDIES

Predictions of financial distress are becoming an increasingly significant issue in financial decision-making. The worldwide financial meltdown highlighted the weaknesses in risk models used in credit risk management **Jorion (2009)**. The issue of financial distress has caught the attention of many researchers from the past several years. The rising incidence of industrial illness has been a significant factor in the sharp slowdown of a country's economic and overall financial health. As a result of the financial crisis, many businesses worldwide are at risk of going out of business. It was emphasised that even strong companies must monitor their creditworthiness and the economic condition of the companies with whom they do business on a regular basis **Korol (2013)**. In an era when creditors are confronted with defaulting enterprises, it is vital to foresee corporate distress using some model **Wang and Xia (2014)**. It is necessary to avoid and treat financial stress for new investment to reveal itself in the economy with the shortest possible time lag. Furthermore, in a capital-strapped country, it is critical to identify distress at the appropriate time to avoid wastage and under-utilization of new funding. Thus, it is crucial that businesses avoid distress by developing an efficient prediction model **Čámská (2016); Zhao et al. (2017); du Jardin (2017); Veganzones and Séverin (2018); Altman et al. (2020)**. This advance warning will help management take appropriate steps and decisions to avoid financial distress, which will help mitigate the cost associated with financial distress and resulting business failure **Wu, Gaunt and Gray (2010)**. The selected variables in the distress prediction models can be measured to reflect possible adverse developments **Kliestik, Vrbka and Rowland (2018)**; **Karas and Režňáková (2018); Veganzones and Séverin (2018)**. Reviewing the earlier studies shows a trend of changes in the choice of variables in the distress prediction model **Grice and Ingram (2001); Sulub (2014)**; **Boďa and Úradníček**

(2016). Initially, researchers have used only accounting variables while framing various models, but now several other variables such as market and macroeconomic variables are also being considered for testing various models **Nam et al. (2008)**. Using market and macroeconomic variables together with financial ratios will lead to the better accuracy of designed models **Agarwal and Taffler (2008)**.

Research on financial distress has primarily concentrated on specific indicators distinguishing between a non-distress & distressed organization **Niemann, Schmidt and Neukirchen (2008)**. **Beaver (1966)** model of predicting financial distress with financial ratios on a sample of firms using univariate analysis. The study found that cash flow-to-total debt as the best predictors of failure, but the predictive power of liquid asset ratio was found weak. The result found a better classification of non-failed firms as compared to failed firms by using financial ratios. **Altman (1968)** derived a prediction model with multiple discriminant analyses for publicly held manufacturing corporations. The model used five different financial ratios (Working capital-to-total assets, Retained earnings-to-total assets, Earnings before interest and taxes-to-total assets, Market value of equity-to-Book value of total debt, and Sales-to-Total assets from an initial set of twenty-two ratios. These financial ratios were taken based on their recognition in the prior studies and their significance. **Ohlson (1980)** used ratios like current ratio, working capital-to-total assets ratio, total liabilities-to-total assets, net income-to-total assets ratio, funds applied from operations-to-total liabilities for classification between distress and non-distress firms. **Altman, Marco, and Varetto (1994)** concluded that financial indicators such as capital structure & debt coverage were significant predictors of insolvency in firms operating in Italy. **Lennox (1999)** explored the cause of insolvency in a sample of UK companies and found profitability, debt, cash flow as the key financial distress factors. **Altman (2000)** developed a ZETA model for estimating a firm's financial distress using financial ratios. This model resulted in significant advancements in predicting a company's bankruptcy for one year in advance. **Gu (2002)** estimated a model for the examination of US bankruptcy in restaurants. According to the model, restaurant businesses with low profitability & a high total liability are more likely to file for bankruptcy. The analysis based on financial ratios variables indicated that failed restaurant companies could have relied heavily on leverage to fund growth venues without adequately managing operating and funding costs. To restaurant companies with low Z values and a high probability of bankruptcy, modification of their growth plan and financing policy is recommended. The study suggested that restaurants should follow a strategy with less debt funding and stronger cost management to reduce bankruptcy risk. **Charitou, Neophytou and Charalambous (2004)** explored using financial ratios to forecast UK firms' financial distress. The study found cash flows, leverage, and profitability as critical determinants in predicting future difficulties. **Hussain et al. (2005)** used financial variables for predicting potentially financially distressed firms in Malaysia. The model showed that the likelihood of distress is negatively impacted by current ratio and acid ratio. The current asset ratio was found the most important in assessing the financial distress results. **Bose (2006)** determined whether financial ratios could forecast financial distress based on available information. The study found a return on equity to total assets, sales to market capitalization, and sales to total assets variables, three main predictors. However, the accuracy of the testing or validation sample classification was satisfactory but smaller than that shown in previous research. **Jayadev (2006)** found primary differences between defaulting and non-default companies are: current ratio, debt-equity ratio, operating margin, pre-interest income, and net debt value. **Wu, Gaunt and Gray (2010)** reviewed models of financial distress in the literature and concluded that they provide unique information on the probability of the distress, but their output varies with time. The study found the most important accounting ratios as efficiency, liquidity, and leverage. Specifically, companies are more prone to experience financial difficulty if the profit before interest & tax on total assets is comparatively smaller, net income losses are higher, total assets are relatively small, with high market leverage. **Pal (2013)** assessed the financially healthy and distressed steel companies in India by applying discrimination analysis. The study began with eight ratios selected from various types such as profitability, liquidity, solvency & efficiency. The result found that three ratios, such as return-on-investment, debtor turn-over ratio, and fixed asset turn-over ratio, are significant for distress prediction. The study suggested that steel companies should boost investment returns by introducing an effective debtor and fixed asset management strategy to safeguard their financial health. **Gupta (2014)** investigated the performance of the prediction models using accounting ratios of the firms. The study's goal was to build a model that will use specific financial variables to predict whether or not a business will go insolvent in the future. The study found a decline in sales & net-worth, non-provision of depreciation, and surplus stock as significant variables. **Bredart (2014)** developed a model that can predict bankruptcy using three financial ratios equity-to- total assets for the solvency, the current ratio, and net income-to-total assets for Belgian's small and medium enterprises. **Nanayakkara and Azeez (2015)** done the company's financial distress prediction using cash flow and other financial information for Sri Lankan firms. The study found earnings before interest and taxes, cash flow from sales-to-total debts, retained earnings-to-total assets as significant variables. **Tian, Yu, and Guo (2015)** investigated the role of accounting variables in forecasting business default risk and came to the conclusion that these variables could be used to forecast financial distress. **Lin et al. (2016)** investigated the issue of the default forecasting model for listed Chinese firms using Altman's scoring approach**.** The result found accounting-based determinants from financial statements can be distorted credit risk factors. **Boa and Radnek (2016)** investigated if the z-score model, which incorporates financial ratios, might be used to predict corporate insolvency for Slovak enterprises during periods of economic downturn. The study found this technique quite helpful in determining the precise estimation of failed companies during a recessionary phase. **Lakshan and Wijekoon (2017)** developed a model for anticipating the distress of publicly traded companies in Sri Lanka. The findings indicated that different accounting factors have a high degree of predictability, which management can use to their advantage to avoid financial distress within respective businesses. A study conducted by **Misund (2017)** examined the financial distress prediction models used in the Salmon industry by non-financial businesses. According to the study's findings, companies may be in distress if specific ratios such as the fixed asset turnover ratio and the liquidity ratio of the firm decline significantly. **Karas and Reáková (2018)** conducted a study in which they examined numerous financial ratios for their ability to forecast insolvency in the case of Czech companies. The study discovered that ratios such as "stock turn over ratio, earnings before interest and tax-to-interest, stock-to-total assets, sales-to-operating revenue, sales-to-current liabilities, earnings before tax, depreciation & amortization-to-total assets " were the most critical indicators. **Kliestik, Vrbka, and Rowland (2018)** found ratios like net profit-to-total assets, current liabilities-to-total assets, return-on-equity, cash and cash equivalents-to-total assets significant for distress prediction. **Charalambakis and Garrett (2019)** found accounting variables like leverage ratio, retained earnings-to-total assets ratio as strong predictors to estimate the likelihood of financial distress. Studies done by **Jenkins, Kane and Velury (2009)**; **Bottazzi et al. (2011)**; **Du Jardin (2018); Veganzones and Séverin (2018)** found positive relationship between debt-to-equity ratio and likelihood for distress, which further indicates that the use of debt as the funding tool raises the potential default resulting from the company's failure to repay loans. Since the advent of artificial intelligence algorithms, like neural networks, several studies have investigated artificial intelligence algorithms to discriminate between sound and stressed businesses. According to experts such as **Iturriaga and Sanz (2015)**, a neural network approach can be applied to forecast financial distress in firms using financial indicators.

2.5 MARKET VARIABLES IN FINANCIAL DISTRESS PREDICTION

Financial distress prediction models developed depend primarily on accounting data. Financial ratios derived from company profits and balance sheets are usually calculated after **Beaver (1966)** and **Altman (1968),** as accounting statistics are readily available and somewhat structured. Earlier models used financial ratios derived from financial statement pre-distress and worked well both in-sample and out-of-sample. However, although these data offer significant advantages in predicting financial distress, they suffer several inconveniences, including manipulation. Consequently, if the quality of accounting information is questionable, one may wonder how these changes can influence the accuracy of financial distress prediction models. The literature has made an ongoing effort to create many more predictive models. A significant innovation in literature has been integrating capital market data in financial distress prediction models, such as stock excess returns and stock return volatility. **Van Der Colff and Vermaak (2015)** demonstrated that integrating accounting variables with non-accounting variables resulted in a more accurate prediction of financial distress. Recent scams indicate that the trustworthiness of the information in financial statements like cash flow statements, balance sheets, and profit /loss statements is always questionable**.** A firm can do manipulation of various financial statements to hide the underlying distress. **Lin, Lo and Wu (2016)**. **Du Jardin (2018); Veganzones and Séverin (2018)** found that businesses may try to present their financial statements according to different circumstances and thus distort their actual financial image. It was found that earnings management can influence financial variables and affect any model based on accounting data. So, taking additional variables along with accounting variables may help increase the accuracy level of distress prediction models. When additional variables are used, prediction accuracy in the sample improved **Nanayakkara and Azeez (2015); Barboza, Kimura and Altman (2017)**. Apart from financial variables, other variables have also been considered to improve the predictive accuracy of default prediction models or explain business stress causes. Those efforts include incorporation of market variables **Nanayakkara and Azeez (2015); Duffie, Saita and Wang (2007); Li and Faff (2019)**. **Shumway (2001)** used market capitalization and volatility of stock return in his study. Market capitalization was taken to reflect the fact that when a firm approaches default, it is usually discounted by the market. The volatility of stock return was considered because higher volatility of the stock is caused by higher volatility of cash-flows, which puts a firm at higher risk of not being able to meet its interest payments. **Chava and Jarrow (2004)** demonstrated that market variables reflect all publicly available information regarding firm distress. It was shown that the predictive power of the market-based model would significantly outperform an accounting-based model as stock prices discount the company's future financial position. Furthermore, **Beaver, McNichols and Rhie (2005)** provided evidence in favour of this viewpoint by demonstrating that including market-based factors increased the forecasting capacity compared to using solely financial metrics. **Campbell, Hilscher and Szilagyi (2008)** further propose using the logarithm of market capitalization to that of the S&P 500 index. The results obtained from a market variables-based prediction model indicate that the financial distress variable was negative in terms of market capitalization, overall debt, & stock prices.

2.6 MACROECONOMIC VARIABLES IN FINANCIAL DISTRESS PREDICTION

Despite the increase in research efforts in the last decade in terms of distress modelling, few studies have incorporated the effect on corporate distress of macroeconomic conditions. **Hol (2007); Carling et al. (2007); Nordal and Syed (2010); Bhattacharjee and Han (2014); Mahtani and Garg (2018)**. From the last few years, there has been increasing focus to examine how business failures are impacted by macroeconomic changes **Jacobsen and Kloster (2005); Giesecke et al. (2011)**. Macroeconomic variables are added to the model to correct the variable of mismatch in timing. Macroeconomic covariates help to observe macroeconomic changes through time. Macroeconomic variables are not taken as predictors, but they should be taken as control variables. The purpose is to include controls for the state of the economy as the sample observations are arranged in an event time. However, unlike firm-specific covariates, macroeconomic factors vary over time but not by case. So, for all companies existing in a period, macroeconomic conditions will have the same impact **Agarwal and Taffler (2008)**. **Tirapat and Nittayagasetwat (1999)** combined financial characteristics with macroeconomic variables. The study examined various macroeconomic variables like monthly changes in production manufacturing index, consumer price index, interest rate, and money supply for assessing the effect on financial distress in the case of firms in Thailand. The findings suggested that macroeconomic conditions are crucial indicators of a company's future financial crisis. The study indicated that the more inflation-sensitive a corporation is, the greater the company's vulnerability to financial distress. **Liu (2004)** studied the robustness of the prediction model by including macroeconomic factors like fluctuations of foreign exchange and interest rates as a proxy for various macroeconomic changes. The result showed that the accuracy of financial distress prediction increases by incorporating macroeconomic variables in the model. **Rosch and Scheule (2005)** developed a multifactor model for estimating default rates. It was found that default rates fluctuate cyclically, and systematic risk factors have some degree of influence on it. The result suggested that identifying these risk factors and incorporating them into the primary model improves model performance and reduces the possibility of model misspecification. **Hol (2007)** framed the financial distress prediction model to analyze unlisted companies in Norway based on their financial and macroeconomic variables. By contrast with financial statements alone, this approach increases the distress forecast. Macroeconomic variables such as the GDP, money supply M1, the industrial production index were found significant. The use of this model can increase the likelihood of identifying distressed companies. **Carling et al. (2007)** framed a model during 1994 and 2000 of default in the corporate loan portfolio in Sweden banks. The model considers various financial ratios and macroeconomic variables like the yield curve and customers' future economic growth expectations using a Monte-Carlo simulation approach. In addition to different popular financial ratios, the study discovered that macroeconomic variables have strong explanatory power for corporate default risk. **Liu (2009)** examined the corporate failures in the U.K. concerning various macroeconomic factors. The study explored whether macroeconomic factors could consider the observed fluctuations in the period 1966–2003 of business failures. The study found that failures can be impacted by various macroeconomic conditions like credit policy, and inflation. **Bonfim (2009)** examined the linkage between credit risk and macroeconomic developments like CPI, inflation, bank interest rates, bond yields, and GDP. It was found that by taking macroeconomic variables, the accuracy level of estimating potential default increased significantly. Similarly, **Figlewski, Frydman and Liang (2012)** tested different macroeconomic & company-related rating values of various firms in the period 1981–2002. The result found that the probability of a default occurrence is highly affected by both types of factors included. **Michala, Grammatikos and Ferreira Filipe (2013)** framed models of distress prediction for non-financial SMEs using a dataset of eight European countries during the 2000-2009 period and validated the superiority of models which integrate macroeconomic variables like exchange rate. **Agrawal and Maheshwari (2014)** identified and examined the effect of the macroeconomic situation in forecasting financial distress. This study examined the interrelation of the rate of decline of businesses with different macroeconomic variables like credit availability, economic cycles, and investor confidence. It was found that one of the most important reasons for failure is credit squeeze, particularly in the period of restrictive monetary and debt policy. **Mare (2015)** analysed the impact of economic conditions on the small bank failure in Italy by taking variables like interbank deposit rate, region unemployment. The result found an increase in failure risk of banks with deteriorating economic conditions. Corporate distress is unwanted, and advance recognition of imminent distress is often desirable. The detection and implementation of corrective steps of financially distress companies are better than security under bankruptcy law.

2.7 MODELLING TECHNIQUES USED

The early techniques of financial distress modeling were typically focused on a univariate strategy, multivariate method, financial variables, and other estimation techniques to boost prediction accuracy **Keasey and Watson (1991); Prado et al. (2016); Altman et al. (2020)**. Different researchers have used various techniques to estimate the financial distress prediction depending upon the nature of the sample taken in different countries across the world. In the previous studies, techniques like multiple discriminant analysis, logit model, etc. were frequently used **Altman and Narayanan (1997); Bellovary, Giacomino and Akers (2007); Achim, Mare and Borlea (2012); Prado et al. (2016); du Jardin (2018)**. Earlier univariate methods were quite popular for modeling financial distress prediction. **Beaver (1966)** used this method for classification between distress and sound firms. The significance of each financial ratio was determined individually as per its ability to correctly discriminate between the two groups of firms. Hence, if a firm value is higher than a particular cut-off point, then it would signify a sound financial position otherwise weak. **Pal (2013)** assessed the financially healthy and distressed steel companies in India by applying discrimination analysis, as multiple factors determine a company's financial position, so a single ratio cannot explain the phenomena accurately. **Altman (1968)** developed a multivariate discriminant analysis model where a z-score was estimated to observe the distress among firms. The focus of multivariate analysis was to incorporate the values of different ratios into a single weighted index rather than taking one ratio at a time, as in the case of univariate analysis. This technique has been used by other researchers like **Blum (1974)** and **Karels and Prakash (1987)**. **Peres and Antão (2017); Kliestik, Vrbka and Rowland (2018)** found multiple discriminant analyses as being inadequate to assess the company's financial health instead of other approaches. Further**, Ohlson (1980); Lennox (1999; Westgaard and Vander Wijst (2001); Shumway (2001)**; **Charitou, Neophytou and Charalambous (2004); Crone and Finlay (2012); Nanayakkara and Azeez (2015)**; **Jabeur (2017); Sayari and Mugan (2017)** used logit and probit models in prediction of distress among companies and found these techniques to be the reliable classifier of distress companies**.** It is based on a cumulated logistic probability function, and this model will give probability whether a particular company is in financial distress or a non-distress state **Maalouf (2011)**; **Klieštik, Kočišová and Mišanková (2015).** Similarly, **Mahtani and Garg (2020)** found that a logistic regression model performance using financial factors is accurate when assessing an airline's financial distress in India. Apart from the traditional statistical techniques, artificial intelligence and machine learning approaches have replaced statistical methods and were also used by various researchers **Jones, Johnstone and Wilson (2017)**; **Camska and Klecka (2020)**. These methods comprise neural networks, fluctuating logic, supporting vectors, & group classification approaches. **Aziz and Dar (2006)** found predictive accuracies of various predictive models of business bankruptcy are typically comparable. **Chen and Du (2009)** found both artificial intelligence (AI) approach, and traditional statistics, appropriate methodology for anticipating a company's probable financial distress. **Barboza, Kimura and Altman (2017)** found both machine learning & traditional models demonstrate reasonable accuracy. **Altman, Marco and Varetto (1994); Tsai, Lee and Sun (2009); Iturriaga and Sanz (2015)** done default prediction using neural network modelling techniques. "A neural network technique is a multilayer perceptron for financial distress prediction. In this method, the hidden layer determines the mapping relationships between input and output layers, and the relationships between neurons are stored as weights of the connecting links. Neural network technique has some advantages over the traditional statistical methods due to its strong mapping ability based on the network structure, and there is greater diversity in certain areas than traditional approaches" **Jo, Han and Lee (1997); Hosaka (2019). Delina and Packova (2013)** found good performance of neural network techniques for distress prediction. While neural networks provide many advantages, classical statistical methods are still the most widely used. Also, in this method, the statistical relationships among the various factors are not necessarily to be taken into consideration **Wilson and Sharda (1994); Bellovary, Giacomino and Akers (2007)**; **Alaka et al. (2018)**. But due to its complex nature, researchers generally found it difficult to apply. Moreover, it is unable to provide any evidence on the predictive variables' relevance. As a result, determining the contribution of the predictor variables to predicting financial distress is more complicated. Another artificial intelligence technique, support vector machines, was applied by **Min and Lee (2005); Yang, You and Ji (2011); Musa (2013); Cartus, Bodnar and Naimi (2020)**. Recently, **Kim, Lee and Ahn (2019)** used support vector machines (SVMs) to boost the accuracy of financial distress prediction models. SVMs only need small samples of training and have little overfitted. "It is based on the structural risk minimization principle rather than the empirical risk minimization principle. A support vector machine is a commanding and promising data classification and function estimation tool" **Shin, Lee and Kim (2005)**. But after comparing the accuracy of support vector machines with neural networks, both **Bose (2006); Barboza, Kimura and Altman (2017)** found this technique less effective as compared to the later one. According to **Geng, Bose and Chen (2015)** performance of neural networks are more reliable than other classification methods like support vectors machines. Support vector machines are often criticized because of their architectural drivers **Kim, Lee and Ahn (2019)**. **Lin (2009)** studied financial distress prediction techniques and built reliable models for Taiwanese companies. According to the findings, logit and neural networks methodologies, which were applied in this investigation, were found to be more accurate and generalised. However, the neural method will get greater predictive precision if the data does not follow the statistical assumptions. The models adopted in this research were useful in predicting the likelihood of a firm failure in Taiwan for investors, creditors, executives, auditors, and regulatory agencies. **Zhao et al. (2017)** proposed an efficient prediction of bankruptcy using the KELM approach. The results obtained demonstrate proposed KELM served as an effective early warning system with excellent performance in bankruptcy prediction. Overall, **Chen (2011)** suggested that an artificial intelligence solution might be a more effective technique than conventional statistics for very short-term analysis of a company's potential financial distress, whereas the logistic method, on the contrary, increases prediction accuracy over the medium to long term. Logistic regression is more capable of an extrapolation than neural networks. According to the study, while neural networks offer superior classification and managing complex underlying relationships, logistic regression provides a superior solution approach and interpretability. Additionally, although the weights obtained by logistic regression are straightforward to read, the weights for the neural network model are more challenging to explain. Thus, logistic regression outperforms neural networks in extrapolation since it fits a statistical relationship rather than identifying patterns **Kumar, Rao and Soni (1995); Delina and Packova (2013); Musa (2013); Alaka et al. (2018)**. The logit model is less complex and can be easily interpreted; it precisely estimates the likelihood of failure **Maalouf (2011)**; **Klieštik, Kočišová and Mišanková (2015)**.

2.8 RATIONAL AND RESEARCH GAP

A timely prediction of financial distress is a significant problem in the present economic environment, given the impact of the global financial crisis on world business over the past decade. The worldwide financial crisis has exposed the severe weaknesses in the risk models used to handle credit risk, and available models on distress prediction lack in terms of their accuracy. Financial distress literature concludes that they provide unique information on the probability of financial distress, but their output varies with time and region. The recession has shown that even the best businesses in the world always need to track their economic conditions and those of the companies they deal with. In the light of the literature review undertaken, it has been found that previous studies (particularly in India) have not considered the combined effect of financial ratios, market and macroeconomic variables for predicting financial distress in the Indian context comprehensively. Secondly, with the introduction of new insolvency and bankruptcy law in 2016, there is an urgent need to develop distress prediction models for early warning of financial distress for enterprises under this legislation. This research focuses on the usefulness of accounting, market, and macroeconomic variables to predict the financial distress of listed companies in India, referred to both BIFR and IBC. Third, past research on the financial distress of listed firms estimated financial distress one year in advance. The present study has estimated financial distress for up to three years. Building a new model with key variables and adding a new variable is necessary to increase these models' efficiency. The models are intended to provide more precise findings than prior academic studies.

Chapter – 3

TRENDS AND PATTERNS AMONG VARIOUS LISTED FIRMS

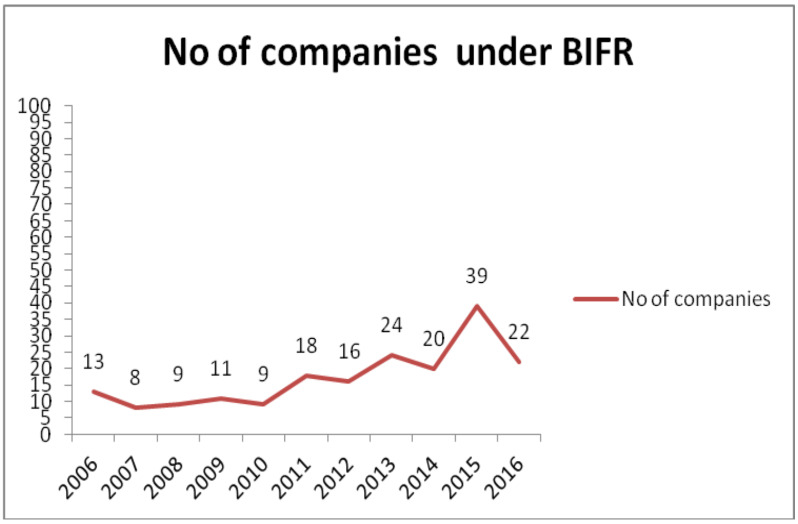
3.1 INTRODUCTION

In the past decade, due to the booming economy and increase in financial savings, there has been a phenomenal increase in investment in stock markets via mutual funds, insurance companies, and direct investment routes. With the growing default risk in India's listed companies in recent years, investors in these firms are concerned about these firms' performance and financial health to protect their capital. In this study, an attempt has been made to conduct the trend and pattern analysis of financial distress prevailing in the listed companies in India and draw some conclusions for various stakeholders. The study has been undertaken to outline the trends and patterns in financial distress in Indian firms. The study assesses the prevailing direction of corporate distress using five important ratios like interest coverage ratio (ICR), debt to market capitalization (DMCAP), current ratio (CR), debt-equity ratio (DER), and net profit margin (NP), to assess financial vulnerabilities of India's nonfinancial corporate sector since 2005. The study's findings will assist policymakers and creditors in understanding the underlying trend and taking preventive measures such as imposing strict credit terms and conditions or increasing risk weight. Because investment in equities is classified based on size, sector, ownership, etc., so there is a need to investigate the magnitude and composition patterns of financial distress in listed space. So, the study investigated financial distress patterns among various firms referred under both Board for industrial and financial reconstruction (BIFR) and Insolvency & Bankruptcy Code (IBC). Data has been further analyzed by taking a percentage of the number of firms found under a particular pattern to a total number of firms under the study.

The result of the study will assist investors in understanding the extent and composition of financial distress in India, which will help in asset allocation, portfolio diversification, and churning of their equity portfolios. In addition, the result of the study will benefit regulators, lenders, and investors in their decision-making process.

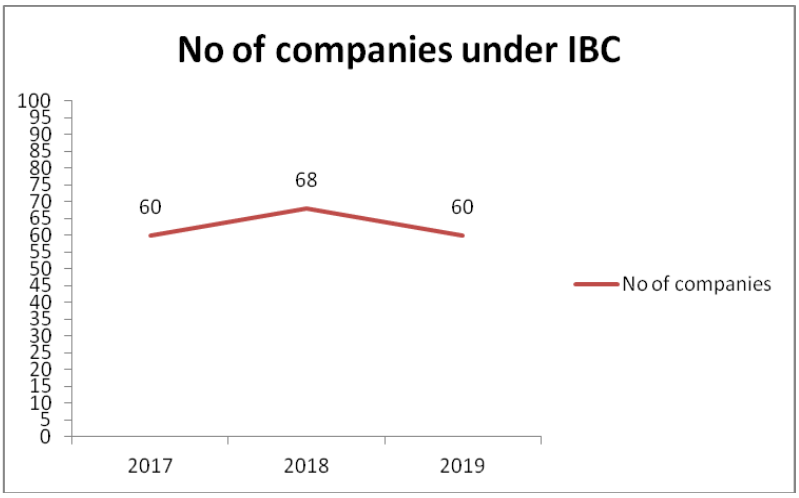
3.2 RESULT AND ANALYSIS

3.2.1 Year Wise Number of Listed Companies



Source:BIFR database

Figure: 3.1: Year wise number of listed companies referred under BIFR



Source: NCLT Database

Figure: 3.2: Year wise number of listed companies referred under IBC

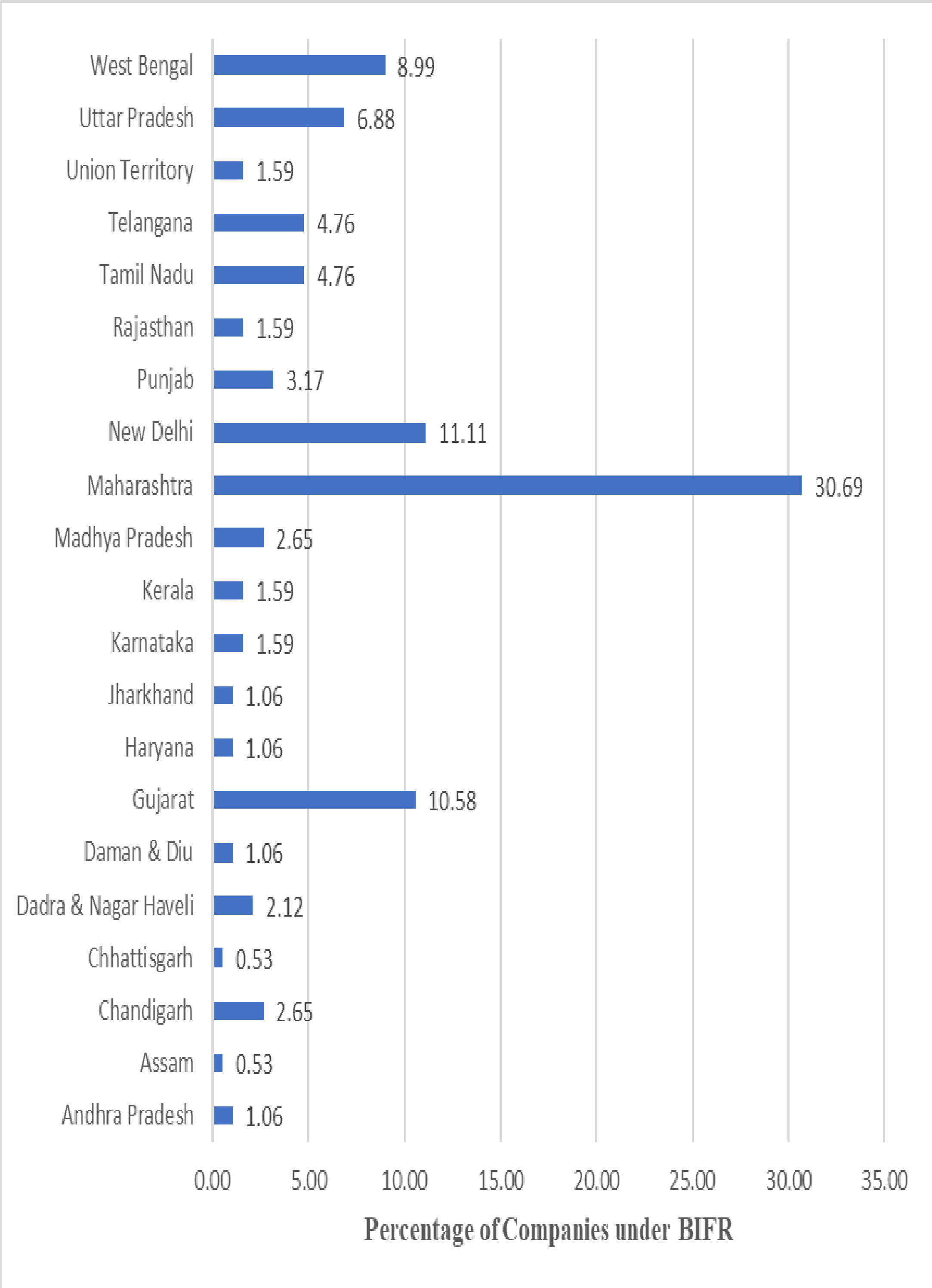
According to the above figure 3.1, the number of firms referred to BIFR has increased significantly after the global financial crisis, as the number of listed companies referred increased from 8 in 2007 to 18 in 2011**,** compared to just 9 before the crisis hit the global financial system. The number of listed company cases referred to BIFR has further increased to 39 in 2015 because of depressed earnings, the highest level in more than a decade. The BIFR, established in 1987 under the SICA, assists distressed businesses in rehabilitating possibly viable units & closing others. Because the board also provides protection from lenders, it is frequently used as a haven from creditors. As a result, both genuine distress and an effort to deter off creditors have led to a rise in referrals to BIFR. IBC, **2**016 is a major reform for India. It fundamentally alters the way a company handles stress. According to figure 3.2, there has been a huge surge in the number of listed companies registered under IBC law due to the strain on the balance sheets of various firms. From 2017 to 2019, the number of cases reported under the IBC law increased to more than 60. Liquidity shocks of demonetization and disruption caused by goods and services tax significantly impacted corporate finances, resulting in an overall slowdown in the Indian economy and financial stress in the corporate world. In addition to that, aggressive use of the bankruptcy code by lenders, even with the smallest delay in loan repayments, has also contributed to the rise in admitted cases during this period.

3.2.2 Statewise Companies

Table 3.1 : Statewise Pattern: Number of Companies under BIFR

State	No of Companies under BIFR
Andhra Pradesh	2
Assam	1
Chandigarh	5
Chhattisgarh	1
Dadra & Nagar Haveli	4
Daman & Diu	2
Gujarat	20
Haryana	2
Jharkhand	2
Karnataka	3
Kerala	3
Madhya Pradesh	5
Maharashtra	58
New Delhi	21
Punjab	6
Rajasthan	3
Tamil Nadu	9
Telangana	9
Union Territory	3
Uttar Pradesh	13
West Bengal	17

Source: Author ‘s calculations based on company data from BIFR website



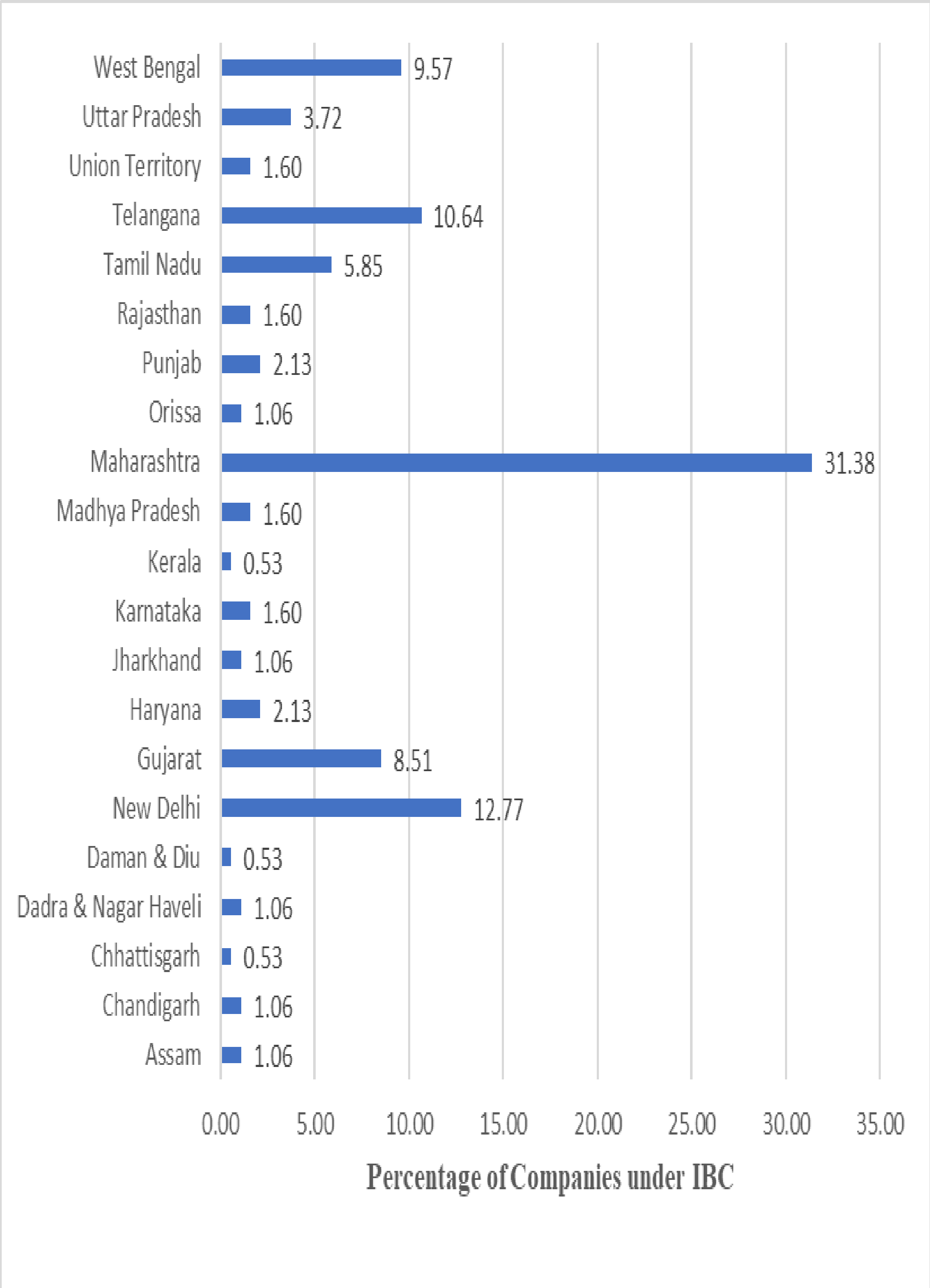
Source: Author 's calculations based on company data from BIFR website

Figure 3.3 : Statewise companies referred under BIFR

Table 3.2 : Statewise Pattern: Number of Companies under IBC

State	No of Companies under IBC
Assam	2
Chandigarh	2
Chhattisgarh	1
Dadra & Nagar Haveli	2
Daman & Diu	1
New Delhi	24
Gujarat	16
Haryana	4
Jharkhand	2
Karnataka	3
Kerala	1
Madhya Pradesh	3
Maharashtra	59
Orissa	2
Punjab	4
Rajasthan	3
Tamil Nadu	11
Telangana	20
Union Territory	3
Uttar Pradesh	7
West Bengal	18

Source: Author 's calculations based on company data from NCLT website



Source: Author 's calculations based on company data from NCLT website

Figure 3.4 :Statewise companies referred under IBC

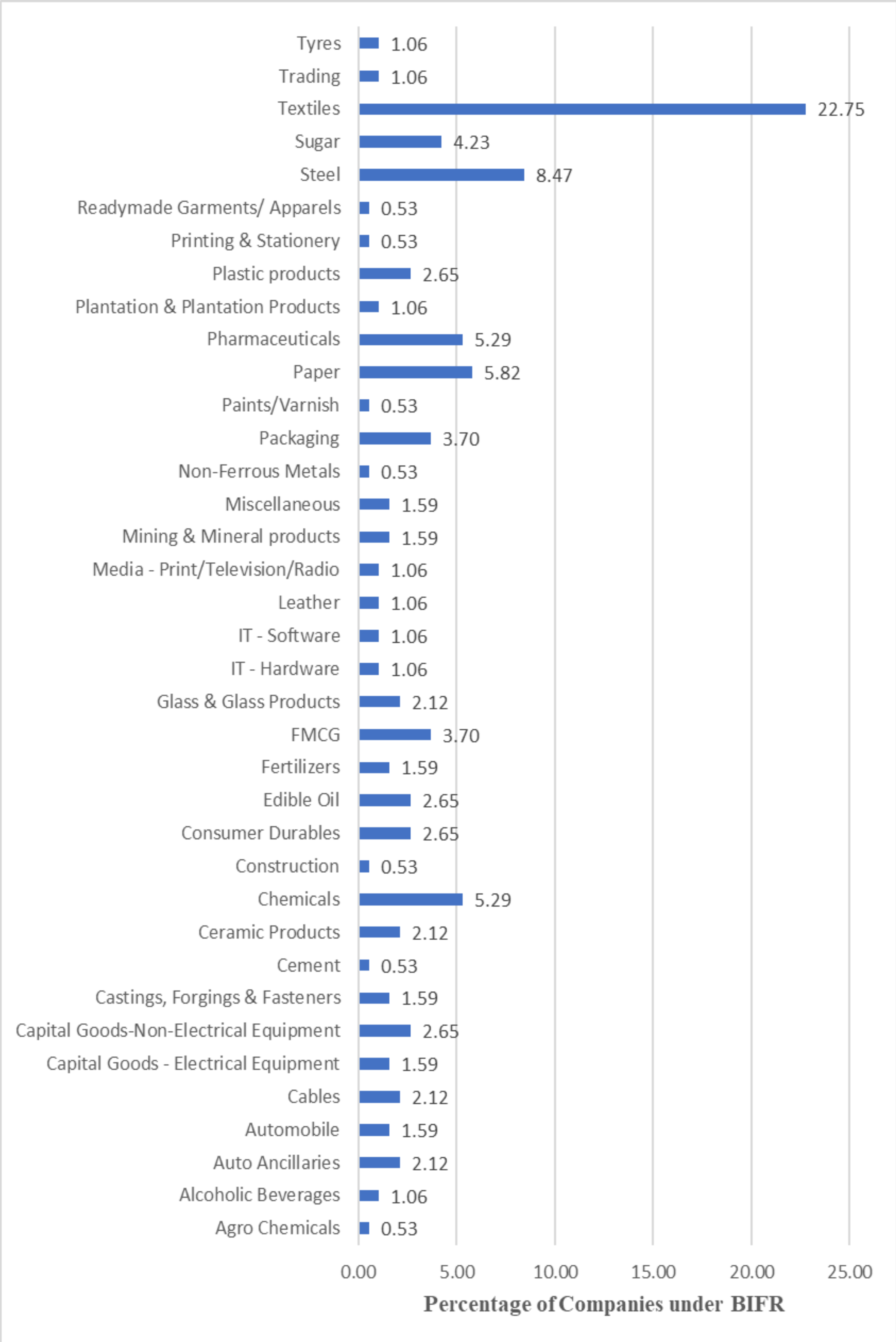
Table 3.1 & 3.2 depicts statewise patterns for companies referred to under BIFR and IBC. According to the above figures 3.3 and 3.4, Maharashtra has the maximum percentage of listed companies referred to both BIFR and IBC, followed by New Delhi, Gujarat & West Bengal in the case of BIFR and New Delhi, Telangana, and West Bengal in the case of IBC. In the case of BIFR, 30.69% of NSE & BSE listed companies were from Maharashtra from the year 2006 to 2016, 11.11% of companies were from New Delhi, 10.58% of companies were from Gujarat, 8.99% of companies were from West Bengal and 6.8% of companies were from Uttar Pradesh. Further in the IBC, from 2017 to 2019, 31.38% of NSE and BSE listed companies were from Maharashtra; 12.77% were from New Delhi; 10.64% were from Telangana; 9.57% were from West Bengal; 8.51% were from Gujarat, and 5.85% were from Tamil Nadu. The major industrialized states in India are Maharashtra, Tamil Nadu, Gujarat, Telangana, and Uttar Pradesh, and the majority of listed companies referred to both BIFR and IBC are from these industrial hubs only.

3.2.3 Sector-wise Companies

Table 3.3 : Sector-wise Pattern: Number of Companies under BIFR

Sector	No of companies under BIFR
Agro Chemicals	1
Alcoholic Beverages	2
Auto Ancillaries	4
Automobile	3
Cables	4
Capital Goods - Electrical Equipment	3
Capital Goods-Non-Electrical Equipment	5
Castings, Forgings & Fasteners	3
Cement	1
Ceramic Products	4
Chemicals	10
Construction	1
Consumer Durables	5
Edible Oil	5
Fertilizers	3
FMCG	7
Glass & Glass Products	4
IT - Hardware	2
IT - Software	2
Leather	2
Media - Print/Television/Radio	2
Mining & Mineral products	3
Miscellaneous	3
Non-Ferrous Metals	1
Packaging	7
Paints/Varnish	1
Paper	11
Pharmaceuticals	10
Plantation & Plantation Products	2
Plastic products	5
Printing & Stationery	1
Readymade Garments/ Apparels	1
Steel	16
Sugar	8
Textiles	43
Trading	2
Tyres	2

Source: Author ‘s calculations based on company data from BIFR website



Source : Author 's calculations based on company data from BIFR website

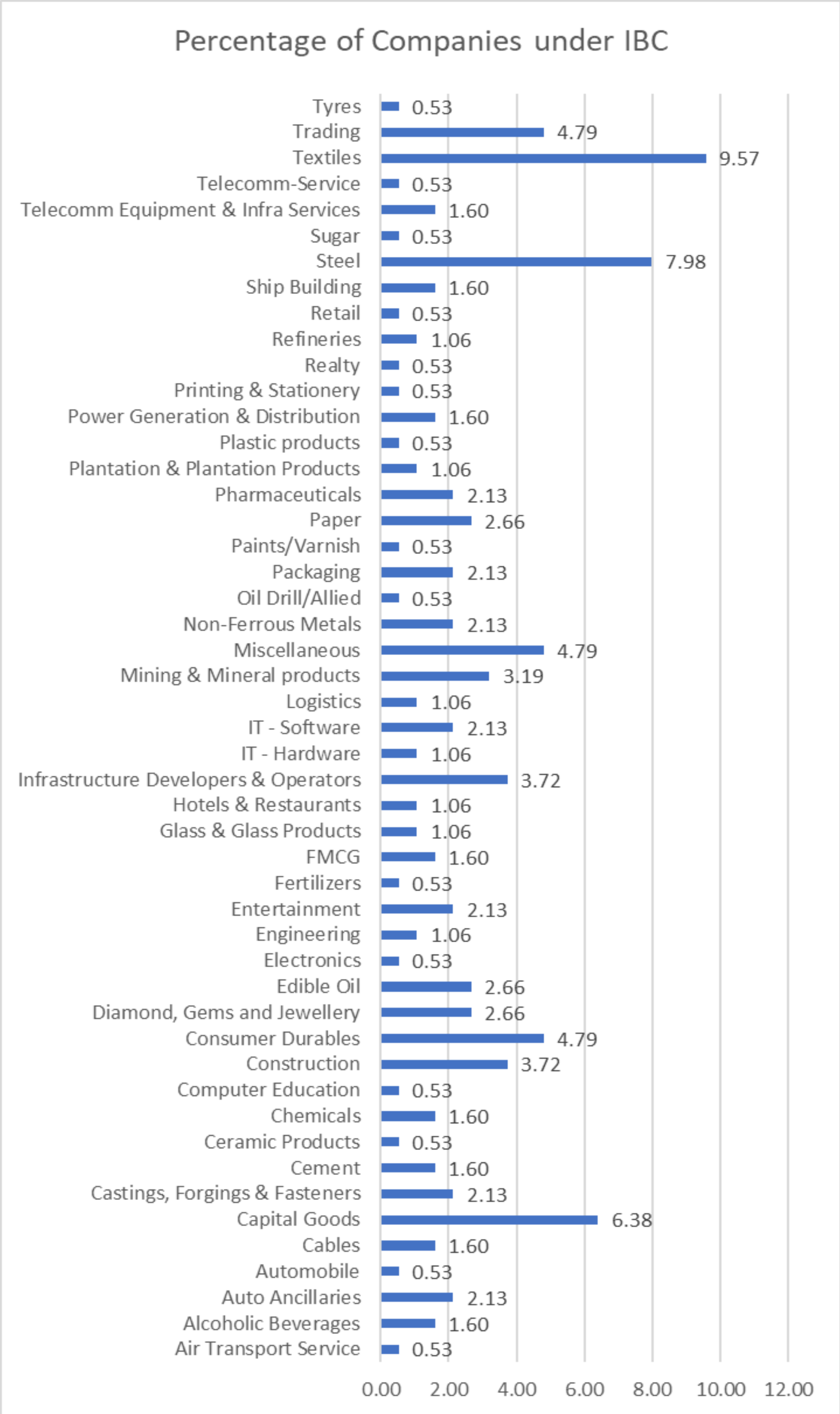
Figure 3.5: Sector-wise companies referred under BIFR

Table 3.4 Sector-wise Pattern: Number of Companies under IBC

Sector	No of companies under IBC
Air Transport Service	1
Alcoholic Beverages	3
Auto Ancillaries	4
Automobile	1
Cables	3
Capital Goods	12
Castings, Forgings & Fasteners	4
Cement	3
Ceramic Products	1
Chemicals	3
Computer Education	1
Construction	7
Consumer Durables	9
Diamond, Gems and Jewellery	5
Edible Oil	5
Electronics	1
Engineering	2
Entertainment	4
Fertilizers	1
FMCG	3
Glass & Glass Products	2
Hotels & Restaurants	2
Infrastructure Developers & Operators	7
IT - Hardware	2
IT - Software	4

Sector	No of companies under IBC
Logistics	2
Mining & Mineral products	6
Miscellaneous	9
Non-Ferrous Metals	4
Oil Drill/Allied	1
Packaging	4
Paints/Varnish	1
Paper	5
Pharmaceuticals	4
Plantation & Plantation Products	2
Plastic products	1
Power Generation & Distribution	3
Printing & Stationery	1
Realty	1
Refineries	2
Retail	1
Ship Building	3
Steel	15
Sugar	1
Telecomm Equipment & Infra Services	3
Telecomm-Service	1
Textiles	18
Trading	9
Tyres	1

Source: Author ‘s calculations based on company data from NCLT website



Source: Author 's calculations based on company data from NCLT website

Figure 3.6 -Sector-wise companies referred under IBC

Table 3.3 & 3.4 depicts sector- wise patterns for companies referred to under BIFR and IBC. Figure 3.5 depicts the sector-wise breakdown of companies referred to BIFR. Out of various sectors, Textile sector has the highest number of companies referred to BIFR followed by Steel, Paper and Pharmaceuticals, Chemicals, Sugar, Packaging, FMCG, Consumer durables and Edible oil sector. The sector-wise breakdown of companies admitted under IBC has been shown in Figure 3.6. The textile sector has the highest number of companies admitted under the IBC, followed by the steel, capital goods, trading, consumer durables, infrastructure, construction, and mining & mineral products industries.

Different sectors faced financial distress for various reasons. Stiff competition, changing consumer preferences, obsolete machinery, and outdated technology leads to low efficiency, and poor-quality products have resulted in financial distress in the textile sector. Furthermore, textile mills were hampered by a severe lack of electricity, which forced them to rely on manual machines that produced low-quality products and were more expensive to maintain Assocham (2015). Companies in the steel sector have been severely affected due to inadequate capital investments, high levels of debt, excess capacity, low global price, dependence on imported coking coal, dumping from China and Brazil, resulting in deceleration in domestic demand, RBI Financial Stability Report, (2015). Firms in the edible oil sector suffered due to an increase in the cost of production, droughts, and cheap imports. Further food oil sellers found it more convenient to import cheap palm oil from Malaysia and Indonesia directly and sell in domestic markets, which has decreased the margin for edible oil processing plants CARE Ltd (2016). Firms in the paper industry have dealt with rising raw material, and fuel costs as domestic wood and coal prices rise due to a fall in the rupee exchange rate. According to several project implementation organizations, infrastructure firms faced time overruns and difficulties in acquiring land & forest approval. Other reasons include funding constraints, geographical surprises, geo mining, low civil work advancement, insufficient contracting mobilization, Maoist issues, and court cases. The capital goods sector has experienced a protracted slowdown due to factors such as overcapacity, high-interest rates, and issues in land acquisition. The construction sector has faced stress due to project delays, environmental issues, high debt in the balance sheet, stalled infrastructure assets, and high receivables, especially by government agencies. (Report by Department of Economic Affairs (2021)).

3.2.4 Ownership Pattern

Table 3.5: Ownership Classification Parameters

Ownership Pattern	Shareholding on Year End By
“Family held”	“(Promoter and promoter Group) + (Custodians hold) > 50%”
“Widely held”	“(Non promoters (including FPIs) Holds) > 50%”
“Foreign held”	“(Foreign promoter holds) > 50%”
“Mix-family held”	“(Indian and Foreign promoter together hold) > 50%”

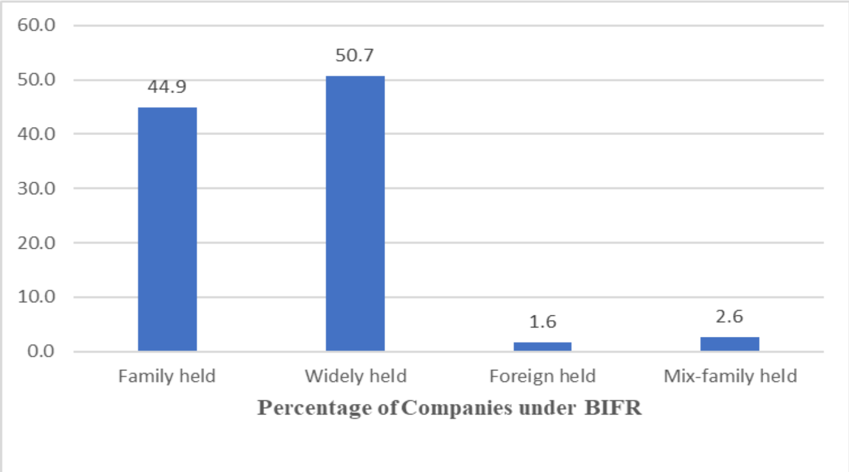
Source : Sridharan and Joshi (2018)

Table 3.5 depicts the ownership-based arrangement based on four ownership classification parameters: family, widely, foreign, and mixed family-held firms. Various firms have been classified based on their year-end shareholding. Firms having above 50% shareholding holding by the Indian promoters are classified as family held. Similarly, firms with greater than fifty percent shareholding by foreign promoters have been classified as foreign-held. Those with greater than fifty percent shareholding by non-promoters have been classified as widely-held firms. Whereas those firms with greater than fifty percent of the combined shareholding by both Indian & foreign promoters have been classified as mixed-family- held. This criterion for deciding ownership based on more than fifty percent ownership is superior compared to other methods. **Sridharan and Joshi (2018)**.

Table 3.6: Ownership Pattern: Number of Companies under BIFR

Ownership Pattern	No of Companies under BIFR
“Family held”	85
“Widely held”	96
“Foreign held”	3
“Mix-family held”	5

Source: Author ‘s calculations based on company data from capitaline



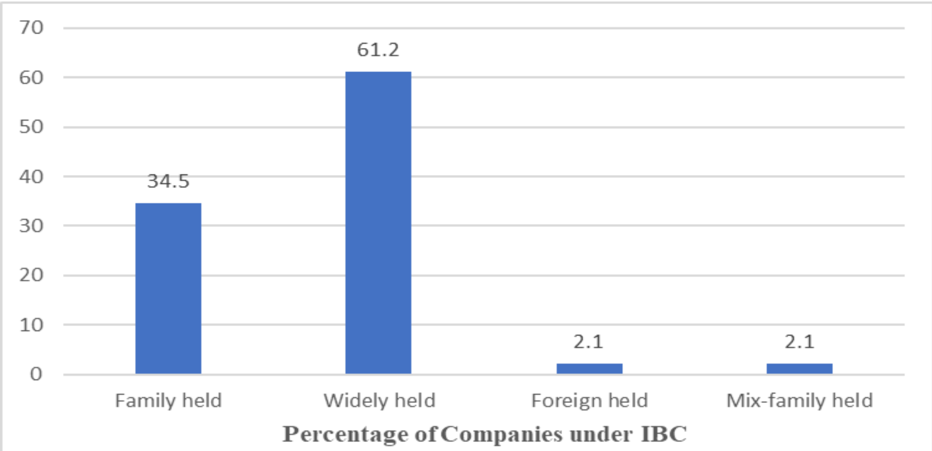
Source: Author 's calculations based on company data from capitaline

Figure 3.7 - Ownership Pattern of Companies referred under BIFR

Table 3.7: Ownership Pattern: Number of Companies under IBC

Ownership Pattern	No of Companies under IBC
"Family held"	65
"Widely held"	115
"Foreign held"	4
"Mix-family held"	4

Source: Author's calculations based on company data from capitaline



Source: Author's calculations based on company data from capitaline

Figure 3.8 : Ownership Pattern of Companies referred under IBC

Table 3.6 & 3.7 depicts the ownership-based arrangement for companies under BIFR and IBC. Shareholders are better positioned to determine ongoing trends in the industry and the efficiency of higher management of a firm **Wruck (1990)**. So, the ownership structure is an important aspect of deciding the effect of financial distress and is a significant factor in the strength and survival of companies after distress **Poletti- Hughes and Ozkan (2014); Kam, Citron and Muradoglu (2008)**. As per the above figure 3.7, the maximum percentage of companies registered with BIFR was either widely held (50.7%) or family-held firms (44.9%). Very few companies were under the mix-family (2.6%) and foreign-held category (1.6%). Figure 3.8 depicts similar kinds of ownership patterns in the case of companies registered under the insolvency and bankruptcy code, where 61.2 percent were widely held, 34.5 percent were family held, and only 2.1% were under both foreign and mixed-family categories**.** Thus, both in the case of BIFR and IBC, the majority of firms have either widely held or family-owned ownership. According to **Helwege, Pirinsky and Stulz (2007)**, firms with higher CAPEX, debt, and lower cash flows have lower insider shareholding and more widely held ownership.

Similarly, the majority of companies have higher insider shareholdings in their early stages of development but eventually end up with dispersed ownership. Likewise, family successions in firms are unfavourable to performance because likely successors have lower managerial skills and enthusiasm to manage the firm effectively. **Pérez-González (2001)**. On the other hand, very few firms in the mix-family & foreign-held category experienced financial distress, indicating their superior performance. Numerous studies have found evidence to support improved corporate performance under foreign ownership. An earlier study by **Nashier and Gupta (2016)** confirmed that foreign institutional ownership has a favourable effect on firm performance because they actively monitor the firm's management in which they invest, resulting in improved firm performance. Foreign investment in firms yields a higher return on assets because foreign shareholders focus on profitability, create high-level monitoring & control systems, and offer managers more incentives that push managers to enhance financial performance **Sridharan and Joshi (2015)**.

3.2.5 Firm Life Cycle Classification Pattern

Table 3.8:Firm life cycle classification parameters: Eight patterns are collapsed into five stages

Sign of cash flow	Introduction	Growth	Mature	Shakeout	Shakeout	Shakeout	Decline	Decline
Cash flow from operating activites	-ve	+ve	+ve	-ve	+ve	+ve	-ve	-ve
Cash flow from investing activites	-ve	-ve	-ve	-ve	+ve	+ve	+ve	+ve
Cash flow from financing activites	+ve	+ve	-ve	-ve	+ve	-ve	+ve	-ve

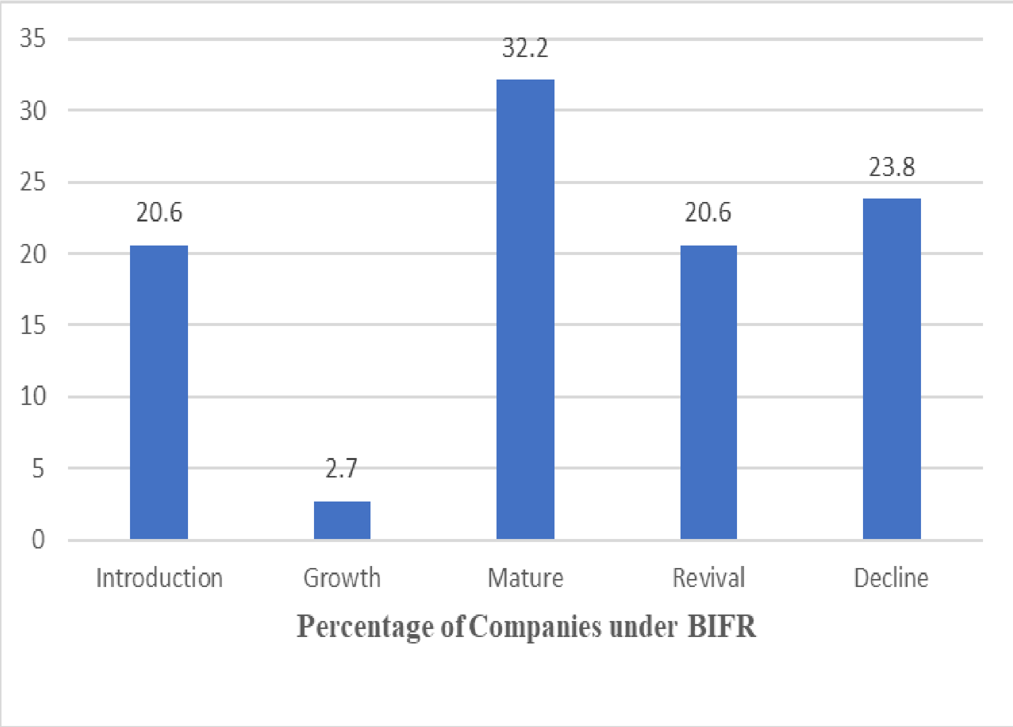
Source : Dickinson (2011)

Table 3.8 depicts the firm life cycle classification pattern for five different life cycle stages: Introduction, growth, mature, shakeout, and decline. A number of performance indicators and company features are found to be non-linearly linked to the firm life cycle. As a result, monotonic sorting on those characteristics to assess the life cycle stage leads to misclassification. Financial analysts and researchers can examine & control for differences in various firms' parameters cost-effectively by using the cash flow pattern proxy as a proxy for life cycle information. In the previous studies, the cash flow pattern proxy was found to be superior and more predictive of future profitability than other life cycle proxies. Table 3.8 shows how the present study captured the concept of the firm life cycle using basic accounting information of the firms. Based on the sign of cash flows from operating, investing, and financing activities, there can be a total of eight distinct combinations. The eight patterns have been further broken down into five phases.: Introduction, Growth, Mature, Revival and Decline **Dickinson (2011)**.

Table 3.9:Firm life cycle classification parameters: Number of Companies under BIFR

Firm Life Cycle Classification Pattern	No of Companies under BIFR
Introduction	39
Growth	5
Mature	61
Revival	39
Decline	45

Source: Author 's calculations based on company data from capitaline



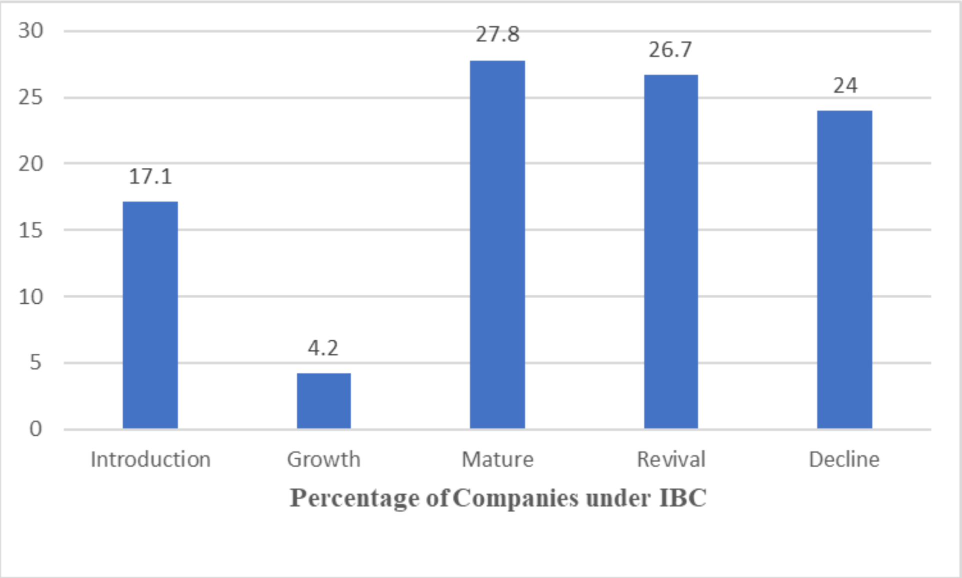
Source: Author 's calculations based on company data from capitaline

Figure 3.9 - Life cycle stage of companies referred under BIFR

Table 3.10: Firm life cycle classification parameters: Number of Companies under IBC

Firm Life Cycle Classification Pattern	No of Companies under IBC
Introduction	32
Growth	8
Mature	52
Revival	50
Decline	45

Source: Author's calculations based on company data from capitaline



Source: Author 's calculations based on company data from capitaline

Figure 3.10: Life cycle stage of companies referred under IBC

Table 3.9 & 3.10 depicts the life cycle stage of companies under BIFR and IBC. There are five key stages of a firm life cycle **Miller and Friesen (1984)**. The birth stage depicts smaller, newer businesses attempting to develop their position with significant innovative products. A corporation in its growth phase is distinguished by more prominent, quickly expanding firms that are extending their market niche and establishing a more effective organization. In the maturity phase, companies have stability and efficiency as their objective, their level of invention falls, and a more bureaucratic structure is introduced. Companies in the maturity phase strive for steadiness and competence, and their innovation declines as a result. Product diversification is a crucial component of the revival phase, which prioritizes innovation and formal regulations. The decline phase exhibits businesses that are beginning to fall because of diminishing markets and product line discontinuance. According to Figures 3.9 and 3.10, the majority of firms that experienced financial distress were in the maturity stage of their life cycle, with 32.2% in BIFR & 27.8% in IBC.

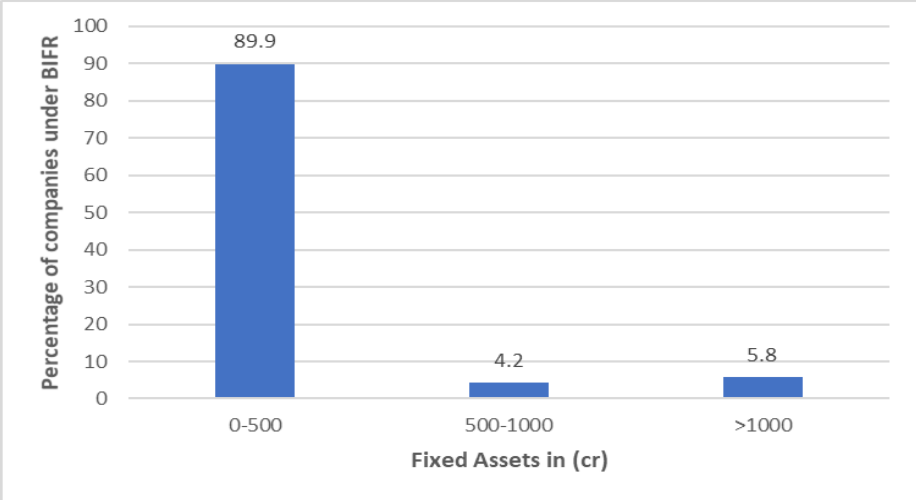
In contrast, few firms experienced distress in the growth stage of their life cycle, with only 2.7 percent in BIFR & 4.2 percent in the case of IBC. Firms in growth stages are likely to have a relatively weaker ability to access capital from external sources such as debt and equity as compared to mature firms **Koh et al. (2015)**. Firms facing financial distress in the introductory stage of their life cycle are 17.1% under IBC & 20.6% under BIFR. Companies in the revival stage accounted for 20.6 percent of firms in BIFR & 26.7 percent of firms in IBC, while firms in the decline stage accounted for 23.8 percent of firms in BIFR & 24 percent of firms in IBC. Companies in their introduction and decline stages are typically less profitable and riskier, whereas growth companies are likely to be more profitable and have lesser risk.

3.2.6 Size Wise Pattern

Table 3.11: Size Wise Pattern: Number of Companies under BIFR

Fixed Assets in (cr)	No of Companies under BIFR
0-500	170
500-1000	8
>1000	11

Source: Author’s calculations based on company data from capitaline



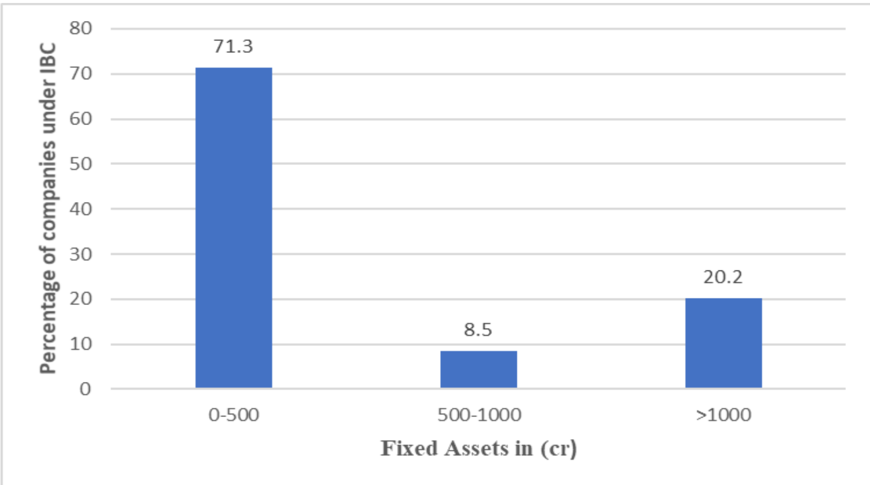
Source: Author's calculations based on company data from capitaline

Figure 3.11:Fixed Assets of Listed Firms referred under BIFR

Table 3.12: Size Wise Pattern: Number of Companies under IBC

Fixed Assets in (cr)	No of Companies under IBC
0-500	134
500-1000	16
>1000	38

Source: Author's calculations based on company data from capitaline.



Source: Author's calculations based on company data from capitaline

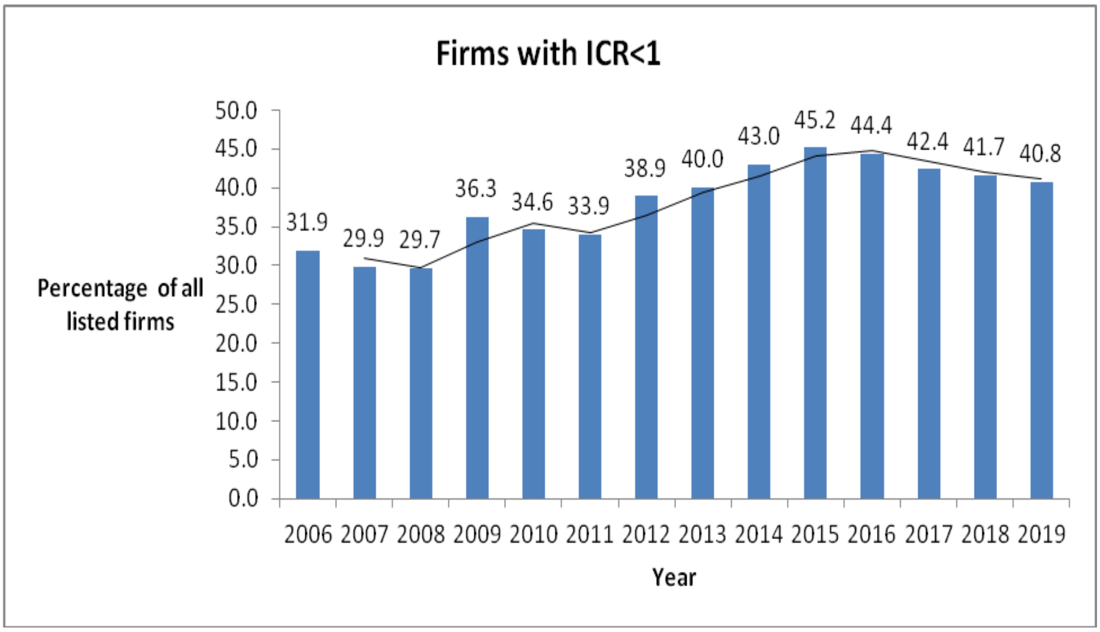
Figure 3.12:Fixed Assets of Listed Firms referred under IBC

Table 3.11 & 3.12 depicts size-wise patterns of companies under BIFR and IBC.The effect of leverage on an organization's performance is influenced by its size. Fixed assets of various firms were used to examine the size-wise pattern of the distressed companies. According to Figures 3.11 & 3.12, most of the distressed firms admitted under BIFR and IBC have fixed assets in the range of 0–500 cr. 89.9% of listed firms referred under BIFR, and 71.3% under IBC have fixed assets up to Rs 500cr. An adverse effect of leverage on the performance of small organizations is evident, but this negative influence reduces as the size of the business increases, gradually diminishing when the firm's size reaches the expected threshold **Ibhagui and Olokoyo (2018)**. Like firms with fixed assets in the range of 500-1000 crores were only 4.2% in BIFR and 8.5% in IBC, whereas companies with fixed assets of more than 1000 crores were 5.8 percent in BIFR and 20.2 percent in IBC. In India, an increasing number of small businesses are falling victim to the economic slowdown, and small businesses have mostly been hit harder than larger businesses.

During every slowdown, smaller businesses confront exacerbated operational and financial challenges. Small and medium-sized businesses that are direct or indirect suppliers to larger businesses frequently face payment delays from larger customers, which increases their working capital requirements. When large corporations have cash flow problems, the problem is passed on to smaller corporations as well. Small and medium-sized businesses (SMEs) have been particularly hard hit, with banks becoming increasingly reluctant to lend to them and companies exhausting all options to save their businesses, with some applying for corporate debt restructuring. In the past, the Reserve Bank of India raised concern over commercial banks discriminating against small and marginal borrowers in debt restructuring. Small and medium-sized firms are a significant part of the economy, and sustainable accounts in these industries must not be discriminated against while considering restructuring to address temporary issues RBI (2019). In spite of the fact that India's economic development has accelerated, corporate earnings have lagged, putting pressure on large enterprises. With a higher number of large firms admitted under IBC than BIFR, there has been an increase in financial distress among large firms in recent times.

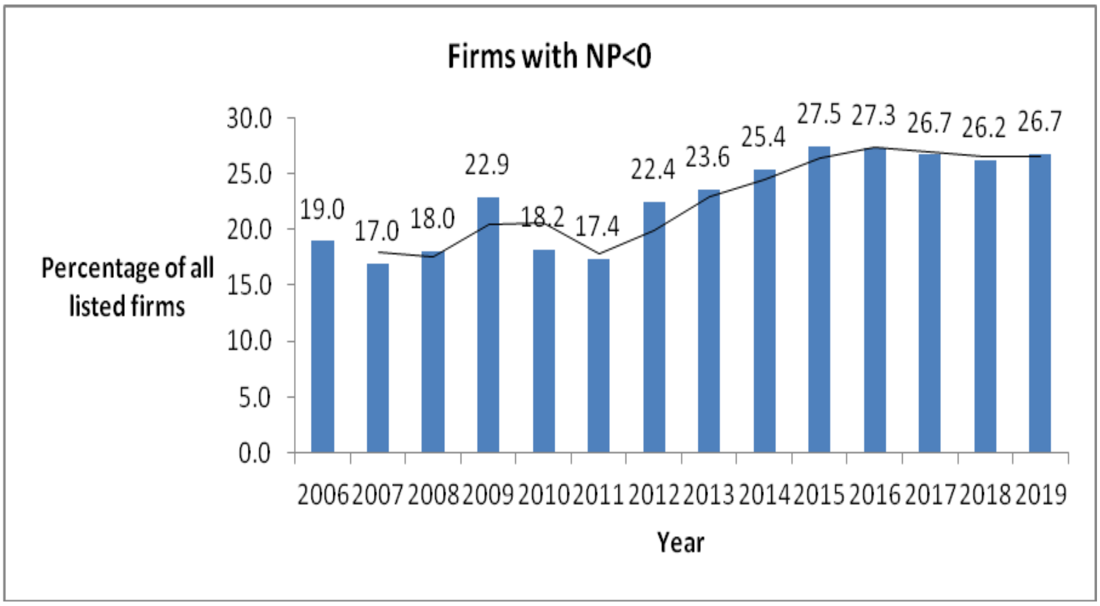
3.2.7 Financial Stress among Listed Firms: Over Time

Various key reports emphasize increasing company debt and consequently increasing the vulnerabilities of Indian companies. Since the global financial crisis, the balance sheet susceptibility of Indian firms to economic instability has increased further. The IMF (2016), for instance, highlighted the financial downturn in the Indian corporate sector since the recession. The report highlight that the business sector has increased its vulnerability to large structural shocks to an incomparable degree. In addition, the RBI underlines the issue of increased corporate leverage and lower profitability, and diminishing investment growth. This research determines the prevailing trend of business distress using five vital accounting metrics: interest coverage ratio, net profit margin, current ratio, debt-equity ratio, and debt to market capitalization, to assess the financial vulnerabilities of India's non-financial listed firms since 2005. The sample of research includes non-financial listed firms on both BSE and NSE. Capitaline database has been used to estimate financial ratios from 2005-2006 to 2018-19. Companies with no data are removed from the final study; thus, the final number of companies differs for each year under study.



Source: Author’s calculations based on company data from capitaline

Figure 3.13 : Listed Non-Financial Firms with ICR<1



Source: Author's calculations based on company data from capitaline

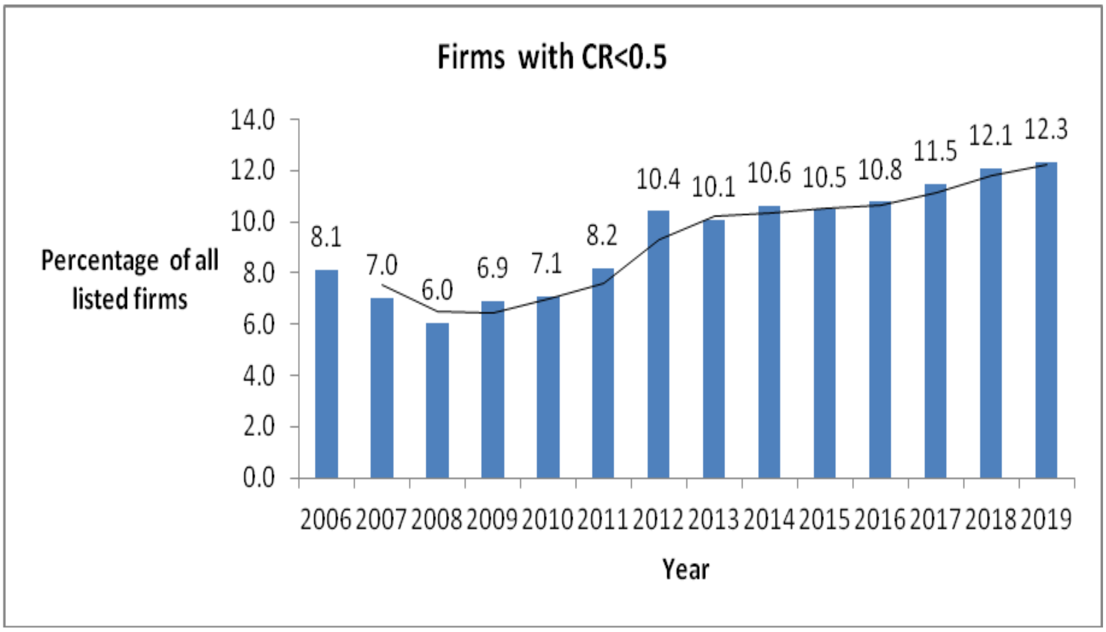
Figure 3.14: Listed Non-Financial Firms with Net Profit Margin <0

Interest coverage ratios and net profit margins indicate a firm's short-term profitability, measuring how much interest spending is financed through its combined operational and financial activities. The low level of ICR is an excellent systematic vulnerability measure. The declining interest coverage ratio is one of the most noticeable symptoms of business distress **Lindner and Jung (2014)**. The interest coverage ratio(ICR) is computed as a %ge of (earnings before interest & taxes)/ (interest expenses), which indicates the firm's capacity to cover financing costs. A value of interest coverage ratio <1 signals significant distress, as the firm's earnings are insufficient to meet financial obligations. These businesses are at substantial risk of default as their earnings are inadequate to support interest charges.

Figure 3.13 depicts the percentage of all listed firms having an interest coverage ratio of less than one over a period of 2006 to 2019. It can be seen that the percentage of firms has decreased from 31.9% to 29.9% in 2005–2006 to 2006- 2007 but rose to 36.3% in 2008–2009 after the global slowdown due to worldwide financial crises. The global downturn has resulted in a corresponding decline in the net profit margin of listed companies during this period, as evident from figure 3.14. Further, percentage of listed companies with negative net profit margins substantially increased to 22.9% at the end of the year 2009 from just 17% in 2007. The percentage of companies with a negative net profit margin declined slightly in 2010 and 2011, but then increased gradually from 2011 to 2019, indicating a surge in the number of organizations experiencing financial difficulties.

Further, analysis of interest coverage ratio reveals that the percentage of weak firms with interest coverage ratio < 1 have deteriorated between 2010-11 and 2014-2015 and increased to 45.2% by the end of year 2014-2015 as the economy has slowed, which indicate a sharp surge in the number of listed companies, which have insufficient earnings to meet financial obligations, putting potential risk to lenders. But after that witnessed a sharp improvement in this percentage to 40.8 by 2019. With the series of repo rates cut by RBI from 2015 onward, companies are not undertaking fresh investments, resulting in companies going slow on fresh borrowings with many corporate deleveraging with outstanding debt and further improvements in earnings, leading to an improvement in listed firms' debt-servicing capacity, RBI Financial Stability Report, (2018). Furthermore, in order to access cheaper loans, many businesses are turning to financial institutions or the debt market, where interest rates are more sensitive to changes in policy rates.

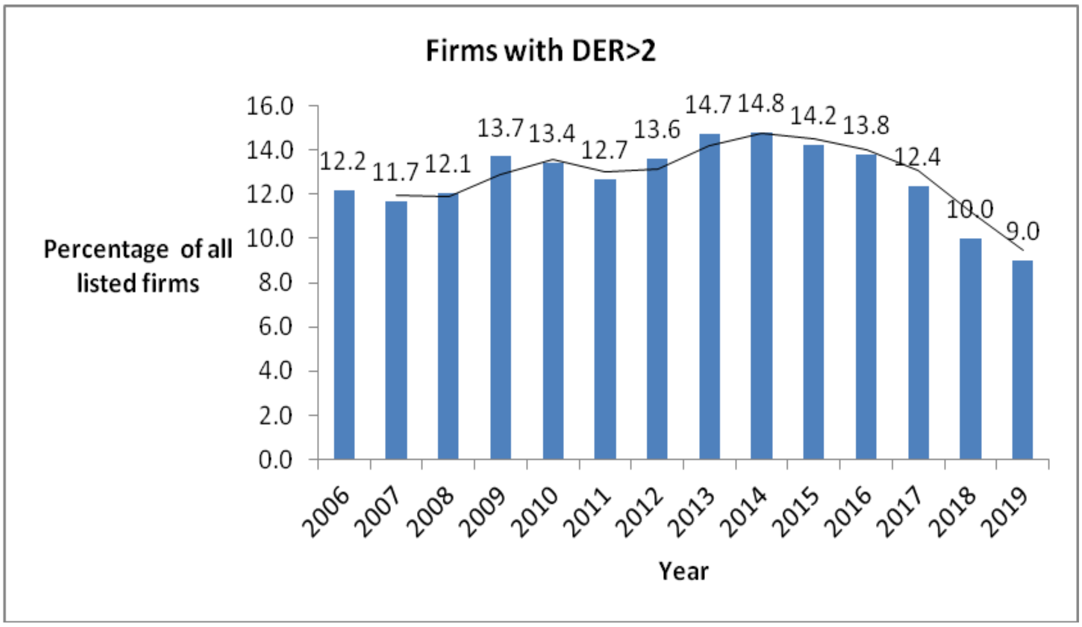
An interest coverage ratio of less than one does not show imminent financial distress. Companies might have liquid investments or use them as collateral to borrow money, open lines of credit, or access other forms of funding to carry out their plans and objectives. The interest coverage ratio of a company can be improved by selling assets or increasing profit margins. Better profitability is essential for companies to strengthen their interest coverage ratio or even maintain their current level. Higher interest costs increased working capital requirements, inflationary input costs, and a depreciating rupee, on the other hand, may make it difficult for companies to achieve higher EBITDA growth. To conclude, because the interest coverage ratio improvement is occurring only in pockets, broad-based deleveraging may take longer than expected.



Source: Author's calculations based on company data from capitaline

Figure 3.15 : Listed Non-Financial firms with Current Ratio<0.5

The interest coverage ratio does not have to account for all of the capital available to a company to meet its debt service obligations, but liquidity metrics, such as current ratios, exist to provide a complete picture of its problems. The current ratio is a valuable measure of a company's liquidity and short-term creditworthiness. A high current ratio usually indicates a strong and steady liquidity position of the company. The higher the current ratio, the better it is for a creditor, especially a short-term creditor like a supplier **Subramanyam (2014)**. A firm with a current ratio of below 0.5; would find it challenging to meet its current liabilities in the event of a credit squeeze. Figure 3.15 depicts, percentage of all listed firms having a current ratio of less than 0.5 over a period of 2006 to 2019. As evident from the figure, the current ratio of listed firms has deteriorated over time. It can be seen that the percentage of firms with a current ratio of less than one has decreased from 8.1 percent to 6 percent from 2005–2006 to 2007–2008, but the situation has worsened subsequently the worldwide financial catastrophe, as percentage of companies has gradually increased from 6 percent in 2007–2008 to 12.3 percent in 2018–2019, indicating increased corporate vulnerability.

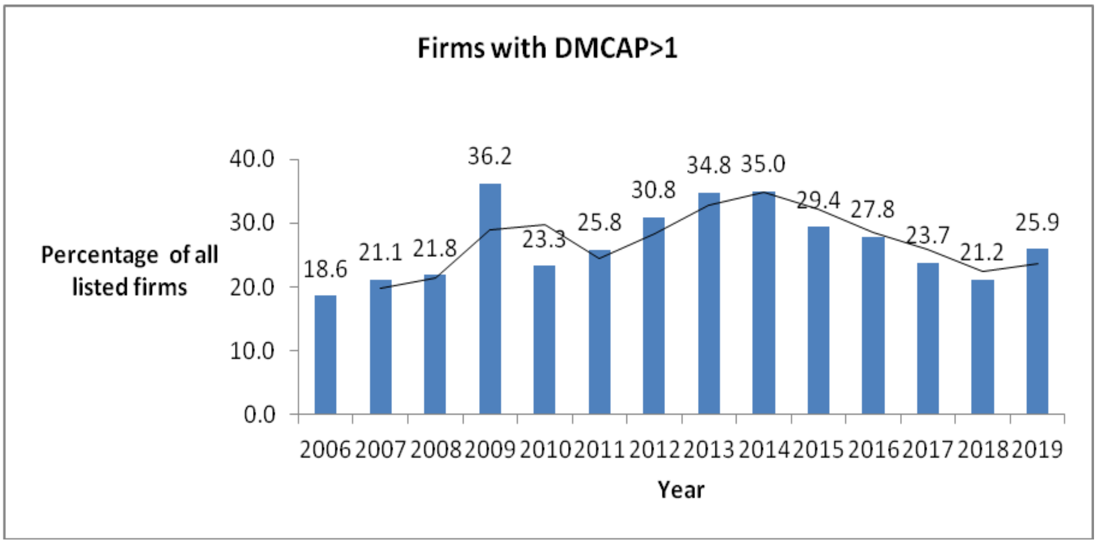


Source: Author's calculations based on company data from capitaline

Figure 3.16 : Listed Non-Financial Firms with DER >2

Debt-to-equity is a basic metric that indicates how much debt can still be used to fund a business. It is generally accepted that if a business's debt-to-equity ratio is substantial, it indicates possible financial distress faced by it; therefore, unable to service its debts. However, if the ratio is too low, it suggests that a corporation depends too much on equity to finance its operations, which can be both expensive and ineffective **Dhananjaya (2021)**. Figure 3.16 depicts, percentage of listed firms having a debt-to-equity of more than two. Figure 3.16 exhibits the percentage of publicly traded companies with a debt-to-equity ratio greater than two. As shown in Figure 3.16, there was a gradual increase in this percentage from 12.2 percent to 14.8 percent from 2006-2007 to 2013-2014, and it peaked at 14.8 percent, followed by a subsequent reversal in trend, with this percentage falling to 9 percent at the end of 2018-2019.

It has been found that there has been a systemic deleveraging of Indian firms since the fiscal year 2013-14, with deleveraging occurring almost equally in manufacturing and non-producing firms. Factors contributing to such deleveraging include institutional deficits in the form of underdeveloped corporate bond markets and a drop in corporate investment, which lead to a decrease in debt ratios over time. Moreover, companies faced difficulties obtaining funds for expansion from the credit market; as a result, under-investing **Chauhan (2017)**. Furthermore, if firms choose to shed debt, boost resources, or use an increasing percentage of internal finance via retained earnings rather than external credit, debt ratios will fall. As a result, the drop can be attributed primarily to debt reduction and increased use of internal funds by businesses to meet their financial needs.



Source – Author’s calculations based on company data from capitaline

Figure 3.17: Listed Non-Financial firms with Debt to Marketcapilization>1

Figure 3.17 depicts the percentage of all listed firms having a debt to market-capitalization more than one over a period of 2006 to 2019. It can be seen that the percentage of firms has increased dramatically from 18.6 percent to 36.2 percent between 2005–2006 and 2008–2009. The continued sharp decline in their market capitalizations subsequent to the 2007 worldwide financial disaster reflects the pressure on these listed companies' financials. Following that, there was some improvement in 2009-2010 to 23.3 percent due to stock price recovery. The percentages of firms continued to rise until the 2013-2014 fiscal year due to increasing stress. It peaked at 35 percent since there was a significant deterioration in the market capitalization of the listed firms due to weak profitability and an increase in debt levels. Market capitalization reflects the future growth potential of a company, which further confirms uncertainty in profitability and future growth opportunity. It is demonstrated by the rising percentage of listed firms with negative net profit margins and debt-to-equity ratios greater than two, as shown in figures 3.14 and 3.16. This was followed by a trend reversal, with the percentage falling to 21.2 percent by the end of 2017-2018 and then rising to 25.9 percent in 2018-2019. The booming stock prices & fall in debt levels of the companies due to restricted spending caused a reversal in this trend during this period.

3.3 CONCLUSION

About financial distress, this study examined the various types of trends and patterns that have emerged among publicly traded companies over the last fifteen years. Subsequent to the worldwide financial crisis, the number of firms referred to the BIFR increased dramatically. A rise in referrals to the BIFR has been attributed to both real distress and a desire to keep creditors away. There has been a considerable surge in the number of listed companies registered under IBC law due to the strain on the balance sheets of various firms. Liquidity shocks and aggressive use of the bankruptcy code by lenders have also contributed to the rise in admitted cases during this period. The global slowdown that began in 2008 has reduced listed companies' interest coverage ratios and their net profit margins. However, from 2014-15 to 2018-2019, there was a significant improvement. With companies not making new investments, resulting in corporate deleveraging, the RBI's series of repo rate cuts beginning in 2015, combined with continued earnings growth, has improved the company's debt-servicing capacity. The percentage of firms with a current ratio of less than one has decreased from 8.1 percent to 6 percent from 2005–2006 to 2007–2008, but the situation has deteriorated since the global financial crisis, with the percentage of companies gradually increasing, indicating increased corporate vulnerability.

Further, the percentage of publicly traded firms with a debt-to-equity ratio higher than two gradually increased from 2006-2007 to 2013-2014, peaking at 14.8 percent, followed by a subsequent trend reversal, falling to 9 percent at the end of 2018-2019. Since the fiscal year 2013-14, there has been a systemic deleveraging of Indian firms, with deleveraging occurring almost equally in manufacturing and non-producing firms. After a significant financial catastrophe during 2007, with the continued sharp decline in their market capitalizations, increased the number of companies with debt to market capitalization ratios of more than one, between 2005–2006 and 2008–2009, reflecting the financial pressures of these listed companies. Due to increased stress, the percentages of firms continued to rise until the fiscal year 2013-2014 but then dropped due to booming stock prices and falling corporate debt levels due to limited spending, causing this trend to reverse. While indicators such as debt-equity, debt-market capitalization have improved, but interest coverage ratio, net profit margin & current ratio, in particular, demonstrate that the risk of unsustainable business debt remains significant, as many firms have difficulty servicing existing debt, posing concerns to lenders. It emphasizes the importance of keeping a close eye on the business environment.

Various patterns were investigated among listed companies referred to BIFR and IBC with different characteristics such as sector, ownership structure, firm life cycle, and size. It has been found, Maharashtra has the most percentage of listed companies referred to both BIFR and IBC, followed by New Delhi, Gujarat, & West Bengal in the case of BIFR and New Delhi, Telangana, and West Bengal in the case of IBC. Out of various sectors, the Textile sector has the highest number of companies referred to both BIFR and IBC, followed by Steel, Paper and Pharmaceuticals, Chemicals, Sugar, Packaging, FMCG, Consumer durables and Edible oil sector in BIFR & steel, capital goods, trading, consumer durables, infrastructure, construction, and mining & mineral products industries in IBC. Different sectors faced financial distress for various reasons like stiff competition, changing consumer preferences, high levels of debt, excess capacity, low global price, cheap imports, rising raw material and fuel costs, fall in the rupee exchange rate, high-interest rates, and issues in land acquisition, project delays and high receivables, especially by government agencies. The maximum percentage of companies registered with both BIFR & IBC was either widely held or family-held firms. Very few companies were under the mix-family and foreign-held category. Thus, both in the case of BIFR and IBC, the majority of firms have either widely held or family-owned ownership. On the other hand, few firms in the mix-family & foreign-held category experienced financial distress, indicating superior performance. In both BIFR and IBC, most firms that experienced financial distress were in the maturity stage of their life cycle. In contrast, few firms experienced distress in the growth stage of their life cycle, indicating that growth firms are more likely to be profitable and have a lower risk. Similarly, most distressed firms admitted under both the BIFR and IBC have fixed assets ranging from 0-500cr, showing the negative impact of leverage on small business performance. However, the negative impact diminishes as the size of the business grows, as only a few firms have fixed assets in the 500-1000cr range. Thus, small businesses have suffered more than larger ones due to the economic slowdown.

Chapter – 4

FINANCIAL DISTRESS PREDICTION MODELS USING FINANCIAL VARIABLES

4.1 MODEL VARIABLES FOR BIFR

Various accounting ratios were examined in the database of 50 variables for companies referred to BIFR. The final ratios selected are mentioned below. The approach to the selection was focused on findings, theoretical ideas and empirical reviews previously reported. The data were cleaned and tracked strictly. The final choice for regressors using both univariate and multivariate (logit) methods were conducted in specific experiments. The probability of incorrect results was minimised by discarding or eliminating variables that have not proved their contribution to prior studies. Also, indicators that have proven helpful in previous research in addressing the given model were used. Variables that are strongly correlated and can result in multicollinearity, along with redundant variables, were discarded **Acosta-González and Fernández-Rodríguez (2014)**. Models of financial distress do not need a large number of variables to achieve the desired efficiency **Zmijewski (1984); Pindado, Rodrigues and Torre (2008)**. Like **Zmijewski (1984)** and **Pindado, Rodrigues and Torre (2008)** used just three financial variables to build financial distress models with high accuracy. Finally, new variables that have the potential to help address the model were tested. The ultimate model predicts distress in the future using logistic regression based on the three ratios after analysing a variety of existing ratios to predict distress: Debt-to-equity ratio (DE), (Adjusted gross profit + interest)/sales * 100 (PBIDTM) and net sales-to-total assets ratio (NSTA) (as shown in table 4.1).

Table 4.1 : Financial Variables used for predicting Financial Distress in BIFR Firms

Symbol	**Ratio**	**Description**
DE	(Debt)/(Equity)	It is a leverage ratio that illustrates how well a firm can cover its debt.
NSTA	(Net Sales)/(Total Assets)	It indicates a business's capacity to generate revenue. It is one metric for assessing management's ability to manage competitiveness effectively.
PBIDTM	(Adjusted gross profit +Interest) / Sales)*100	It indicates the ability of a business to generate profits from its sales.

Accounting ratios like DE, PBIDTM & NSTA were found to be significant. It was found that the ratio of debt-to-equity is consistently lower, whereas PBIDTM and the sales-to-total assets ratio were higher for healthy firms. Therefore, healthy firms are lesser indebted and have more profitability. All of the ratio’s signs measured were as per the expectation. The positive value of the coefficient indicates that the likelihood of distress increases when the values of the ratio increase, while the negative value of the coefficient indicates the opposite result. The debt-to-equity ratio signifies the long-term soundness of a business. Debt-to-equity ratio presents the sum of long-term money borrowed as a percentage of the shareholder’ capital. An increased ratio means a higher level of risk, and a lower number suggests a safe financial position for the firm. PBIDTM serves as an indicator of profitability for a firm. The superior value will disclose the efficiency of management of the concerned company. The ratios of (Net Sales/ (Total Assets) assess the efficiency of a firm in allocating the resources with respect to the revenue earned—the greater the ratio, the less the company’s investment to produce sales and the greater profits. If a firm has a poor ratio, it means it is inefficient in utilising its various resources to produce revenue. In the following section, logistic regression was used to forecast financial distress for different listed companies referred to BIFR over a time period of one to three years.

4.2 MODEL TESTING

The Chi-square test is for the goodness of fit for the model, which has the null hypothesis that intercepts, and all coefficients are zero. The pseudo-R-squares: Cox & Snell R^2 & Nagelkerke R^2 is not corresponding R-squared value, which is used in the case of OLS regression. Nagelkerke R^2 is a further adjustment to Cox & Snell R^2, as it does not attain a value of 1. So, it is preferable to report the value of Nagelkerke R^2 and are used in the relative evaluation of models. These values are only being used for making comparisons for different models. In previous studies, classification tables were used as a supplementary method to calculate the distress predictive accuracy of models. This research uses cross-validation of 70-30 to test a static model for a sample and to test it on a separate sample. Data collected for one to three years before financial distress has been randomly divided into 70 percent and 30 percent cases. It's standard practice to use 70 percent of the cases to frame models before determining their accuracy in the remaining 30 percent cases. A classification table, the outcome of crossing the initial variable and prediction variables, whose values are obtained from calculated logistic likelihood, can be expressed as effects of the fitted model. It is a key method that demonstrates how a good predictor of the dependent variable is the model. It illustrates how precisely the model-built forecasts one group for each case studied. The consistency of the classification model, i.e., the percentage of accurate model predictions 0.5, is used as a cut-off in the projected classification table based on a training sample and validation sample.

4.3 ONE-YEAR BEFORE FINANCIAL DISTRESS USING FINANCIAL VARIABLES: FOR BIFR COMPANIES

This section estimates the 1-year before model using accounting ratios variables of financially distressed and healthy companies in the year t-1, i.e., one year before the year in which a financial distressed incident happened for a listed company referred to BIFR, matching with a healthy company in the same year. It summarizes the findings of the one-year prior financially distressed model, including Omnibus tests, Pseudo R-squares, Model Classification table, Wald statistic, p-values, and odds ratios, ROC curve, and Area under the curve.

Table 4.2: Correlation Statistics: 1-year before FD using Financial Variables for BIFR and Healthy Companies

	DE	PBIDTM	NSTA
DE	1.000	.009	.122
PBIDTM	.009	1.000	.428
NSTA	.122	.428	1.000

Values are significant at 1% level

Source: Author 's calculations

Table 4.3: Multicollinearity Statistics: 1-year before FD using Financial Variables for BIFR and Healthy Companies

		DE	PBIDTM	NSTA
Collinearity Statistics	Tolerance	.974	.978	.968
	VIF	1.026	1.023	1.033

Source: Author 's calculations

In the above Table 4.2 and 4.3, the matrices of correlation and multicollinearity are measured to make sure there is no multicollinearity between all the variables. Above table 4.2 provides a matrix of correlations of all covariates. Correlations among the covariates are generally small, indicating that the covariates give different & unique details and are statistically significant. Correlation among (Adjusted gross profit + interest)/(sales) * 100, (Net Sales)/(Total Assets) is largest and is equal to 0.428. Thereafter among (Debt)/(Equity) ratio, (Net Sales)/(Total Assets) of 0.122. They are not significant enough to trigger collinearity problems as similar high correlations have been identified in previous studies: the correlation between (EBIT)/(Total Assets) & (Sales)/(Total Assets) was -0.78 in **Altman (1968)** and -0.49 between (Liabilities/(Total Assets) in **Ohlson (1980)**. In the case of multicollinearity, independent variables have a linear relationship, which can further result in unstable coefficient values. Variance Inflation (VIF) and its inverse, Tolerance Value (TOL), is calculated to identify the presence of multicollinearity among variables. A value of

VIF of more than 10 indicates significant collinearity. Results found that regressors have VIF's near to 1 with VIF values of 1.026, 1.023 and 1.033 for (Debt)-to-(equity) ratio, (adjusted gross profit + interest)-to-(sales) * 100, (Net sales)-to-(total assets) respectively, which mean that the collinearity between the regressors has not affected the level of the coefficients & the model does not have multicollinearity, and therefore, the model is capable of reliable performance.

Table 4.4 : Omnibus Tests for the Financial Variables: 1-year before FD for BIFR Companies

Omnibus Tests			
	Chi-square	df	sig.
Step	202.207	3	0.000
Block	202.207	3	0.000
Model	202.207	3	0.000

Source: Author ‘s calculations

Table 4.5 : Model Summary: 1-year before FD for BIFR Companies using Financial Variables

Summary of the model		
-2 log likelihood	Cox & Snell $R^{\wedge 2}$	Nagelkerke $R^{\wedge 2}$
102.778	0.601	0.802

Source: Author’s calculations

Table 4.6 : Hosmer and Lemeshow Test using Financial Variables: 1-year before FD for BIFR Companies

Hosmer & Lemeshow test		
Chi-square	df	sig.
11.422	8	0.179

Source: Author’s calculations

4.3.1 Testing for the Significance of the Model

The model evaluation process can now start with the Omnibus test of model coefficients. The Omnibus test results check whether this variable block is a substantial contributor to the model's fitness. Table 4.4 contains the outcome of the test. It is the likelihood of achieving this statistic (202.207), if the independent variables have no effect on the dependent variable. The null hypothesis for the test is intercept, as well as all the coefficients are zero. As the p-value is < 0.05, thus the model is significant. Nagelkerke R Square is not corresponding R-squared value, which is used in the case of OLS regression. Nagelkerke R^2 is a further adjustment to Cox & Snell R^2, as it does not attain a value of 1. So, it is *preferable* to report the value of Nagelkerke R^2. As the value increases, the stronger the fitness of the model. As per table 4.5, in this model, the value for Nagelkerke R^2 is 0.802, which depicts reasonable fitness. The Hosmer-Lemeshow test is a test of goodness of fit for the model. Like other fitness assessments, the smaller p values (generally below 5%) indicate that the model is a poor fit. But big p-values do not inherently suggest that the model suits well, but there is insufficient evidence to imply it is poor. Hosmer-Lemeshow test (Table 4.6) depicts the model is a good fit as p=0.179 (>.05)

Table 4.7 : Classification Table of the Model using Financial Variables: 1-year before FD for BIFR Companies

<table>
<tr><th colspan="8">Classification Table</th></tr>
<tr><th colspan="2" rowspan="4">Observed</th><th colspan="6">Predicted</th></tr>
<tr><th colspan="3">Selected Cases</th><th colspan="3">Holdout Sample</th></tr>
<tr><th colspan="2">State</th><th rowspan="2">Correct Percentage</th><th colspan="2">State</th><th rowspan="2">Correct Percentage</th></tr>
<tr><th>0</th><th>1</th><th>0</th><th>1</th></tr>
<tr><td rowspan="2">Type</td><td>0</td><td>74</td><td>3</td><td>96.1</td><td>33</td><td>0</td><td>100</td></tr>
<tr><td>1</td><td>5</td><td>72</td><td>93.5</td><td>7</td><td>26</td><td>78.8</td></tr>
<tr><td colspan="2">Overall %ge</td><td></td><td></td><td>94.8</td><td></td><td></td><td>89.4</td></tr>
<tr><td colspan="8">The cut value is .500</td></tr>
</table>

Source: Author’s Calculations

4.3.2 Assessing Fitness of Model

This section refers to how well the result attribute, often referred to as its fitness, is projected in the model. The model of predicting financial distress is used to forecast the state for financial distress or healthy company. The value of the cut-off is 0.5. If the company's calculated probability of financial distress is > 0.5, then the company is expected to be financially distressed. Table 4.7 shows the classification of the cross-classification matrix of the outcome variable with dichotomized variable; if the estimated likelihood exceeds the cut-off point, then the computed variable is equal to one; otherwise, it is equal to zero. If the estimated probability value is 0.5 or more, it will predict financial distress (as financial distress = 1) and healthy if it is lesser than 0.5 (as Healthy =0). One year before the financial distress model was framed based on the 70% observations, the remaining 30% observations (holdout sample) can be used to verify its goodness of fit. As per table 4.7, the financial distress prediction model developed correctly classifies 96.1% of healthy firms & 93.5% of sampled financially distressed firms and 100% of healthy firms & 78.8% of financially distressed firms for the holdout sample. The development of the model predicts a total of one hundred fifty-four samples. The forecast includes one hundred forty-six accurate samples and eight incorrect samples. The precise estimate is 94.8%. The outcome of the experiment was shown to be preferable. For the holdout sample, the model predicts a total of sixty-six samples. The forecast includes fifty-nine accurate samples and seven incorrect samples. The precise estimate is 89.4%. The overall logistic model forecasts correctly 94.8% of the cases for the development of the model and 89.4% of the cases in the holdout sample.

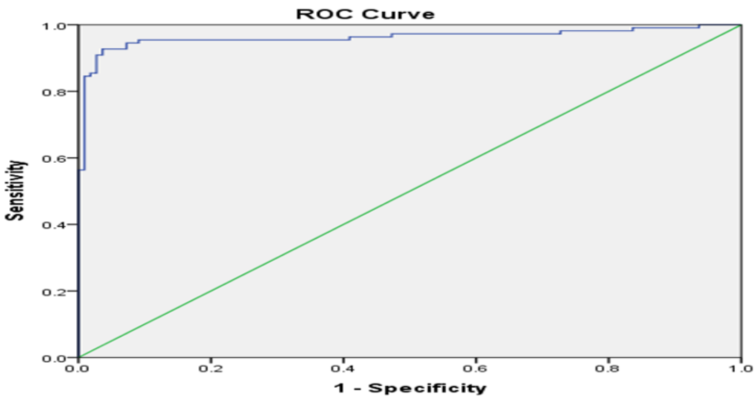
Table 4.8 : Variables in the model to predict FD using financial variables: 1-year before for BIFR companies

Equation variables							
		b	S.E.	wald	df	sig.	exp (b)
	DE	0.516	0.159	10.606	1	0.000	1.676
	PBIDTM	-0.323	0.061	27.857	1	0.000	0.724
	NSTA	-0.848	0.269	9.904	1	0.000	0.428
	Constant	2.894	0.925	9.781	1	0.000	18.063

Source: Author’s calculations

4.3.3 Interpreting the Fitted Logistic Regression Model

The independent variable's slope coefficient measures how much logit varies with the unit change in an independent variable. Positive coefficients indicate a greater likelihood of distress as the ratio value increases; however, negative coefficients mean conversely. P-value of Wald test statistics in Table 4.8 indicates independent variables are statistically significant. The significance value of the Wald test for each predictor indicates that debt-to-equity ratio, adjusted gross profit + interest/sales * 100, Net sales-to-total assets significantly predict financial distress ($p<0.05$). The values of exp (b) of 1.676 for DE ratio indicates that if the percentage of DE ratio goes up by one, then odds of financial distress will also increase. As exp (b) is greater than one, which means with every unit increase in DE ratio, the likelihood of financial distress will increase by 1.6 times than the firms that do not experience a surge in DE ratio. The values of exp (b) of 0.724 for PBIDTM indicates that if the percentage of PBIDTM goes up by one, then odds of financial distress will decrease. As exp (b) is less than one, which means with every unit increase in adjusted gross profit + interest-to-sales * 100, the likelihood of financial distress will reduce by 0.724 times than the companies do not experience an increase in this ratio. The values of exp (b) of 0.428 for NSTA indicates that if the percentage of NSTA goes up by one, then odds of financial distress will decrease. As exp (b) is less than one, which means with every unit increase in NSTA, the likelihood of financial distress will decline by 0.428 times than the firms that do not experience an increase in this ratio.



Source: Author's calculations

Figure 4.1: ROC Curve: 1- year before FD for BIFR Companies using Financial Variables

Table 4.9 : Area under the Curve: 1- year before FD for BIFR Companies using Financial Variables

AUC				
Test result variable(s)	Predicted probability			
Area	SE.	Asymptotic Sig.	Asymptotic 95% confidence interval	
			Lower bound	Upper bound
0.962	0.015	0.000	0.933	0.991

Source: Author's calculations

An alternative approach to calculate the predictive precision of a predictive model is the ROC curve. The AUC reflects the possibility that a randomly selected failing company is more suspect of failure than a randomly chosen successful company. There is a general principle if a model provides perfect discriminating strength, the AUC it achieves will be 1. In Figure 4.1, using logistic regression, the ROC curve was used to verify the predictive ability of the one-year financial distress model. The AUC gives a degree of discrimination that is likely to result in a failure of a financial distress enterprise being higher than a healthy one. As per table 4.9, AUC is 0.962, indicating that for a randomly selected distress company and randomly selected healthy company, there is a 0.962 likelihood that for a financial distress company, the model estimated the likelihood of distress would be more than for a healthy company. The AUC ranges from 0.933 to 0.991 at a 95% confidence interval. As per the general rule of Hosmer and Lemeshow (2000), one year before the financial distress model presents outstanding in-sample discrimination.

4.4 TWO-YEAR BEFORE FINANCIAL DISTRESS USING FINANCIAL VARIABLES: FOR BIFR COMPANIES

This section estimates two-year before to financial distress model using accounting ratios of companies, i.e., two years prior to the year in which a financial distressed incident happened for a listed company referred to BIFR, matching with a healthy company in the same year. It summarizes the findings of the two-year prior financially distressed model, including Pseudo R-squares, Model Classification table, Wald statistic, Odds ratios, ROC curve, and Area under the curve.

Table 4.10 : Correlation Statistics: 2-year before FD using Financial Variables for BIFR and Healthy Companies

	DE	PBIDTM	NSTA
DE	1.000	-.304	-.294
PBIDTM	-.304	1.000	.536
NSTA	-.294	.536	1.000

Values are significant at 1% level

Source: Author's calculations

Table 4.11 : Multicollinearity Statistics: 2-year before FD using Financial Variables for BIFR and Healthy Companies

		DE	PBIDTM	NSTA
Collinearity Statistics	Tolerance	0.961808	0.957492	0.974433
	VIF	1.039709	1.044395	1.026238

Source: Author's calculations

Table 4.10 provides a matrix of correlations of all covariates. In all categories, the observed correlations are statistically significant. Correlations among the covariates are generally small, indicating that the covariates give different and unique details. Correlation among (adjusted gross profit + interest)-to-(sales) * 100, (Net sales)-to-(total assets) is largest and is equal to 0.536. Thereafter among (Debt)-to-(equity) ratio, (Net sales)-to-(total assets) of -0.294. They are not significant enough to trigger collinearity problems as similar high correlations have been identified in previous studies Altman (1968); Ohlson (1980). In the case of multicollinearity, independent variables have a linear relationship, which can further result in unstable coefficient values. Variance Inflation (VIF) and its inverse, Tolerance Value (TOL) are calculated to identify the presence of multicollinearity among variables. A value of

VIF of more than 10 indicates significant collinearity. As per table 4.11, all regressors have VIF's near to 1 with VIF value of 1.039, 1.044 and 1.026 for (Debt)-to-(equity) ratio, (adjusted gross profit + interest)-to-(sales) * 100 and (Net sales)-to-(total assets), respectively, which mean that the collinearity between the regressors has not affected the level of the coefficients & the model does not have multicollinearity, and therefore, the model is capable of reliable performance.

Table 4.12: Omnibus Tests for the Financial Variables: 2-year before FD for BIFR Companies

Omnibus Tests			
	Chi-square	df	sig.
Step	148.551	3	0.000
Block	148.551	3	0.000
Model	148.551	3	0.000

Source: Author's calculations

Table 4.13 : Model Summary: 2-year before FD for BIFR Companies using Financial Variables

Summary of the model		
-2 log likelihood	Cox & Snell $R^{\wedge 2}$	Nagelkerke $R^{\wedge 2}$
87.119	0.583	0.777

Source: Author's calculations

Table 4.14 : Hosmer and Lemeshow Test using Financial Variables: 2-year before FD for BIFR Companies

Hosmer & Lemeshow test		
Chi-square	df	sig.
4.949	8	0.763

Source: Author's calculations

4.4.1 Testing for the Significance of the Model

The result of the Omnibus test is shown in Table 4.12. A p-value (sig) < 0.05 suggests that the model is statistically significant and model with independent variables reflects a substantial improvement in the model without variables. The null hypothesis for the test is intercept, as well as all the coefficients are zero. As the p-value is lower than 0.05, so this model is statistically significant. As per table 4.13, the pseudo-R-squares value for Nagelkerke R^2 is 0.777, which shows higher goodness of fit for the predictive model. But the predictive capacity of the chosen explanatory variables decreases from 0.802 in the one year before the financial distress model to 0.777 in the two years before the financial distress model. Hosmer and Lemeshow test (Table 4.14) suggests the model is a good fit as p=0.763 (>.05).

Table 4.15 : Classification Table of the model using Financial Variables: 2-year before FD for BIFR Companies

Classification Table								
Observed		Predicted						
		Selected Cases			Holdout Sample			
		Type		Correct Percentage	Type		Correct Percentage	
		0	1		0	1		
Type	0	79	6	92.9	34	3	91.9	
	1	11	74	87.1	8	29	78.4	
Overall %ge				90			85.1	

Source: Author's calculations

4.4.2 Assessing Fitness of Model

This section refers to how well the result attribute, often referred to as its fitness, is projected in the model. The model of predicting financial distress is used to forecast the state for financial distress or healthy company. The value of the cut-off is 0.5. If the company's calculated probability of financial distress is > 0.5, the firm is expected to be financially distressed. Table 4.15 shows the classification of the cross-classification matrix of the outcome variable with dichotomized variable; if the estimated likelihood exceeds the cut-off point, then the computed variable is equal to one; otherwise, it is equal to zero. The financial distress prediction model correctly classifies 92.9% of healthy firms & 87.1% of sampled financially distressed firms and 91.9% of healthy firms & 78.4% of financially distressed firms for the holdout sample. In table 4.15, the development of the model predicts a total of one hundred seventy samples. The forecast includes one hundred fifty-three accurate samples and seventeen incorrect samples. The precise estimate is 90%. For the holdout sample, the model predicts a total of seventy-four samples. The forecast includes sixty-three accurate samples and eleven incorrect samples. The precise estimate is 85.1%. The overall logistic model forecasts correctly 90% of the cases for the development of the model and 85.1% of the cases in the holdout sample.

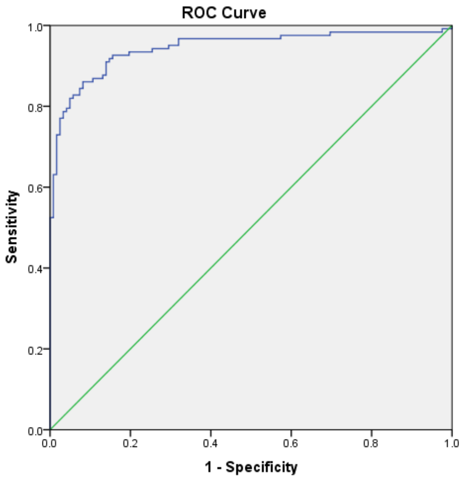
Table 4.16 : Variables in the Model to Predict FD using Financial Variables: 2-year before for BIFR Companies

Equation variables							
		B	**S.E.**	**Wald**	**df**	**Sig.**	**Exp(B)**
	DE	1.837	0.358	26.261	1	0.000	6.277
	PBIDTM	-0.221	0.053	17.575	1	0.000	0.802
	NSTA	-1.221	0.365	11.198	1	0.000	0.295
	Constant	1.310	0.969	9.830	1	0.000	3.708
Variable(s) entered: DE, PBIDTM, NSTA.							

Source: Author’s calculations

4.4.3 Interpreting the Fitted Logistic Regression Model

As per Table 4.16, the Wald test's significance value for each predictor shows that the (Debt)-to-(equity) ratio, (Adjusted gross profit + interest)-to-(sales) * 100, (Net Sales)-to-(total assets) significantly predict financial distress ($p<0.05$). The values of exp (b) of 6.277 for (debt)-to-(equity) ratio indicates that if the percentage of (debt)-to-(equity) ratio goes up by one, then odds of financial distress will also increase, as exp (b) is greater than one, which means with every unit increase in (debt)-to-(equity), the likelihood of financial distress will increase by 6.277 times. Values of exp (b) of 0.802 for (Adjusted gross profit + interest)-to-(sales) * 100 indicates that if the percentage of (Adjusted gross profit + interest)-to-(sales) * 100 goes up by one, then odds of financial distress will decrease, as exp (b) is less than one, which means with every unit increase in (Adjusted gross profit + interest)-to-(sales) * 100, the likelihood of financial distress will decline by 0.802 times. The values of exp (b) of 0.295 for (Net sales)-to-(total assets) indicates that if the percentage of (Net sales)-to-(total assets) goes up by one, then odds of financial distress will decrease, as exp (b) is less than one, which means with every unit increase in (Net sales)-to-(total assets), the likelihood of financial distress will decline by 0.295.



Source: Author's calculations

Figure 4.2 : ROC curve: 2-year before FD for BIFR Companies using Financial Variables

Table 4.17 : Area under the Curve: 2- year before FD for BIFR Companies using Financial Variables

AUC				
Test result variable(s)	**Predicted probability**			
Area	**SE.**	**Asymptotic Sig.**	**Asymptotic 95% confidence interval**	
			Lower bound	**Upper bound**
0.944	0.016	0.000	0.914	0.975

Source: Author's calculations

In Figure 4.2, using logistic regression, the ROC curve was used to verify the predictive ability of the two-year financial distress model. The AUC gives a degree of discrimination that is likely to result in a failure of a financial distress enterprise being higher than a healthy one. As per table 4.17, AUC is 0.944, indicating that for a randomly selected distress company and randomly selected healthy company, there is a 0.944 likelihood that for a financial distress company, the model estimated the likelihood of distress would be more than for a healthy company. The AUC ranges from 0.914 to 0.975 at a 95% confidence interval. As per the general rule of Hosmer and Lemeshow (2000), two years before the financial distress model presents outstanding in-sample discrimination.

4.5 THREE-YEAR BEFORE FINANCIAL DISTRESS USING FINANCIAL VARIABLES: FOR BIFR COMPANIES

This section estimates the three-year before to financial distress model using accounting ratios of financially distressed and healthy companies in the year t-3, i.e., three years before the year in which a financial distressed incident happened for a listed company referred to BIFR, matching with a healthy company in the same year. It summarizes the findings of the three-year prior financially distressed model, including Pseudo R-squares, Model classification table, Wald statistic, p-values, Odds ratios, ROC curve, and Area under the curve.

Table 4.18 : Correlation Statistics: 3-year before FD using Financial Variables for BIFR and Healthy Companies

	DE	**PBIDTM**	**NSTA**
DE	1.000	-.141	-.050
PBIDTM	-.141	1.000	.314
NSTA	-.050	.314	1.000

Values are significant at 1% level

Source: Author’s calculations

Table 4.19 : Multicollinearity Statistics: 3-year before FD using Financial Variables for BIFR and Healthy Companies

		DE	PBIDTM	NSTA
Collinearity Statistics	**Tolerance**	.994	.996	.990
	VIF	1.006	1.005	1.010

Source: Author's calculations

Table 4.18 provides a matrix of correlations of all covariates for three years before the financial distress model. In all categories, the observed correlations are statistically significant. Correlations among the covariates are generally small, indicating that the covariates give different and unique details. Correlation among (Adjusted gross profit + interest)-to-(sales) * 100, (Net Sales)-to-(total assets) is largest and is equal to 0.314. Thereafter among the (Debt)-to-(equity) ratio, (Adjusted gross profit + interest)-to-(sales) * 100 of -0.141. They are not significant enough to trigger problems of collinearity. In table 4.19, Variance Inflation (VIF) and its inverse, Tolerance Value (TOL), are calculated to identify the presence of multicollinearity. A value of VIF of more than 10 indicates significant collinearity. All variables have VIF's near to 1 with VIF value of 1.006, 1.005 and 1.010 for (Debt)-to-(equity) ratio, (Adjusted gross profit+ interest)-to-(sales)*100 and (Net Sales)-to-(total assets), respectively, which mean that the collinearity between the regressors has not affected the level of the coefficients & the model does not have multicollinearity, and therefore, the model is capable of reliable performance.

Table 4.20 : Omnibus Tests for the Financial Variables: 3-year before FD for BIFR Companies

Omnibus Tests				
		Chi-square	**df**	**sig.**
	Step	49.038	3	0.000
	Block	49.038	3	0.000
	Model	49.038	3	0.000

Source: Author's calculations

Table 4.21 : Model Summary: 3-year before FD for BIFR Companies using Financial Variables

Summary of the model		
-2 log likelihood	Cox & Snell R^2	Nagelkerke R^2
45.23	0.514	0.685

Source: Author's calculations

Table 4.22 : Hosmer and Lemeshow Test using Financial Variables: 3-year before FD for BIFR Companies

Hosmer & Lemeshow test		
Chi-square	df	sig.
3.382	8	0.908

Source: Author 's calculations

4.5.1 Testing for the Significance of the Model

The result of the Omnibus test is shown in Table 4.20. The null hypothesis for the test is intercept, as well as all the coefficients are zero. A p-value (sig) below 0.05 suggests that the model is statistically significant. In table 4.21, the pseudo-R-squares value for Nagelkerke R^2 is 0.685, which shows higher goodness of fit for the predictive model. But the predictive capacity of the chosen explanatory variables decreases from 0.802 in the one year before to financial distress model to 0.777 in the two years before to financial distress model & to 0.685 in the three years before to financial distress model. Hosmer and Lemeshow test (Table 4.22) suggests the model is a good fit as p=0.908 (>.05)

Table 4.23 : Classification Table of the Model using Financial Variables: 3-year before FD for BIFR Companies

Classification Table							
Observed		Predicted					
		Selected Cases			Holdout Sample		
		Type		Correct Percentage	Type		Correct Percentage
		0	1		0	1	
Type	0	67	13	83.8	29	5	85.2
	1	17	63	78.8	8	26	76.4
Overall % ge				81.3			80.8

Source: Author's calculations

4.5.2 Assessing Fitness of Model

This section refers to how well the result attribute, often referred to as its fitness, is projected in the model. The model of predicting financial distress is used to forecast the state for financial distress or healthy company. The value of the cut-off is 0.5. If the company's calculated probability of financial distress is > 0.5, then the company is expected to be financially distressed. The table 4.23 shows the classification of the cross-classification matrix of the outcome variable with a dichotomized variable; if the estimated likelihood exceeds the cut-off point, then the computed variable is equal to one. Otherwise, it is equal to zero. As per table 4.23, the financial distress prediction model developed correctly classifies 83.8% of healthy firms & 78.8 % of sampled financially distressed firms and 85.2% of healthy firms & 76.4% of financially distressed firms for the holdout sample. The development of the model predicts a total of one hundred sixty samples. The forecast includes one hundred thirty accurate samples and thirty incorrect samples. The precise estimate is 81.3%. For the holdout sample, the model predicts a total of sixty-eight samples. The forecast includes fifty-five accurate samples and thirteen incorrect samples. The precise estimate is 80.8%. The overall logistic model forecasts correctly 81.3% of the cases for the development of the model and 80.8% of the cases in the holdout sample.

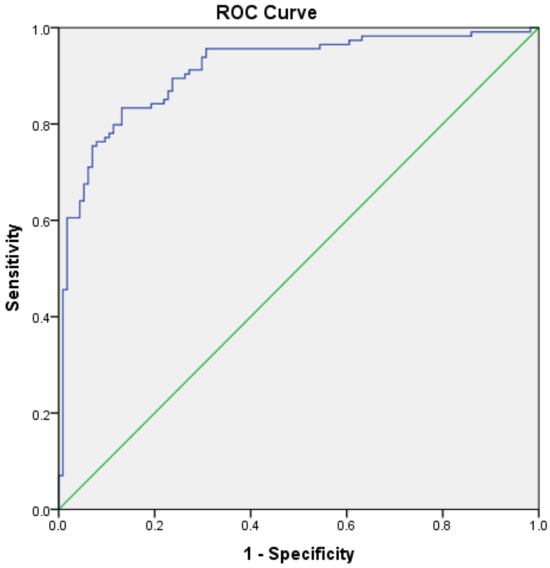
Table 4.24 : Variables in the Model to Predict FD using Financial Variables: 3-year before for BIFR Companies

Equation variables						
	b	**S.E.**	**wald**	**df**	**sig.**	**exp (b)**
DE	0.922	0.233	15.602	1	0.000	2.515
PBIDTM	-0.171	0.038	19.884	1	0.000	0.843
NSTA	-0.813	0.244	11.102	1	0.000	0.444
Constant	1.625	0.455	12.755	1	0.000	5.077
Variable(s) entered: DE, PBIDTM, NSTA.						

Source: Author's calculations

4.5.3 Interpreting the Fitted Logistic Regression Model

As per Table 4.24, the Wald test's significance value for each predictor indicates that (Debt)-to-(equity) ratio, (Adjusted gross profit + interest)-to-(sales) * 100, (Net Sales)-to- (total assets) significantly predict financial distress ($p<0.05$). The values of exp (b) of 2.515 for (debt)-to-(equity) ratio indicates that if the percentage of (debt)-to-(equity) ratio goes up by one, then odds of financial distress will also increase. As exp (b) is greater than one, which means with every unit increase in (debt)-to-(equity) ratio, the likelihood of financial distress will increase by 2.515 times. The values of exp (b) of 0.843 for (Adjusted gross profit + interest)-to-(sales) * 100 indicates that if the percentage of (Adjusted gross profit + interest)-to-(sales) goes up by one, then odds of financial distress will decrease. As exp (b) is less than one, which means with every unit increase in (Adjusted gross profit + interest)-to-(sales), the likelihood of financial distress will decline by 0.843 times than the companies with no increase in this ratio. The values of exp (b) of 0.444 for (Net sales)-to-(total assets) indicates that if the percentage of (Net sales)-to-(total assets) goes up by one, then odds of financial distress will decrease. As exp (b) is less than one, which means with every unit increase in (Net sales)-to-(total assets), the likelihood of financial distress will decline by 0.444 times than firms that do not experience a surge in this ratio.



Source: Author ‘s calculations

Figure 4.3: ROC curve: 3- year before FD for BIFR Companies using Financial Variables

Table 4.25 : Area under the Curve: 3- year before FD for BIFR Companies using Financial Variables

AUC				
Test result variable(s)	Predicted probability			
Area	SE.	Asymptotic sig.	Asymptotic 95% confidence interval	
			Lower bound	Upper bound
0.913	0.02	0.000	0.874	0.951

Source: Author’s calculations

In Figure 4.3, using logistic regression, the ROC curve was used to verify the predictive ability of the three-year financial distress model. The AUC gives a degree of discrimination that is likely to result in a failure of a financial distress enterprise being higher than a healthy one. As per table 4.25, AUC is 0.913, indicating that for a randomly selected distress company and randomly selected healthy company, there is a 0.913 likelihood that for a financial distress company, the model estimated the likelihood of distress would be more than for a healthy company. The AUC ranges from 0.874 to 0.951 at a 95% confidence interval. As per the general rule of Hosmer and Lemeshow (2000), three years before the financial distress model presents outstanding in-sample discrimination.

Table 4.26 : Result of the Logistic Regression for BIFR Companies using Financial Variables

Year before Financial Distress	Pseudo R-squares	AUC	Classification Accuracy Model Development	Classification Accuracy Holdout Sample
1	0.802	0.962	94.8%	89.4%
2	0.777	0.944	90%	85.1%
3	0.685	0.913	81.3%	80.8%

Source: Author’s calculations

4.6 OVERALL FINDINGS OF THE STUDY

From this section, the logistic regression statistical technique helped forecast financial distress over one to three years for BIFR firms using financial variables. The derived models are significantly relevant to predict financial distress companies over time frames of one to three years. The goodness of fit shown by the Hosmer and Lemeshow test found a high p-value (>0.05) for all three models. Thus, all three models are successful in predicting the outcome and are quite effective. As per earlier studies, the analysis found that the predictive capacity of the models is diminishing with the increase in the period of financial distress using financial variables with deteriorating Pseudo R-squares, AUC values and accuracy level of Classification matrix. Table 4.26 contains Nagelkerke’s R square values for relative evaluation of all three models. As anticipated, the value of Nagelkerke R square decreases for models from years 1 to 3. But the decrease in magnitude is only small, suggesting that the predictors of the models are stable over time and the overall ability to predict is satisfactory. Greater the AUC, the higher a model’s predictive accuracy. The Area under curve value near 1 for all three models shows their higher ability in classification. As per Table 4.26, the value of AUC decreases from 0.962 to 0.913 for models from years 1 to 3. But the decrease in magnitude is only small, and values are above 0.9, which suggests outstanding discrimination of the predictive models. Further, it can be observed in all three models, coefficient values for all three financial ratios; (Debt)/(equity) ratio, (Adjusted gross profit + interest)/ (sales) * 100, (Net sales)/(total assets) are significant at five -percent level with likely positive and negative signs. The debt-to-equity has a positive coefficient value in all three models, which suggests that an increase in this value will further increase companies' likelihood of financial distress and is the most important ratio for predicting distress given its higher odds ratios in all three models. PBIDTM is the second most important variable after debt-to-equity. It has a negative coefficient value in all three models, which suggests that an increase in PBIDTM value will decrease companies' likelihood of financial distress. NSTA has a negative value of the coefficient in all three models, which suggests that increase in its value will decline the likelihood of financial distress of companies. As per Table 4.26, predictive accuracy is highest in the case of one -year before financial distress model with 94.8% of the cases for the model development and 89.4% of the cases in the holdout sample, followed by two-year model with 90% of the cases for the model development and 85.1% of the cases in the holdout sample & three- year model has 81.3% of the cases for the model development and 80.8% of the cases in the holdout sample respectively. Overall, one-year before, the financial distress model had the best predictive accuracy using financial variables for various firms, followed by the two-year and three-year models, respectively.

4.7 MODEL VARIABLES FOR IBC

For companies in IBC, in the database of 50 variables in total, many accounting ratios were examined. The final ratios selected are mentioned below. The approach to the selection was focused on findings, theoretical ideas and empirical reviews previously reported. The data were cleaned and tracked strictly. The probability of incorrect results was minimised by discarding or eliminating variables that have not proved their contribution to prior studies. Also, indicators that have proven useful in previous research in framing models were used. Variables that are strongly correlated and can result in multicollinearity, along with redundant variables, were discarded.

Finally, new variables that have the potential to be useful in addressing the model were tested. The ultimate model predicts distress in the future using three ratios; Debt-to-Equity ratio (DE), (Adjusted net profit + depreciation)-to-sales * 100 (CPM) and Cash flow from operations-to-Interest (CFOINT), after analysing a variety of existing ratios to predict distress as per table 4.27. It is found that the ratio of Debt-to-Equity (DE) is consistently lower whereas (Adjusted net profit + Depreciation)-to-Sales * 100 (CPM) & Cash Flow from Operations-to-Interest (CFOINT) ratios are higher for non-distressed companies. So non-distressed firms are less indebted and have more profitability with higher cash flow from operations to interest obligations. All the ratios' signs measured were as per the expectation. The positive coefficient value indicates the likelihood of distress increases when values of ratio increase, while the negative value of coefficient indicates the opposite result.

Table 4.27 : Financial Variables used for predicting Financial Distress in IBC Firms

Symbol	Ratio	Description
DE	(Debt)/(Equity)	It is a leverage ratio that illustrates how well a firm can cover its debt.
CFOINT	(Cash flow from operations)/ (Interest)	It depicts a company's ability to generate cash from its core operations with respect to interest liabilities.
CPM	(Adjusted net profit + Depreciation) / (Sales) * 100	It indicates the company's ability to generate profits from sales.

The Debt-to-Equity ratio signifies the long-term soundness of a business. DE ratio presents the sum of long-term money borrowed as a percentage of the shareholder' capital. An increased ratio means a higher level of risk, and a lower number suggests a safe financial position for the firm. The ratios of Cash flow from Operations-to-Interest (CFOINT) demonstrate firm cash producing potential from its core business for its interest obligations. (Adjusted net profit + Depreciation) / Sales * 100 (CPM) shows the company ability to generate profits on sales. A higher value will reveal the efficiency of the company management. The greater the ratio, the less the company's investment to produce sales and the greater profits. If a firm has a poor ratio, it means it is inefficient in utilising its various resources to produce revenue. The following section has developed models to forecast financial distress for different firms, using financial ratios over one to three years.

4.8 ONE-YEAR BEFORE FINANCIAL DISTRESS USING FINANCIAL VARIABLES: FOR IBC COMPANIES

This section estimates one year before model using accounting ratios of companies in the year t-1, i.e., one year before the year in which a financial distressed incident happened for a listed company referred to IBC, matching with a healthy company in the same year. It summarizes the findings of the one-year prior financially distressed model, including Pseudo R-squares, Model Classification table, Wald statistic, p-values, Odds ratios, ROC curve, and Area under the curve.

Table 4.28 : Correlation Statistics: 1-year before FD using Financial Variables for IBC and Healthy Companies

	DE	CPM	CFOINT
DE	1.000	-.099	.023
CPM	-.099	1.000	-.216
CFOINT	.023	-.216	1.000

Values are significant at 1% level

Source: Author’s calculations

Table 4.29 : Multicollinearity Statistics: 1-year before FD using Financial Variables for IBC and Healthy Companies

		DE	CPM	CFOINT
Collinearity Statistics	Tolerance	.947	.900	.946
	VIF	1.056	1.057	1.111

Source: Author’s calculations

Table 4.28 provides a matrix of correlations of all covariates. In all categories, the observed correlations are statistically significant. Correlations among the covariates are generally small, indicating that the covariates give different and unique details. Correlation among: Debt-to-equity & Cash flow from operations-to-Interest (CFOINT) is .023; (Adjusted net profit + Depreciation)-to-Sales * 100 (CPM) & Cash flow from operations-to-Interest (CFOINT) is -.216; Debt-to-equity & (Adjusted net profit + Depreciation)-to-Sales*100 (CPM) is -.099. In the case of multicollinearity, independent variables have a linear relationship, which can further result in unstable coefficient values. Variance Inflation (VIF) and its inverse, Tolerance Value (TOL), is calculated to identify the presence of multicollinearity. A value of VIF of more than 10 indicates significant collinearity. As per table 4.29, variables have VIF's near to 1, with VIF values of 1.056,1.057 and 1.111 for Debt-to-equity, (Adjusted net profit + depreciation)-to-Sales * 100 (CPM) and Cash flow from Operations-to-Interest (CFOINT), respectively, which means that the collinearity between the regressors has not affected the level of the coefficients & the model does not have multicollinearity, and therefore, the model is capable of reliable performance.

Table 4.30 : Omnibus Tests for the Financial Variables: 1-year before FD for IBC Companies

Omnibus Tests			
	Chi-Square	**Df**	**Sig.**
Step	215.494	3	0
Block	215.494	3	0
Model	215.494	3	0

Source: Author’s calculations

Table 4.31 : Model Summary: 1-year before FD for IBC Companies using Financial Variables

Summary of the model		
-2 log likelihood	Cox & Snell $R^{\wedge 2}$	Nagelkerke $R^{\wedge 2}$
175.628	0.423	0.564

Source: Author ‘s calculations

Table 4.32 : Hosmer and Lemeshow Test using Financial Variables: 1-year before FD for IBC Companies

Hosmer & Lemeshow test		
Chi-square	df	sig.
5.915	8	0.657

Source: Author 's calculations

4.8.1 Testing for the Significance of the Model

The result of the Omnibus test is shown in Table 4.30. The null hypothesis for the test is intercept, as well as all the coefficients are zero. A p-value (sig) below 0.05 suggests that the model is statistically significant. As per Table 4.31, the pseudo-R-squares value for Nagelkerke R^2 is 0.564, suggesting higher goodness of fit for the predictive model. The result of the Hosmer and Lemeshow test (Table 4.32) depicts the model is a good fit as p equal to 0.657 (> 0.05)

Table 4.33 : Classification Table of the Model using Financial Variables: 1-year before FD for IBC Companies

Classification Table							
Observed		Predicted					
		Selected Cases			Holdout Sample		
		Type		Correct Percentage	Type		Correct Percentage
		0	1		0	1	
Type	0	88	17	83.8	35	10	77.7
	1	21	84	80	12	33	73.3
Overall Percentage				81.9			75.5

Source: Author 's calculations

4.8.2 Assessing Fitness of Model

This section refers to how well the result attribute, often referred to as its fitness, is projected in the model. The value of the cut-off is 0.5. If the company's calculated probability of financial distress is > 0.5, the firm is expected to be financially distressed. Table 4.33 shows the classification of the cross-classification matrix of the outcome variable with dichotomized variable; if the estimated likelihood exceeds the cut-off point, then the computed variable is equal to one; otherwise, it is equal to zero. The financial distress prediction model developed correctly classifies 83.8% of healthy firms & 80 % of sampled financially distressed firms and 77.7% of healthy firms & 73.3% of financially distressed firms for the holdout sample. In table 4.33, the development of the model predicts a total of two hundred ten samples. The forecast includes one hundred seventy-two accurate samples and thirty-eight incorrect samples. The precise estimate is 81.9%. For the holdout sample, the model predicts a total of ninety samples. The forecast includes sixty-eight accurate samples and twenty-two incorrect samples. The precise estimate is 75.5%. The overall logistic model forecasts correctly 81.9% of the cases for the development of the model and 75.5% of the cases in the holdout sample.

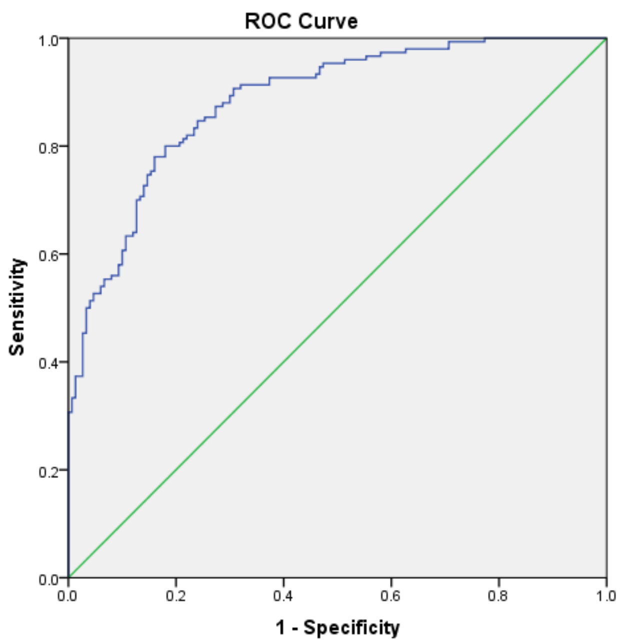
Table 4.34 : Variables in the Model to Predict FD using Financial Variables: 1-year before for IBC Companies

Equation variables						
	b	**S.E.**	**wald**	**df**	**sig.**	**exp (b)**
DE	1.107	0.229	23.324	1	0.000	3.025
CPM	-0.114	0.029	15.476	1	0.000	0.892
CFOINT	-0.142	0.031	20.982	1	0.000	0.867
Constant	-0.592	0.177	11.186	1	0.000	0.553

Source: Author 's calculations

4.8.3 Interpreting the Fitted Logistic Regression Model

As per Table 4.34, the Wald test's significance value for each predictor shows that the **(**Debt)-to-(Equity) (DE), (Adjusted net profit + Depreciation)-to-(Sales) * 100 (CPM) & (Cash flow from Operations)-to-(Interest) (CFOINT) significantly predict financial distress ($p<0.05$). The values of exp (b) of 3.025 for **(**Debt)/(Equity) (DE) ratio indicates that if the percentage of (Debt)/(Equity) (DE) goes up by one, then odds of financial distress will also increase. As exp (b) is greater than one, which means with every unit increase in this ratio, the likelihood of distress will increase by 3.025 times than firms that do not experience an increase in (Debt)/(Equity) (DE). The values of exp (b) of 0.892 for (Adjusted net profit + Depreciation)/ (Sales) * 100 (CPM) indicates that if the percentage of (Adjusted net profit) + Depreciation)/(Sales) * 100 (CPM) goes up by one, then odds of financial distress will decrease. As exp (b) is less than one, which means with every unit increase in (Adjusted net profit + Depreciation)/ (Sales) * 100 (CPM), the likelihood of distress will decline by 0.892 times. Values of exp (b) of 0.867 for (Cash flow from operations)/(Interest) (CFOINT) indicates that if the percentage of (Cash flow from operations)/(Interest) (CFOINT) goes up by one, then odds of financial distress will decrease. As exp (b) is less than one, which means with every unit increase in (Cash flow from operations)/(Interest) (CFOINT), the likelihood of distress will decline by 0.867 times.



Source: Author's calculations

Figure 4.4 : ROC curve: 1- year before FD for IBC Companies using Financial Variables

Table 4.35 : Area under the Curve: 1- year before FD for IBC Companies using Financial Variables

AUC				
Test result variable(s)	Predicted probability			
Area	SE.	Asymptotic sig.	Asymptotic 95% confidence interval	
			Lower bound	Upper bound
0.884	0.019	0.000	0.847	0.920

Source: Author's calculations

An alternative approach to calculate the predictive precision of a predictive model is a ROC. There is a general principle, if a model provides perfect discriminating strength, the AUC it achieves will be 1. In Figure 4.4, using logistic regression, the ROC curve was used to verify the predictive ability of the one-year financial distress model. The AUC gives a degree of discrimination that is likely to result in a failure of a financial distress enterprise being higher than a healthy one. As per table 4.35, AUC is 0.884, indicating that for a randomly selected distress company and randomly selected healthy company, there is a 0.884 likelihood that for a financial distress company, the model estimated likelihood of distress would be more than for a healthy company. The AUC ranges from 0.847 to 0.920 at a 95% confidence interval. As per the general rule of Hosmer and Lemeshow (2000), one year before the financial distress model presents outstanding in-sample discrimination.

4.9 TWO-YEAR BEFORE FINANCIAL DISTRESS USING FINANCIAL VARIABLES: FOR IBC COMPANIES

This section estimates two-year before model using accounting ratios of companies in the year t-2, i.e., two years prior to the year, a financial distressed incident happened for a listed company referred to IBC, matching with a healthy company in the same year. It summarizes the findings of the two-year prior financially distressed model, including Pseudo R-squares, Model Classification table, Wald statistic, p-values, Odds ratios, ROC curve, and Area under the curve.

Table 4.36 : Correlation Statistics: 2-year before FD using Financial Variables for IBC and Healthy Companies

	DE	CPM	CFOINT
DE	1.000	-.116	.078
CPM	-.116	1.000	-.106
CFOINT	.078	-.106	1.000

Values are significant at 1% level

Source: Author's calculations

Table 4.37 : Multicollinearity Statistics: 2-year before FD using Financial Variables for IBC and Healthy Companies

		DE	CPM	CFOINT
Collinearity Statistics	Tolerance	.936	.926	.869
	VIF	1.069	1.080	1.151

Source: Author 's calculations

Table 4.36 provides a matrix of correlations of all covariates. In all categories, the observed correlations are statistically significant. Correlations among the covariates are generally small, indicating that the covariates give different and unique details. Correlation among: Debt-to-equity & Cash flow from Operations-to-Interest (CFOINT) is .078; (Adjusted net profit + depreciation)-to-Sales * 100 (CPM) & Cash flow from Operations-to-Interest (CFOINT) is -.106. Debt-to-equity & (Adjusted net profit + depreciation)-to-Sales * 100 (CPM) is -.116. Variance Inflation (VIF) and its inverse, Tolerance Value (TOL), is calculated to identify the presence of multicollinearity. A value of VIF of more than 10 indicates significant collinearity. Analyses of all the regressors (table 4.37) obtained show VIF's near to 1, with VIF values of 1.069, 1.080 and 1.151 for Debt-to-equity, (Adjusted net profit + depreciation)-to-Sales * 100 (CPM) and Cash flow from operations-to-Interest (CFOINT), respectively, which means that the collinearity between the regressors has not affected the level of the coefficients & the model does not have multicollinearity, and therefore, the model is capable of reliable performance.

Table 4.38 : Omnibus Tests for the Financial Variables: 2-year before FD for IBC Companies

Omnibus Tests			
	Chi-square	**df**	**sig.**
Step	277.568	3	0.000
Block	277.568	3	0.000
Model	277.568	3	0.000

Source: Author 's calculations

Table 4.39 : Model Summary: 2-year before FD for IBC Companies using Financial Variables

Summary of the model		
-2 log likelihood	Cox & Snell R^2	Nagelkerke R^2
213.554	0.309	0.412

Source: Author 's calculations

Table 4.40 : Hosmer and Lemeshow Test using Financial Variables: 2-year before FD for IBC Companies

Hosmer & Lemeshow test		
Chi-square	df	sig.
10.224	8	0.250

Source: Author 's calculations

4.9.1 Testing for the Significance of the Model

The Omnibus test in table 4.38 checks whether this variable block is a substantial contributor to the model's fitness. The null hypothesis for the test is intercept, as well as all the coefficients are zero. The p-value, which is a measure of significance, is evaluated by comparing it to critical value 0.05 to evaluate the significance of the overall model. As the p-value is < 0.05, thus the model is significant. As per table

4.39, the pseudo-R-squares value for Nagelkerke R^2 is .412, which shows reasonable fitness for the predictive model. But the predictive capacity for the chosen explanatory variables decreases from .564 in the one year before to financial distress model to 0.412 in the two years before to financial distress model. The result of Hosmer and Lemeshow test (Table 4.40) depicts the model is a good fit as p equal to 0.250 (> 0.05).

Table 4.41 : Classification Table of the Model using Financial Variables: 2-year before FD for IBC Companies

<table>
<tr><th colspan="8">Classification Table</th></tr>
<tr><td colspan="2" rowspan="4">Observed</td><td colspan="6">Predicted</td></tr>
<tr><td colspan="3">Selected Cases</td><td colspan="3">Holdout Sample</td></tr>
<tr><td colspan="2">Type</td><td rowspan="2">Correct Percentage</td><td colspan="2">Type</td><td rowspan="2">Correct Percentage</td></tr>
<tr><td>0</td><td>1</td><td>0</td><td>1</td></tr>
<tr><td rowspan="2">Type</td><td>0</td><td>86</td><td>19</td><td>81.9</td><td>38</td><td>6</td><td>86.4</td></tr>
<tr><td>1</td><td>25</td><td>80</td><td>76.2</td><td>13</td><td>31</td><td>70.5</td></tr>
<tr><td colspan="2">Overall %ge</td><td></td><td></td><td>79</td><td></td><td></td><td>78.4</td></tr>
</table>

Source: Author ‘s calculations

4.9.2 Assessing Fitness of Model

This section refers to how well the result attribute, often referred to as its fitness, is projected in two years before model. The value of the cut-off is 0.5. If the company's calculated probability of financial distress is > 0.5, the firm is expected to be financially distressed. Table 4.41 shows the classification of the cross-classification matrix of the outcome variable with dichotomized variable; if the estimated likelihood exceeds the cut-off point, then the computed variable is equal to one; otherwise, it is equal to zero. The financial distress prediction model developed correctly classifies 81.9% of healthy firms & 76.2 % of sampled financially distressed firms and 86.4% of healthy firms & 70.5% of financially distressed firms for the holdout sample. In table 4.41, the development of the model predicts a total of two hundred ten samples. The forecast includes one hundred sixty-six accurate samples and forty-four incorrect samples. The precise estimate is 79%. For the holdout sample, the model predicts a total of eighty-eight samples. The forecast includes sixty-nine accurate samples and nineteen incorrect samples. The precise estimate is 78.4%. The overall logistic model forecasts correctly 79% of the cases for the development of the model and 78.4% of the cases in the holdout sample.

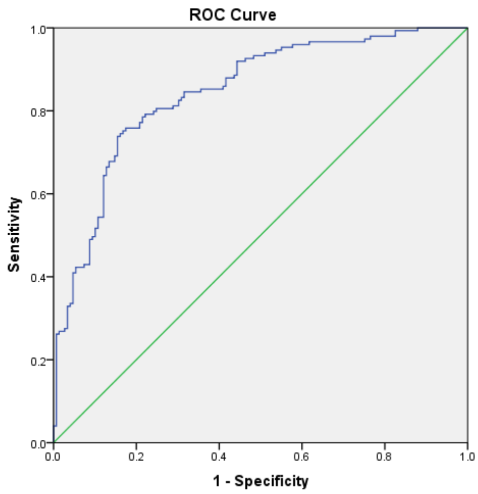
Table 4.42 : Variables in the Model to Predict FD using Financial Variables: 2-year before for IBC Companies

Equation variables						
	b	**S.E.**	**wald**	**df**	**sig.**	**exp (b)**
DE	0.742	0.205	13.127	1	0.000	2.101
CPM	-0.115	0.030	14.835	1	0.000	0.891
CFOINT	-0.324	0.081	15.871	1	0.000	0.723
Constant	0.305	0.070	18.984	1	0.000	1.357

Source: Author ‘s calculations

4.9.3 Interpreting the Fitted Logistic Regression Model

As per Table 4.42, the Wald test's significance value for each predictor shows that the Debt-to-equity ratio, (Adjusted net profit + depreciation)-to-sales * 100 (CPM) & Cash flow from operations-to-Interest (CFOINT) significantly predict financial distress ($p<0.05$). The values of exp (b) of 2.101 for debt-to-equity ratio indicates that if the debt-to-equity ratio goes up by one, then odds of financial distress will also increase. As exp (b) is greater than one, which means with every unit increase in this ratio, the likelihood of financial distress will increase by 2.101 times than firms that do not experience an increase in debt-to-equity ratio. The values of exp (b) of 0.891 for (Adjusted net profit + depreciation)-to-sales * 100 (CPM) indicates that if the percentage of (Adjusted net profit + depreciation)-to-sales * 100 (CPM) goes up by one, then odds of financial distress will decrease. As exp (b) is less than one, which means with every unit increase in (Adjusted net profit + depreciation)-to-sales * 100 (CPM), the probability of financial distress will decline by 0.891 times. The values of exp (b) of 0.723 for (Cash flow from operations)/(Interest)(CFOINT) indicates that if the percentage of (Cash flow from operations)/(Interest)(CFOINT) goes up by one, then odds of financial distress will decrease. As exp (b) is less than one, which means with every unit increase in (Cash flow from operations)/(Interest)(CFOINT), the probability of financial distress will decline by 0.723 times than firms that do not experience an increase in this ratio.



Source: Author ‘s calculations

Figure 4.5: ROC curve: 2- year before FD for IBC Companies using Financial Variables

Table 4.43 : Area under the Curve: 2- year before FD for IBC Companies using Financial Variables

AUC				
Test result variable(s)	Predicted probability			
Area	SE.	Asymptotic sig.	Asymptotic 95% confidence interval	
			Lower bound	Upper bound
0.845	0.022	0.000	0.801	0.889

Source: Author ‘s calculations

In Figure 4.5, using logistic regression, the ROC curve was used to verify the predictive ability of the two-year financial distress model. The AUC gives a degree of discrimination that is likely to result in a failure of a financial distress enterprise being higher than a healthy one. As per table 4.43, AUC is 0.845, indicating that for a randomly selected distress company and randomly selected healthy company, there is a 0.845 likelihood that for a financial distress company, the model estimated the likelihood of distress would be more than for a healthy company. The AUC ranges from 0.801 to 0.889 at a 95% confidence interval. As per the general rule of Hosmer and Lemeshow (2000), two years before the financial distress model presents outstanding in-sample discrimination.

4.10 THREE-YEAR BEFORE FINANCIAL DISTRESS USING FINANCIAL VARIABLES: FOR IBC COMPANIES

This section estimates the three-year before model using accounting ratios of companies in the year t-3, i.e., three years before the year in which a financial distressed incident happened for a listed company referred to IBC, matching with a healthy company in the same year. It summarizes the findings of the three-year prior financially distressed model, including Pseudo R-squares, Model Classification table, Wald statistic, p-values, Odds ratios, ROC curve, and Area under the curve.

Table 4.44 : Correlation Statistics: 3-year before FD using Financial Variables for IBC and Healthy Companies

	DE	**CPM**	**CFOINT**
DE	1.000	-.156	-.148
CPM	-.156	1.000	.018
CFOINT	-.148	.018	1.000

Values are significant at 1% level

Source: Author ‘s calculations

Table 4.45 : Multicollinearity Statistics: 3-year before FD using Financial Variables for IBC and Healthy Companies

		DE	CPM	CFOINT
Collinearity Statistics	Tolerance	.927	.935	.950
	VIF	1.079	1.070	1.053

Source: Author 's calculations

Table 4.44 provides a matrix of correlations of all covariates. In all categories, the observed correlations are statistically significant. Correlations among the covariates are generally small, indicating that the covariates give different and unique details. Correlation among: Debt-to-equity & Cash flow from operations/ Interest (CFOINT) is -0.148; (Adjusted net profit + depreciation)-to-sales * 100 (CPM) & Cash flow from operations-to-Interest (CFOINT) is 0.018; Debt-to-equity & (Adjusted net profit + depreciation)-to-sales * 100 (CPM) is -0.156. Variance Inflation (VIF) and its inverse, Tolerance Value (TOL), is calculated to identify the presence of multicollinearity. A value of VIF of more than 10 indicates significant collinearity. Analyses of all the regressors (as per table 4.45) obtained in the methods of the present study show VIF's near to 1, with VIF values of 1.079, 1.070 and 1.053 for Debt-to-equity, (Adjusted net profit + depreciation)-to-sales * 100 (CPM) and Cash flow from operations-to-Interest (CFOINT), respectively, which means that the collinearity between the regressors has not affected the level of the coefficients & the model does not have multicollinearity, and therefore, the model is capable of reliable performance.

Table 4.46 : Omnibus Tests for the Financial Variables: 3-year before FD for IBC Companies

Omnibus Tests			
	Chi-square	df	sig.
Step	208.215	3	0.000
Block	208.215	3	0.000
Model	208.215	3	0.000

Source: Author 's calculations

Table 4.47 : Model Summary: 3-year before FD for IBC Companies using Financial Variables

Summary of the model		
-2 log likelihood	Cox & Snell $R^{\wedge 2}$	Nagelkerke $R^{\wedge 2}$
189.043	0.357	0.476

Source: Author ‘s calculations

Table 4.48 : Hosmer and Lemeshow Test using financial variables: 3-year before FD for IBC companies

Hosmer & Lemeshow Test		
Chi-square	df	sig.
11.113	8	0.195

Source: Author ‘s calculations

4.10.1 Testing for the Significance of the Model

The result of the Omnibus test is shown in Table 4.46. The null hypothesis for the test is intercept, as well as all the coefficients are zero. A p-value (sig) below 0.05 suggests that the model is statistically significant. As per table 4.47, the pseudo-R-squares value for Nagelkerke R^2 is .476, which shows reasonable fitness for the predictive model. But the predictive capacity for the chosen explanatory variables decreases from .564 in the one year before the financial distress model to 0.412 in the two years prior to the financial distress model & 0.476 in the three years before the financial distress model. The result of Hosmer and Lemeshow test (Table 4.48) depicts the model is a good fit as p equal to 0.195 (> 0.05).

Table 4.49 : Classification Table of the model using financial variables: 3-year before FD for IBC companies

Classification Table							
Observed		Predicted					
		Selected Cases			Holdout Sample		
		Type		Correct Percentage	Type		Correct Percentage
		0	1		0	1	
Type	0	76	24	76	34	10	77.2
	1	23	77	77	9	35	79.5
Overall %ge				76.5			78.4

Source: Author ‘s calculations

4.10.2 Assessing Fitness of Model

This section refers to how well the result attribute, often referred to as its fitness, is projected in the model. The value of the cut-off is 0.5. If the company's calculated probability of financial distress is > 0.5, the firm is expected to be financially distressed. Table 4.49 shows the classification of the cross-classification matrix of the outcome variable with dichotomized variable; if the estimated likelihood exceeds the cut-off point, then the computed variable is equal to one; otherwise, it is equal to zero. The financial distress prediction model developed correctly classifies 76% of healthy firms & 77 % of sampled financially distressed firms and 77.2% of healthy firms & 79.5% of financially distressed firms for the holdout sample. In table 4.49, the development of the model predicts a total of two hundred samples. The forecast includes one hundred fifty-three accurate samples and forty-seven incorrect samples. The precise estimate is 76.5%. For the holdout sample, the model predicts a total of eighty-eight samples. The forecast includes sixty-nine accurate samples and nineteen incorrect samples. The precise estimate is 78.4%. The overall logistic model forecasts correctly 76.5% of the cases for the development of the model and 78.4% of the cases in the holdout sample.

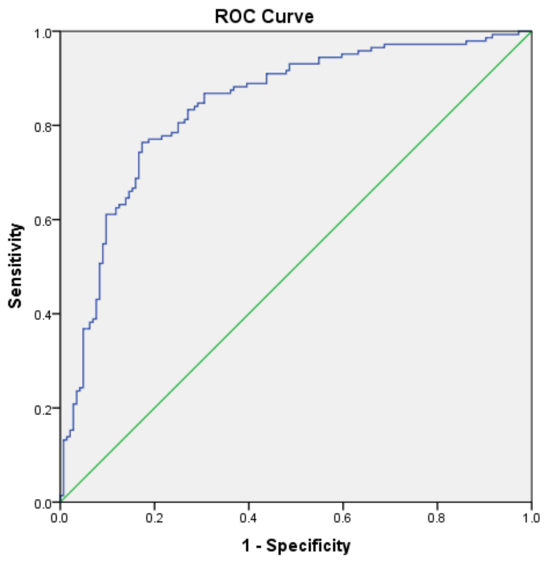
Table 4.50 : Variables in the Model to Predict FD using Financial Variables: 3-year before for IBC Companies

Equation variables						
	b	**S.E.**	**wald**	**df**	**sig.**	**exp (b)**
DE	1.441	0.293	24.171	1	0.000	4.224
CPM	-0.116	0.034	12.028	1	0.000	0.890
CFOINT	-0.284	0.066	18.377	1	0.000	0.753
Constant	-0.304	0.081	14.085	1	0.000	0.738

Source: Author 's calculations

4.10.3 Interpreting the fitted logistic regression model

As per Table 4.50, the Wald test's significance value for each predictor shows that Debt-to-equity ratio, (Adjusted net profit + depreciation)-to-sales * 100 (CPM) & Cash flow from operations-to-Interest (CFOINT) significantly predict financial distress ($p<0.05$). The values of exp (b) of 4.224 for (debt)-to-(equity) ratio indicates that if the percentage of (debt)-to-(equity) ratio goes up by one, then odds of financial distress will also increase. As exp (b) is greater than one, which means with every unit increase in this ratio, the probability of financial distress will increase by 4.224 times than firms that do not experience a surge in this ratio. Values of exp (b) of 0.890 for (Adjusted net profit + depreciation)-to-sales * 100 (CPM) indicates that if the percentage of (Adjusted net profit + depreciation)-to-sales * 100 (CPM) goes up by one, then odds of financial distress will decrease. As exp (b) is less than one, which means with every unit increase in (Adjusted net profit + depreciation)-to-sales * 100 (CPM), the likelihood of financial distress will decline by 0.890 times. Values of exp (b) of 0.753 for (Cash flow from operations)/(Interest) (CFOINT) indicates that if the percentage of (Cash flow from operations)/(Interest) (CFOINT) goes up by one, then odds of financial distress will decrease. As exp (b) is less than one, which means with every unit increase in (Cash flow from operations)/(Interest)(CFOINT), the probability of financial distress will decline by 0.753 times than firms that do not experience an increase in this ratio.



Source: Author ‘s calculations

Figure 4.6: ROC curve: 3- year before FD for IBC companies using financial variables

Table 4.51 : Area under the Curve: 3-year before FD for IBC companies using financial variables

AUC				
Test result variable(s)	Predicted probability			
Area	SE.	Asymptotic sig.	Asymptotic 95% confidence interval	
			Lower bound	Upper bound
0.840	0.024	0.000	0.793	0.887

Source: Author ‘s calculations

Using logistic regression, the ROC curve was used to verify the predictive ability of the three-year financial distress model, as shown in Figure 4.6. The AUC gives a degree of discrimination that is likely to result in a failure of a financial distress enterprise being higher than a healthy one. As per table 4.51, AUC is 0.840, indicating that for a randomly selected distress company and randomly selected healthy company, there is a 0.840 likelihood that for a financial distress company, the model estimated the likelihood of distress would be more than for a healthy company. The AUC ranges from 0.793 to 0.887 at a 95% confidence interval. As per the general rule of Hosmer and Lemeshow (2000), three years before the financial distress model presents outstanding in-sample discrimination.

Table 4.52 : Result of the logistic regression for IBC companies using financial variables

Year before financial distress	Pseudo R-squares	AUC	Classification accuracy Model development	Classification accuracy Holdout Sample
1	0.564	0.884	81.9%	75.5%
2	0.412	0.845	79%	78.4%
3	0.476	0.840	76.5%	78.4%

Source: Author ‘s calculations

4.11 Overall Findings of the Study

From this section, the logistic regression statistical technique helped to forecast financial distress over one to three years using financial variables. The derived models are significantly relevant to predicting financial distress companies over time frames of one to three years. The result of the goodness of fit for three models shown by Hosmer and Lemeshow test found low chi-square static <15 and a high p-value >0.05 for all three models. Thus, all three models are quite effective for predicting the aforementioned outcome. As per earlier studies, the analysis found that the predictive capacity of the models is diminishing with the increase in the period of financial distress using financial variables with deteriorating Pseudo R-squares and accuracy level of classification matrix. Tables 4.52 contain Nagelkerke’s R square for the relative evaluation of all three models and are only being used to compare different models. As anticipated, the value of Nagelkerke R square decreases for models from years 1 to 3. But the decrease in magnitude is only small, suggesting that predictors are stable over time and the overall ability to predict is satisfactory. Greater the AUC, the higher a model’s predictive accuracy. The AUC reflects the possibility that a randomly selected failing company is more suspect of failure than a randomly chosen successful company. The Area under curve value near 1 for all three models shows their higher ability in classification. As per table 4.52, the value of AUC decreases from 0.884 to 0.840 for models from years 1 to 3. But the decrease in magnitude is only small, and values are above 0.8, which suggests outstanding discrimination of the predictive models. It can be observed in all three models, coefficient values for all three financial ratios; Debt-to-equity ratio, (Adjusted net profit + depreciation)-to-sales * 100 (CPM) & Cash flow from operations-to-Interest (CFOINT) are significant at five -percent level with likely positive and negative signs. The debt-to-equity ratio has a positive value of the coefficient in all three models, which suggests that increase in this ratio will further increase the likelihood of distress of companies and is the most important ratio for predicting distress given its higher odds ratios in all three models. (Adjusted net profit + depreciation)-to-sales * 100 (CPM) is the second most important variable after debt-to-equity and has a negative value of the coefficient in all three models, which suggests that increase in CPM value will decrease the likelihood of financial distress. Cash flow from operations-to-Interest (CFOINT) has a negative coefficient value in all three models, which suggests that an increase in its value will decrease the likelihood of financial distress. Predictive accuracy is highest in case of one -year before financial distress model with 81.9% of the cases for the development of model followed by two- year model with 79% of the cases for the development of model & three- year model with 76.5% of the cases for the development of model respectively. Overall, one- year before, the financial distress model had the best predictive accuracy using financial variables for various firms followed by the two-year and three-year models, respectively.

Chapter – 5

TESTING MARKET AND MACROECONOMIC VARIABLES FOR PREDICTING FINANCIAL DISTRESS

5.1 MARKET VARIABLES FOR PREDICTING FINANCIAL DISTRESS

Share prices are supposed to provide important information on the risk of business failure. Market values are believed to serve as a supplement to the accounting variables and will enhance the financial distress prediction of companies. This research tested eleven market variables, including ‘Price to Book value’, ‘Price to Earnings per Share’, ‘Market Capitalization to Sales’, ‘Market value to Shareholder Funds’, ‘Market value of Equity’ to ‘Total Debt’, ‘Excess Return’, ‘Standard Deviation’, ‘Beta’, ‘Logarithm of Firm Market Capitalization to that of the Index’, ‘Logarithm of Price per Share’, ‘Market Capitalization to Total liabilities’ in the accounting models for firms referred to BIFR and IBC. Variables that are strongly correlated and can result in multicollinearity, along with redundant variables, were rejected. Finally, new variables that have the potential to be useful in addressing the model were tested. Finally, only one market variable, excess return, was found to be vital for companies referred to BIFR. The implementation of market variable; Excess Returns (ER) enhanced the prediction accuracy of the model. Excess return is used to determine the potential of the company to outperform the market return. Excess Return (ER) is calculated as the difference between stock return (Rs) and the benchmark index return (Ri): $[\log(1 + Rs) - \log(1 + Ri)]$. It has been found that the ratio of Excess return is consistently higher for non-distressed companies. So non-distressed firms have a higher stock return as compared to the broader market. The negative value of the coefficient indicates the likelihood of distress decreases when values of ratio increase. An increased ratio means that stock return can outperform the market, which further reflects better future performance expected by the market participants from the company. Similarly, two market variables, “Market value to shareholder funds” (MVSF) & “Standard Deviation” (STDEV) of daily stock returns, are found to be helpful along with various accounting ratios for companies referred to IBC. The implementation of these market variables enhanced the prediction accuracy of the model. It has been found that the ratio of Market value to shareholder funds (MVSF) is consistently higher for non-distressed companies. The negative value of the coefficient indicates the likelihood of distress decreases when values of ratio increase. Whereas Standard- Deviation (STDEV) is consistently lower for non-distressed companies. The positive value of the coefficient indicates the likelihood of distress increases when values of ratio increase. The study tested nine macroeconomic variables, including 'Gross Domestic Product', 'Wholesale Price Index', 'Exchange Rate', 'Index of Industrial Production', 'Money Supply', 'Repo Rate', 'Government Bond Yield', 'Call Money Rate', 'Unemployment Rate' in the accounting & market models to assess their effects on the predictive capacity for firms referred to BIFR and IBC. Only one macroeconomic variable, change in rupee-dollar exchange rate (EX), was found to be little helpful in financial distress prediction along with various financial and market variables for companies referred to both BIFR and IBC. Logistic regression has been applied to frame models for listed firms over a period of one to three years using accounting ratios along with market and macroeconomic variables. Thus, the probability of a corporation tumbling into financial distress based on financial ratios, market & macroeconomic variables has been estimated.

5.2 ONE-YEAR BEFORE FINANCIAL DISTRESS USING FINANCIAL & MARKET VARIABLES: FOR BIFR COMPANIES

This part estimate one-year prior to the financial distress model for BIFR firms based on financial & market variables of financially distressed and healthy companies in the year t-1, one year before to the year in which a financial distressed event occurred for a distressed company, matching with the healthy company in the same year. This research aims to evaluate the usefulness of market variables in enhancing the accuracy and prediction power of financial distress models along with accounting variables. It summarizes the findings of the one-year prior financially distressed model, including Pseudo R-squares, Model Classification table, Wald statistic, p-values, Odds ratios, ROC curve, and Area under the curve.

Table 5.1: Correlation Statistics: 1-year before FD using financial & market variables for BIFR and Healthy companies

	DE	PBIDTM	NSTA	ER
DE	1.000	-.024	-.008	-.024
PBIDTM	-.024	1.000	.551	.211
NSTA	-.008	.551	1.000	-.162
ER	-.024	.211	-.162	1.000

Values are significant at 1% level

Source: Author's calculations

Table 5.2 : Multicollinearity Statistics: 1-year before FD using financial & market variables for BIFR and Healthy companies

		DE	PBIDTM	NSTA	ER
Collinearity Statistics	Tolerance	.945	.973	.910	.891
	VIF	1.058	1.027	1.099	1.122

Source: Author 's calculations

Matrices of correlation and multicollinearity were measured to make sure there was no multicollinearity between all the variables. Table 5.1 provides a matrix of correlations of all covariates. In all categories, the observed correlations are statistically significant. Correlations among the covariates are generally small, indicating that the covariates give different and unique details. Correlation among (Adjusted gross profit + interest)-to-sales * 100, Net sales-to-total assets is largest and is equal to 0.551. Thereafter among (Adjusted gross profit + interest)-to-sales * 100 and Excess Return of 0.211. They are not significant enough to trigger collinearity problems as similar high correlations have been identified in previous studies: the correlation was -0.78 in **Altman (1968)** and -0.49 in **Ohlson (1980)**. In the case of multicollinearity, independent variables have a linear relationship, which can further result in unstable coefficient values. Variance Inflation (VIF) and its inverse, Tolerance Value (TOL) are calculated to identify the presence of multicollinearity. A value of VIF of more than 10 indicates significant collinearity. Analyses of all the regressors (as per table 5.2) obtained in the methods of the present study show they all have VIF's near to 1, with VIF values of 1.058, 1.027, 1.099 and 1.222 for debt-to-equity ratio, (adjusted gross profit + interest)/sales * 100, net sales / total assets and excess return respectively, which mean that the collinearity between the regressors has not affected the level of the coefficients & the model does not have multicollinearity, and therefore, the model is capable of reliable performance.

Table 5.3 : Omnibus Tests for the financial & market variables: 1-year before FD for BIFR companies

Omnibus Tests			
	Chi-Square	**Df**	**Sig.**
Step	168.222	4	0.000
Block	168.222	4	0.000
Model	168.222	4	0.000

Source: Author’s calculations

Table 5.4 : Model Summary: 1-year before FD for BIFR companies using financial & market variables

Summary of the Model		
-2 log likelihood	Cox & Snell R^2	Nagelkerke R^2
45.267	0.665	0.886

Source: Author ‘s calculations

Table 5.5: Hosmer and Lemeshow Test using financial & market variables: 1-year before FD for BIFR companies

Hosmer & Lemeshow test			
	Chi-square	df	sig.
	6.795	8	0.559

Source: Author ‘s calculations

5.2.1 Testing for the Significance of the Model

The model evaluation process can now start with the Omnibus test of model coefficients. The result of the Omnibus test (in table 5.3) checks whether this variable block is a substantial contributor to the fitness of the model. As p-value (sig) is below 0.05, which shows that the model is statistically significant. Pseudo-R^2 is not corresponding R-squared value, which is used in the case of OLS regression. Nagelkerke R^2 is a further adjustment to Cox & Snell R^2, as it does not attain a value of 1. So, it is preferable to report the value of Nagelkerke R^2. As the value increases, the stronger the fitness of the model. In this model, the value for Nagelkerke R^2 is 0.886 (in table 5.4), which shows higher goodness of fit for the model. In Hosmer-Lemeshow(HL) test, like other fitness assessments, smaller p values (generally below 5%) indicate that the model is a poor fit. But big p-values do not inherently suggest that the model suits well, but there is insufficient evidence to imply it is poor. The result of HL test (Table 5.5) depicts the model is a good fit as p equal to 0.559 (> 0.05).

Table 5.6 : Classification Table of the Model using Financial & Market Variables: 1-year before FD for BIFR Companies

<table>
<tr><th colspan="8">Classification Table</th></tr>
<tr><td colspan="2" rowspan="4">Observed</td><td colspan="6">Predicted</td></tr>
<tr><td colspan="3">Selected Cases</td><td colspan="3">Holdout Sample</td></tr>
<tr><td colspan="2">Type</td><td rowspan="2">Correct Percentage</td><td colspan="2">Type</td><td rowspan="2">Correct Percentage</td></tr>
<tr><td>0</td><td>1</td><td>0</td><td>1</td></tr>
<tr><td rowspan="2">Type</td><td>0</td><td>73</td><td>4</td><td>94.8</td><td>33</td><td>0</td><td>100</td></tr>
<tr><td>1</td><td>7</td><td>70</td><td>90.9</td><td>9</td><td>24</td><td>72.7</td></tr>
<tr><td colspan="2">Overall %ge</td><td></td><td></td><td>92.9</td><td></td><td></td><td>86.4</td></tr>
</table>

Source: Author ‘s calculations

5.2.2 Assessing Fitness of Model

This section refers to how well the result attribute, often referred to as its fitness, is projected in one year before the model. The use of the model of predicting financial distress is to forecast state for financial distress or healthy company. The value of the cut-off is 0.5. If the company's calculated probability of financial distress is > 0.5, the firm is expected to be financially distressed. Table 5.6 shows the classification of the cross-classification matrix of the outcome variable with dichotomized variable; if the estimated likelihood exceeds the cut-off point, then the computed variable is equal to one; otherwise, it is equal to zero. If the estimated probability value is 0.5 or more, it will predict financial distress (as financial distress = 1) and healthy if it is lesser than 0.5 (as Healthy =0). One year before the financial distress model was framed based on the 70% observations, the remaining 30% observations (holdout sample) can be used to verify its goodness of fit. The financial distress prediction model developed correctly classifies 94.8% of healthy firms & 90.9% of sampled financially distressed firms and 100% of healthy firms & 72.7% of financially distressed firms for the holdout sample. As per table 5.6, the development of the model predicts a total of one hundred fifty-four samples. The forecast includes one hundred forty-three accurate samples and eleven incorrect samples. The precise estimate is 92.9%. For the holdout sample, the model predicts a total of sixty-six samples. The forecast includes fifty-seven accurate samples and nine incorrect samples. The precise estimate is 86.4%. The overall logistic model forecasts correctly 92.9% of the cases for the development of the model and 86.4% of the cases in the holdout sample.

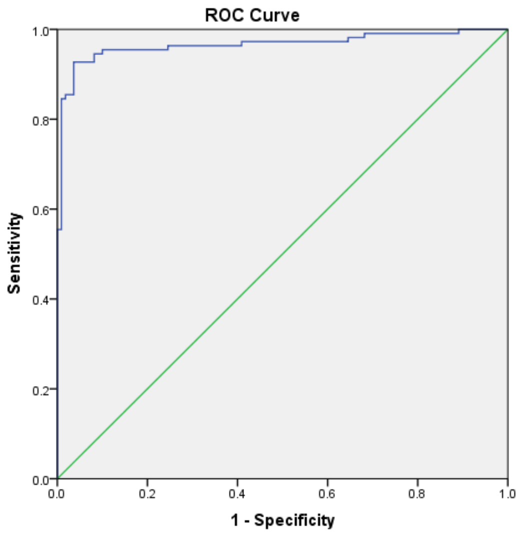
Table 5.7 : Variables in the model to predict FD using financial & market variables: 1- year before for BIFR companies

Equation variables						
	b	**S.E.**	**wald**	**df**	**sig.**	**exp (b)**
DE	0.568	0.179	10.069	1	0.000	1.765
PBIDTM	-0.213	0.059	13.033	1	0.000	0.808
NSTA	-0.311	0.079	15.497	1	0.000	0.733
ER	-1.291	0.405	10.161	1	0.000	0.275
Constant	1.436	0.431	11.100	1	0.000	4.206

Source: Author ‘s calculations

5.2.3 Interpreting the Fitted Logistic Regression Model

The independent variable's slope coefficient measures how much logit varies with an independent variable's unit change. Positive coefficients indicate a greater likelihood of distress as the ratio value increases; however, negative coefficients mean conversely. As per the above table 5.7, all the financial ratios continue to maintain their statistical significance in this model. The value of the Wald test for each predictor indicates that Debt-to-equity ratio, Adjusted gross profit + interest/sales * 100, Net Sales-Total Assets and Excess-Return significantly predict financial distress ($p<0.05$). Values of exp (b) of 1.765 for (debt)/(equity) ratio indicates that if the percentage of (debt)/(equity) ratio goes up by one, then odds of financial distress will also increase. As exp (b) is greater than one, which means with every unit increase in this ratio, the likelihood will increase by 1.765 times. The values of exp (b) of 0.808 for (Adjusted gross profit + interest)-to-sales * 100 indicates that if the percentage of (Adjusted gross profit + interest)-to-sales * 100 goes up by one, then odds of financial distress will decrease. As exp (b) is less than one, which means with every unit increase in (Adjusted gross profit + interest)-to-sales * 100, the likelihood will decline by 0.808 times. Values of exp (b) of 0.733 for (Net sales)/(total assets) indicates that if the percentage of (Net sales)/(total assets) goes up by one, then odds of financial distress will decrease. As exp (b) is less than one, which means with every unit increase in Net Sales / Total Assets, the likelihood will decline by 0.733 times. The values of exp (b) of 0.275 for Excess Return indicates that if the percentage of Excess Return goes up by one, then odds of financial distress will decrease. As exp (b) is less than one, which means with every unit increase in Excess Return, the likelihood will decline by 0.275 times than firms that do not experience an increase in this ratio.



Source: Author 's calculations

Figure 5.1: ROC curve: 1- year before FD for BIFR companies using financial & market variables

Table 5.8 : Area under the Curve: 1- year before FD for BIFR companies using financial & market variables

AUC				
Test result variable(s)	Predicted probability			
Area	SE.	Asymptotic sig.	Asymptotic 95% confidence interval	
			Lower bound	Upper bound
0.966	0.013	0.000	0.940	0.992

Source: Author 's calculations

An alternative approach to calculating the predictive precision of a predictive model is the ROC curve. The AUC reflects the possibility that a randomly selected failing company is more suspect of failure than a randomly chosen successful company. There is a general principle, if a model provides perfect discriminating strength, the AUC it achieves will be 1. In Figure 5.1, using logistic regression, the ROC curve was used to verify the predictive ability of the one-year financial distress model. The

AUC gives a degree of discrimination that is likely to result in a failure of a financial distress enterprise being higher than a healthy one. As per table 5.8, AUC is 0.966, indicating that for a randomly selected distress company and randomly selected healthy company, there is a 0.966 likelihood that for a financial distress company, the model estimated the likelihood of distress would be more than for a healthy company. The AUC ranges from 0.940 to 0.992 at a 95% confidence interval. As per the general rule of Hosmer and Lemeshow (2000), one year before financial distress model presents outstanding in-sample discrimination, using financial & market variables**.**

5.3 TWO-YEAR BEFORE FINANCIAL DISTRESS USING FINANCIAL & MARKET VARIABLES: FOR BIFR COMPANIES

This section estimates the two-year before to financial distress model based on financial & market variables of financially distressed and healthy companies in the year t-2, two years before the year in which a financial distressed event occurred for a distressed company, matching with the healthy one company in the same year. It summarizes the findings of the two-year prior financially distressed model, including Pseudo R-squares, Model Classification table, Wald statistic, p-values, Odds ratios, ROC curve, and Area under the curve.

Table 5.9 : Correlation Statistics: 2-year before FD using financial & market variables for BIFR and Healthy companies

	DE	**PBIDTM**	**NSTA**	**ER**
DE	1.000	-.300	-.153	.015
PBIDTM	-.300	1.000	.509	-.038
NSTA	-.153	.509	1.000	-.175
ER	.015	-.038	-.175	1.000

Values are significant at 1% level

Source: Author ‘s calculations

Table 5.10 :Multicollinearity Statistics: 2-year before FD using financial & market variables for BIFR and Healthy companies

		DE	PBIDTM	NSTA	ER
Collinearity Statistics	Tolerance	.940	.910	.905	.861
	VIF	1.064	1.099	1.105	1.162

Source: Author ‘s calculations

Table 5.9 provides a matrix of correlations of all covariates. In all categories, the observed correlations are statistically significant. Correlations among the covariates are generally small, indicating that the covariates give different and unique details. Correlation among (Adjusted gross profit + interest)/sales * 100, Net sales / total assets is largest and is equal to 0.509. But it is not significant enough to trigger collinearity problems as similar high correlations have been identified in previous studies. Variance Inflation (VIF) and its inverse, Tolerance Value (TOL) are calculated to identify the presence of multicollinearity. A value of VIF of more than 10 indicates significant collinearity. Analyses of all the regressors obtained (as per table 5.10) show they all have VIF's near to 1, with VIF values of 1.064, 1.099, 1.105 and 1.162 for Debt-to-equity ratio, (Adjusted gross profit + interest)/sales * 100, Net Sales / Total Assets and Excess Return respectively, which mean that the collinearity between the regressors has not affected the level of the coefficients & the model does not have multicollinearity, and therefore, the model is capable of reliable performance.

Table 5.11 : Omnibus Tests for the financial & market variables: 2-year before FD for BIFR companies

Omnibus Tests			
	Chi-square	Df	sig.
Step	155.41	4	0.000
Block	155.41	4	0.000
Model	155.41	4	0.000

Source: Author ‘s calculations

Table 5.12 : Model Summary: 2-year before FD for BIFR companies using financial & market variables

Summary of the model		
-2 Log likelihood	Cox & Snell $R^{\wedge 2}$	Nagelkerke R^^{2}
80.260	0.599	0.799

Source: Author ‘s calculations

Table 5.13 : Hosmer and Lemeshow Test using financial & market variables: 2-year before FD for BIFR companies

Hosmer & Lemeshow test		
Chi-square	df	sig.
12.878	8	0.116

Source: Author ‘s calculations

5.3.1 Testing for the Significance of the Model

The result of the Omnibus test is shown in Table 5.11. The null hypothesis for the test is intercept, as well as all the coefficients are zero. A p-value (sig) below 0.05 suggests that the model is statistically significant. In this model, the value for Nagelkerke R^2 is 0.799 (as per table 5.12), which shows higher goodness of fit for the predictive model. The Hosmer-Lemeshow test (HL test) is a test of goodness of fit in the case of the logistic regression model. The result of the test (Table 5.13) depicts the model is a good fit as p equal to 0.116 (> 0.05)

Table 5.14 :Classification Table of the model using financial & market variables: 2-year before FD for BIFR companies

<table>
<tr><th colspan="8">Classification Table</th></tr>
<tr><td colspan="2" rowspan="4">Observed</td><td colspan="6">Predicted</td></tr>
<tr><td colspan="3">Selected Cases</td><td colspan="3">Holdout Sample</td></tr>
<tr><td colspan="2">Type</td><td rowspan="2">Correct Percentage</td><td colspan="2">Type</td><td rowspan="2">Correct Percentage</td></tr>
<tr><td>0</td><td>1</td><td>0</td><td>1</td></tr>
<tr><td rowspan="2">Type</td><td>0</td><td>80</td><td>5</td><td>94.1</td><td>34</td><td>3</td><td>91.9</td></tr>
<tr><td>1</td><td>10</td><td>75</td><td>88.2</td><td>7</td><td>30</td><td>81.1</td></tr>
<tr><td colspan="2">Overall %ge</td><td></td><td></td><td>91.2</td><td></td><td></td><td>86.5</td></tr>
</table>

Source: Author ‘s calculations

5.3.2 Assessing Fitness of Model

The financial distress prediction model developed correctly classifies 94.1% of healthy firms & 88.2% of sampled financially distressed firms and 91.9% of healthy firms & 81.1% of financially distressed firms for the holdout sample. In table 5.14, the development of the model predicts a total of one hundred seventy samples. The forecast includes one hundred fifty-five accurate samples and fifteen incorrect samples. The precise estimate is 91.2%. For the holdout sample, the model predicts a total of seventy-four samples. The forecast includes sixty-four accurate samples and ten incorrect samples. The precise estimate is 86.5%. The overall logistic model forecasts correctly 91.2% of the cases for the development of the model and 86.5% of the cases in the holdout sample.

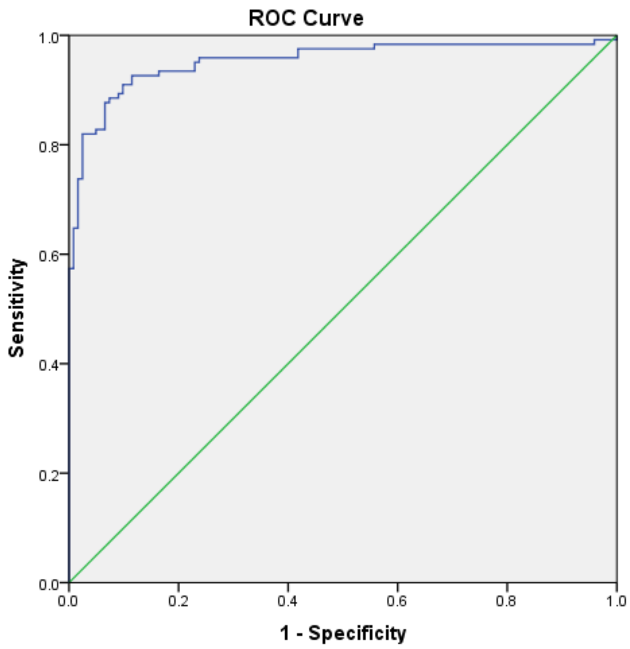
Table 5.15 :Variables in the model to predict FD using financial & market variables: 2- year before for BIFR companies

Equation variables						
	b	**S.E.**	**wald**	**df**	**sig.**	**exp (b)**
DE	1.737	0.374	21.585	1	0.000	5.682
PBIDTM	-0.209	0.059	12.710	1	0.000	0.811
NSTA	-0.946	0.281	11.333	1	0.000	0.388
ER	-1.338	0.388	11.891	1	0.000	0.262
Constant	0.692	0.198	12.214	1	0.000	1.997

Source: Author ‘s calculations

5.3.3 Interpreting the Fitted Logistic Regression Model

Positive coefficients indicate a greater likelihood of distress as the ratio value increases; however, negative coefficients mean conversely. As per the above table 5.15, all the financial ratios continue to be significant in the model. As per Table 5.15, the Wald test’s value for each predictor shows that Debt-to-equity ratio, (Adjusted gross profit + interest)/sales * 100, Net sales/total assets and Excess-return significantly predict distress ($p<0.05$). Values of exp (b) of 5.682 for (debt)/(equity) ratio indicates that if the percentage of (debt)/(equity) ratio goes up by one, then odds of financial distress will also increase. As exp (b) is greater than one, which means with every unit increase in this ratio, the likelihood of distress will increase by 5.682 times than firms that do not experience a surge in this ratio. The values of exp (b) of 0.811 for (Adjusted gross profit + interest)/sales * 100 indicates that if the percentage of (Adjusted gross profit + interest)/sales * 100 goes up by one, then odds of financial distress will decrease. As exp (b) is less than one, which means with every unit increase in (Adjusted gross profit + interest)/sales * 100, the likelihood of distress will decline by 0.811 times. Values of exp (b) of 0.388 for Net sales/total assets indicates that if the percentage of Net sales/total assets goes up by one, then odds of financial distress will decrease. As exp (b) is less than one, which means with every unit increase in Net sales/total assets, the likelihood of distress will decline by 0.388 times. The values of exp (b) of 0.262 for Excess Return indicates that if the percentage of Excess Return goes up by one, then odds of financial distress will decrease. As exp (b) is less than one, which means with every unit increase in Excess Return, the likelihood of distress will decrease by 0.262 times.



Source: Author ‘s calculations

Figure 5.2: ROC curve: 2- year before FD for BIFR companies using financial & market variables

Table 5.16 : Area under the Curve: 2- year before FD for BIFR companies using financial & market variables

AUC				
Test result variable(s)	Predicted probability			
Area	SE.	Asymptotic sig.	Asymptotic 95% confidence interval	
			Lower bound	Upper bound
0.953	0.014	0.000	0.925	0.981

Source: Author 's calculations

As per table 5.16, AUC is 0.953, indicating that for a randomly selected distress company and randomly selected healthy company, there is a 0.953 likelihood that for a financial distress company, the model estimated the likelihood of distress would be more than for a healthy company. The AUC ranges from 0.925 to 0.981 at a 95% confidence interval. As per the general rule of Hosmer and Lemeshow (2000), two years before, the financial distress model presented outstanding in-sample discrimination using both financial and market variables.

5.4 Three-year before financial distress using financial & market variables: for BIFR companies

This section estimates three-year before to financial distress model based on financial & market variables of financially distressed and healthy companies in the year t-3, i.e., three years before the year in which a financial distressed incident happened for a listed company referred to BIFR, matching with a healthy company in the same year. It summarizes the findings of the three-year prior financially distressed model, including Pseudo R-squares, Model Classification table, Wald statistic, p-values, Odds ratios, ROC curve, and Area under the curve.

Table 5.17 : Correlation Statistics: 3-year before FD using financial & market variables for BIFR and Healthy companies

	DE	**PBIDTM**	**NSTA**	**ER**
DE	1.000	-.201	-.075	-.145
PBIDTM	-.201	1.000	.321	.057
NSTA	-.075	.321	1.000	-.082
ER	-.145	.057	-.082	1.000

Values are significant at 1% level

Source: Author ‘s calculations

Table 5.18 : Multicollinearity Statistics: 3-year before FD using financial & market variables for BIFR and Healthy companies

		DE	**PBIDTM**	**NSTA**	**ER**
Collinearity Statistics	Tolerance	.994	.978	.971	.965
	VIF	1.007	1.023	1.030	1.037

Source: Author ‘s calculations

In the above table 5.17, the observed correlations are statistically significant. Correlations among the covariates are generally small, indicating that the covariates give different and unique details. Correlation among (Adjusted gross profit + interest)/sales * 100, Net sales/total assets is largest and is equal to 0.321. In the case of multicollinearity, independent variables have a linear relationship, which can further result in unstable coefficient values. Variance Inflation (VIF) and its inverse, Tolerance Value (TOL), is calculated to identify the presence of multicollinearity. A value of VIF of more than 10 indicates significant collinearity. As per table 5.18, all the regressors have VIF's near to 1, with VIF value of 1.007, 1.023, 1.030 and 1.037 for Debt-to-equity ratio, (Adjusted gross profit + interest)/sales * 100, Net sales / total assets and Excess return respectively, which mean that the collinearity between the regressors has not affected the level of the coefficients & the model does not have multicollinearity, and therefore, the model is capable of reliable performance.

Table 5.19 : Omnibus Tests for the financial & market variables: 3-year before FD for BIFR companies

Omnibus Tests			
	Chi-square	df	sig.
Step	54.486	4	0.000
Block	54.486	4	0.000
Model	54.486	4	0.000

Source: Author 's calculations

Table 5.20 : Model Summary: 3-year before FD for BIFR companies using financial & market variables

Summary of the model		
-2 log likelihood	Cox & Snell $R^{\wedge 2}$	Nagelkerke $R^{\wedge 2}$
39.782	0.551	0.735

Source: Author 's calculations

Table 5.21 : Hosmer and Lemeshow Test using financial & market variables: 3-year before FD for BIFR companies

Hosmer & Lemeshow test		
Chi-square	df	sig.
5.551	8	0.697

Source: Author's calculations

5.4.1 Testing for the Significance of the Model

The result of the Omnibus test is shown in Table 5.19. The null hypothesis for the test is intercept, as well as all the coefficients are zero. A p-value (sig) < 0.05 suggests that the model is statistically significant. The pseudo-R-squares value (as per table 5.20) for Nagelkerke R^2 is 0.735, which depicts higher goodness of fit for the predictive model. As per table 5.21, the result of the Hosmer and Lemeshow test shows the model is a good fit as p equal to 0.697 (> 0.05)

Table 5.22 : Classification Table of the model using financial & market variables: 3-year before FD for BIFR companies

Classification Table							
Observed		Predicted					
		Selected Cases			Holdout Sample		
		Type		Correct percentage	Type		Correct percentage
		0	1		0	1	
Type	0	66	14	82.5	33	1	97.1
	1	17	63	78.8	9	25	73.5
Overall %ge				80.6			85.3

Source: Author ‘s calculations

5.4.2 Assessing Fitness of Model

The financial distress prediction model developed correctly classifies 82.5% of healthy firms & 78.8% of sampled financially distressed firms and 97.1% of healthy firms & 73.5% of financially distressed firms for the holdout sample. In table 5.22, the development of the model predicts a total of one hundred sixty samples. The forecast includes one hundred twenty-nine accurate samples and thirty-one incorrect samples. The precise estimate is 80.6%. For the holdout sample, the model predicts a total of sixty-eight samples. The forecast includes fifty-eight accurate samples and ten incorrect samples. The precise estimate is 85.3%. The overall logistic model forecasts correctly 80.6% of the cases for the model development and 85.3% of the cases in the holdout sample.

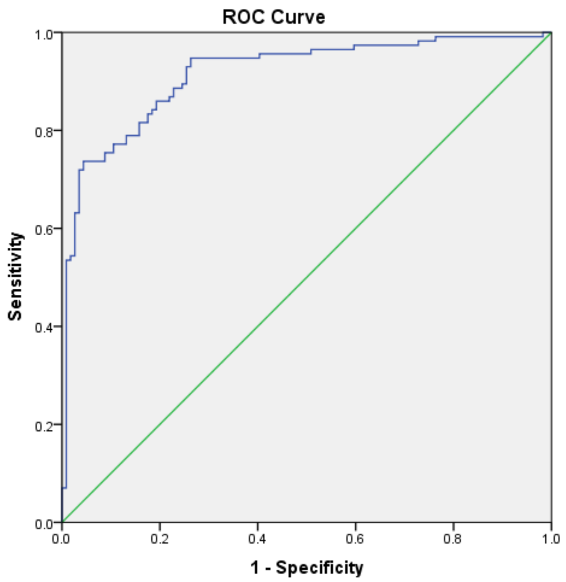
Table 5.23 : Variables in the model to predict FD using financial & market variables: 3- year before for BIFR companies

Equation variables						
	b	**S.E.**	**wald**	**df**	**sig.**	**exp (b)**
DE	0.958	0.236	16.515	1	0.000	2.607
PBIDTM	-0.170	0.039	18.890	1	0.000	0.844
NSTA	-0.731	0.330	4.915	1	0.027	0.481
ER	-0.762	0.209	13.292	1	0.000	0.467
Constant	1.259	0.366	11.832	1	0.000	3.523

Source: Author ‘s calculations

5.4.3 Interpreting the Fitted Logistic Regression Model

Positive coefficients indicate a greater likelihood of distress as the ratio value increases; however, negative coefficients mean conversely. As per the above table 5.23, all the financial ratios continue to be significant. The p-value of Wald test statistics in Table 5.23 indicates that all the independent variables are significant at the 5% level. The value of the Wald test for each predictor indicates that Debt-to-equity ratio, (Adjusted gross profit + interest)/sales * 100, Net sales-total assets and Excess-Return significantly forecast distress ($p<0.05$). Values of exp (b) of 2.607 for (debt)/(equity) ratio indicates that if the percentage of (debt)/(equity) ratio goes up by one, then odds of financial distress will also increase. As exp (b) is greater than one, which means with every unit increase in this ratio, the likelihood of distress will increase by 2.607 times. Values of exp (b) of 0.844 for (Adjusted gross profit + interest)/sales * 100 indicates that if the percentage of (Adjusted gross profit + interest)/sales * 100 goes up by one, then odds of financial distress will decrease. As exp (b) is less than one, which means with every unit increase in (Adjusted gross profit + interest)/sales * 100, the likelihood of distress will decline by 0.844 times. Values of exp (b) of 0.481 for Net sales / total assets indicates that if the percentage of Net sales / total assets goes up by one, then odds of financial distress will decrease. As exp (b) is less than one, which means with every unit increase in Net sales / total assets, the likelihood of distress will decline by 0.481 times. The values of exp (b) of .467 for Excess Return indicates that if the percentage of Excess Return goes up by one, then odds of financial distress will decrease. As exp (b) is less than one, which means with every unit increase in Excess Return, the probability of financial distress will decrease by .467 times than firms that do not experience an increase in this ratio.



Source: Author 's calculations

Figure 5.3: ROC curve: 3- year before FD for BIFR companies using financial & market variables

Table 5.24 : Area under the Curve: 3- year before FD for BIFR companies using financial & market variables

AUC				
Test result variable(s)	Predicted probability			
Area	SE.	Asymptotic sig.	Asymptotic 95% confidence interval	
			Lower bound	Upper bound
0.915	0.019	0.000	0.877	0.953

Source: Author 's calculations

As per table 5.24, AUC is 0.915, indicating that for a randomly selected distress company and randomly selected healthy company, there is a 0.915 likelihood that for a financial distress company, the model estimated the likelihood of distress would be more than for a healthy company. The AUC ranges from 0.877 to 0.953 at a 95% confidence interval. As per the general rule of Hosmer and Lemeshow (2000), three years before financial distress model presented outstanding in-sample discrimination using both financial and market variables.

Table 5.25 : Result of the logistic regression for BIFR companies using financial & market variables

Year before financial distress	Pseudo R-squares	AUC	Classification accuracy Model development	Classification accuracy Holdout Sample
1	0.886	0.966	92.9 %	86.4%
2	0.799	0.953	91.2%	86.5%
3	0.735	0.915	80.6%	85.3%

Source: Author ‘s calculations

5.5 OVERALL FINDINGS OF THE STUDY

In this section, the logistic regression statistical technique helped forecast financial distress over one to three years for BIFR firms using financial & market variables. The derived models are significantly relevant to predicting financial distress companies over time frames of one to three years.

The goodness of fit for three models shown by HL test found a high p-value >0.05 for all three models. Thus, all three models are quite effective for predicting the outcome. As per earlier studies, the analysis found that the forecast ability of models is diminishing with the increase in the time period of financial distress, with deteriorating Pseudo R-squares, AUC values and accuracy level of classification matrix. Table 5.25 contain Nagelkerke’s R square for relative evaluation of all three models. As anticipated, the value of Nagelkerke R square decreases for models from years 1 to 3. But the decrease in magnitude is only small, suggesting that the predictors of the models are stable over time and the overall ability to predict is satisfactory. Greater the AUC, the higher a model's predictive accuracy. The Area under curve value near 1 for all three models shows their higher ability in classification. As per Table 5.25, the value of AUC decreases from 0.966 to 0.915 for models from years 1 to 3. But the decrease in magnitude is only small, and values are above 0.9, which suggests outstanding discrimination of the predictive models.

It can be observed in all three models, coefficient values for all three financial & market variables; Debt-to-equity ratio (DE), (Adjusted gross profit + interest)/sales * 100 (PBIDTM), Net Sales / Total Assets (NSTA) & Excess return (ER) are significant at five -percent level with likely positive and negative signs. DE ratio has a positive coefficient in all three models, which suggests that an increase in this ratio will further increase the likelihood of distress of companies and is the most important ratio for predicting distress given its higher odds ratios in all three models. PBIDTM is the second most important variable after debt-to-equity. It has a negative coefficient value in all three models, which suggests that an increase in PBIDTM value will decrease companies' likelihood of financial distress. (Net sales)/(total assets) ratio have a negative coefficient value in all three models, which suggests that an increase in its value will decrease the likelihood of distress. Similarly, Excess return has a negative value of the coefficient in all three models, which suggest that increase in its value will decrease the likelihood of distress. As per Table 5.25, predictive accuracy is highest in the case of one -year before financial distress model with 92.9 % of the cases for the development of the model and 86.4% of the cases in the holdout sample, followed by two- year model with 91.2% of the cases for the development of the model and 86.5% of the cases in the holdout sample & three-year model has 80.6% of the cases for the development of the model and 85.3% of the cases in the holdout sample respectively. Overall, one- year before financial distress model has the best predictive accuracy using financial & market variables for various firms followed by two year and three-year models, respectively.

5.6 ONE-YEAR BEFORE FINANCIAL DISTRESS USING FINANCIAL & MARKET VARIABLES: FOR IBC COMPANIES

This section estimates 1-year prior to distress model based on financial variables & market variables firms in year t-1, i.e., one year before the year in which a financial distressed incident happened for a listed company referred to IBC, matching with a healthy company in the same year. It summarizes the findings of the one-year prior financially distressed model, including Pseudo R-squares, Model Classification table, Wald statistic, Odds ratios, ROC curve, and Area under the curve.

Table 5.26 : Correlation Statistics: 1-year before FD using financial & market variables for IBC and Healthy companies

	MVSF	STDEV	DE	CPM	CFOINT
MVSF	1.000	-.073	-.435	.300	-.105
STDEV	-.073	1.000	.131	.065	-.147
DE	-.435	.131	1.000	.006	.041
CPM	.300	.065	.006	1.000	-.261
CFOINT	-.105	-.147	.041	-.261	1.000

Values are significant at 1% level

Source: Author ‘s calculations

Table 5.27 : Multicollinearity Statistics: 1-year before FD using financial & market variables for IBC and Healthy companies

		DE	CFOINT	CPM	MVSF	STDEV
Collinearity Statistics	Tolerance	0.930	0.885	0.878	0.941	0.885
	VIF	1.075	1.130	1.138	1.063	1.129

Source: Author ‘s calculations

Table 5.26 provides a matrix of correlations of all covariates. In all categories, the observed correlations are statistically significant. Correlations among the covariates are generally small, indicating that the covariates give different and unique details. Variance Inflation (VIF) and its inverse, Tolerance Value (TOL), is calculated to identify the presence of multicollinearity. A value of VIF of more than 10 indicates significant collinearity. Analyses of all the regressors (in table 5.27) obtained in the methods of the present study show they all have VIF's near to 1, with VIF values of 1.075, 1.130, 1.138, 1.063 and 1.129 for Debt-to-equity, Cash flow from operations/ Interest (CFOINT), (Adjusted net profit + depreciation) / sales * 100 (CPM), Market value to shareholder funds(MVSF) and Standard Deviation (STDEV), respectively, which mean that the collinearity between the regressors has not affected the level of the coefficients & the model does not have multicollinearity, and therefore, the model is capable of reliable performance.

Table 5.28 : Omnibus Tests for the financial & market variables: 1-year before FD for IBC companies

Omnibus Tests			
	Chi-square	**df**	**sig.**
Step	181.88	5	0.000
Block	181.88	5	0.000
Model	181.88	5	0.000

Source: Author ‘s calculations

Table 5.29 : Model Summary: 1-year before FD for IBC companies using financial & market variables

Summary of the model		
-2 log likelihood	Cox & Snell $R^{\wedge 2}$	Nagelkerke $R^{\wedge 2}$
149.242	0.491	0.655

Source: Author ‘s calculations

Table 5.30 : Hosmer and Lemeshow Test using financial & market variables: 1-year before FD for IBC companies

Hosmer & Lemeshow test		
Chi-square	**df**	**sig.**
7.970	8	0.436

Source: Author 's calculations

5.6.1 Testing for the Significance of the Model

The result of the Omnibus test is shown in Table 5.28. The null hypothesis for the test is intercept, as well as all the coefficients are zero. A p-value (sig) below 0.05 suggests that the model is statistically significant. As per table 5.29, the pseudo-R-squares value for Nagelkerke R^2 is 0.655, which depicts higher fitness for the predictive model. The result of the Hosmer and Lemeshow test (Table 5.30) shows the model is a good fit as p equal to 0.436 (> 0.05).

Table 5.31 : Classification Table of the model using financial & market variables: 1-year before FD for IBC companies

Classification Table							
Observed		Predicted					
		Selected Cases			Holdout Sample		
		Type		Correct percentage	Type		Correct percentage
		0	1		0	1	
Type	0	95	10	90.5	38	7	84.4
	1	16	89	84.8	11	34	75.5
Overall %ge				87.6			80

Source: Author 's calculations

5.6.2 Assessing Fitness of Model

The financial distress prediction model developed correctly classifies 90.5% of healthy firms & 84.8% of sampled financially distressed firms and 84.4% of healthy firms & 75.5% of financially distressed firms for the holdout sample. In table 5.31, the development of the model predicts a total of two hundred ten samples. The forecast includes one hundred eighty-four accurate samples and twenty-six incorrect samples. The precise estimate is 87.6%. For the holdout sample, the model predicts a total of ninety samples. The forecast includes seventy-two accurate samples and eighteen incorrect samples. The precise estimate is 80%. The overall logistic model forecasts correctly 87.6% of the cases for the development of the model and 80% of the cases in the holdout sample.

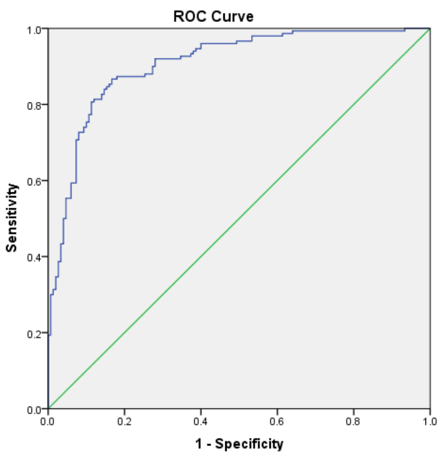
Table 5.32 : Variables in the model to predict FD using financial & market variables: 1- year before for IBC companies

Equation variables						
	b	**S.E.**	**wald**	**df**	**sig.**	**exp (b)**
MVSF	-0.449	0.112	16.140	1	0.000	0.638
STDEV	0.689	0.222	9.657	1	0.000	1.991
DE	1.204	0.262	21.207	1	0.000	3.334
CPM	-0.102	0.029	12.232	1	0.000	0.903
CFOINT	-0.131	0.076	8.960	1	0.000	0.877
Constant	-2.505	0.868	8.335	1	0.001	0.082

Source: Author ‘s calculations

5.6.3 Interpreting the Fitted Logistic Regression Model

In the above table 5.32, Wald test for each predictor indicates that Debt-to-equity ratio, (Adjusted net profit + depreciation) / sales * 100 (CPM), Cash flow from operations/ Interest (CFOINT), Market value to shareholder funds (MVSF) and Standard Deviation (STDEV) significantly predict financial distress ($p<0.05$). The values of exp (b) of 3.334 for (debt)/(equity) ratio indicates that if the percentage of (debt)/(equity) ratio goes up by one, then odds of financial distress will also increase, as exp (b) is greater than one, which means with every unit increase in this ratio, the likelihood of distress will increase by 3.334 times. The values of exp (b) of 0.903 for (Adjusted net profit + depreciation) / sales * 100 (CPM) indicates that if the percentage of (Adjusted net profit + depreciation) / sales * 100 (CPM) goes up by one, then odds of financial distress will decrease, and as exp (b) is less than one, which means with every unit increase in (Adjusted net profit + depreciation) / sales * 100 (CPM), the likelihood of distress will decline by 0.903 times. Values of exp (b) of 0.877 for (Cash flow from operations)/(Interest) (CFOINT) indicates that if the percentage of (Cash flow from operations)/(Interest) (CFOINT) goes up by one, then odds of financial distress will decrease, and as exp (b) is less than one, which means with every unit increase in (Cash flow from operations)/ (Interest) (CFOINT), the likelihood of distress will decline by 0.877 times. Values of exp (b) of 0.638 for Market value to shareholder funds (MVSF) indicates that if the percentage of Market value to shareholder funds (MVSF) goes up by one, then odds of financial distress will decrease, as exp (b) is less than one, which means with every unit increase in Market value to shareholder funds (MVSF), the likelihood of distress will decline by 0.638 times. Value of exp (b) of 1.991 for Standard Deviation (STDEV) indicates that if the percentage of Standard Deviation (STDEV) goes up by one, then odds of financial distress will also increase, as exp (b) is greater than one, which means with every unit increase in Standard Deviation (STDEV) the probability of financial distress will increase by 1.991 times than the firms that do not experience an increase in this ratio.



Source: Author ‘s calculations

Figure 5.4: ROC curve: 1- year before FD for IBC companies using financial & market variables

Table 5.33 : Area under the Curve: 1- year before FD for IBC companies using financial & market variables

AUC				
Test result variable(s)	Predicted probability			
Area	SE.	Asymptotic sig.	Asymptotic 95% confidence interval	
			Lower bound	Upper bound
0.907	0.017	0.000	0.873	0.940

Source: Author ‘s calculations

As per table 5.33, AUC is 0.907, indicating that for a randomly selected distress company and randomly selected healthy company, there is a 0.907 likelihood that for a financial distress company, the model estimated the likelihood of distress would be more than for a healthy company. The AUC ranges from 0.873 to 0.940 at a 95% confidence interval. As per the general rule of Hosmer and Lemeshow (2000), one year before the financial distress model presents outstanding in-sample discrimination using financial and market variables for IBC firms.

5.7 TWO-YEAR BEFORE FINANCIAL DISTRESS USING FINANCIAL & MARKET VARIABLES: FOR IBC COMPANIES

This section estimates the two-year before to financial distress model based on financial & market variables in year t-2, i.e., two years prior to the year when a financial distressed incident happened for a listed company referred to IBC, matching with a healthy company in the same year. It summarizes the findings of the two-year prior financially distressed model, including Pseudo R-squares, Model Classification table, Wald statistic, p-values, Odds ratios, ROC curve, and Area under the curve.

Table 5.34 : Correlation Statistics: 2-year before FD using financial & market variables for IBC and Healthy companies

	MVSF	STDEV	DE	CPM	CFOINT
MVSF	1.000	.034	-.150	-.083	.005
STDEV	.034	1.000	.150	.214	-.042
DE	-.150	.150	1.000	-.004	.125
CPM	-.083	.214	-.004	1.000	-.108
CFOINT	.005	-.042	.125	-.108	1.000

Values are significant at 1% level

Source: Author ‘s calculations

Table 5.35 : Multicollinearity Statistics: 2-year before FD using financial & market variables for IBC and Healthy companies

		DE	CFOINT	CPM	MVSF	STDEV
Collinearity Statistics	Tolerance	0.916	0.860	0.853	0.914	0.892
	VIF	1.092	1.163	1.172	1.095	1.121

Source: Author ‘s calculations

Above table 5.34 provides a matrix of correlations of all covariates. In all categories, the observed correlations are statistically significant. Correlations among the covariates are generally small, indicating that the covariates give different and unique details. Variance Inflation (VIF) and its inverse, Tolerance Value (TOL), is calculated to identify the presence of multicollinearity. A value of VIF of more than 10 indicates significant collinearity. As per table 5.35, analyses of all the regressors obtained show they all have VIF's near to 1, with VIF values of 1.092, 1.163, 1.172, 1.095 and 1.121 for Debt-to-equity(DE), Cash flow from operations/ Interest(CFOINT), (Adjusted net profit + depreciation) / sales * 100 (CPM), Market value to shareholder funds(MVSF) and Standard Deviation(STDEV) respectively, which mean that the collinearity between the regressors has not affected the level of the coefficients & the model does not have multicollinearity, and therefore, the model is capable of reliable performance.

Table 5.36 : Omnibus Tests for the financial & market variables: 2-year before FD for IBC companies

Omnibus Tests			
	Chi-square	**df**	**sig.**
Step	145.812	5	0.000
Block	145.812	5	0.000
Model	145.812	5	0.000

Source: Author 's calculations

Table 5.37 : Model Summary: 2-year before FD for IBC companies using financial & market variables

Summary of the model		
-2 log likelihood	Cox & Snell R^2	Nagelkerke R^2
110.291	0.410	0.547

Source: Author 's calculations

Table 5.38 : Hosmer and Lemeshow Test using financial & market variables: 2-year before FD for IBC companies

Hosmer & Lemeshow test		
Chi-square	df	sig.
10.526	8	0.230

Source: Author 's calculations

5.7.1 Testing for the Significance of the Model

The result of the Omnibus test is shown in Table 5.36. The null hypothesis for the test is intercept, as well as all the coefficients are zero. A p-value (sig) below 0.05

suggests that the model is statistically significant. The pseudo-R-squares value for Nagelkerke R^2 is 0.547 (table 5.37), which shows reasonable fitness for the predictive model. The result of the Hosmer and Lemeshow test (Table 5.38) depicts the model is a good fit as p equal to 0.230 (> 0.05).

Table 5.39 : Classification Table of the model using financial & market variables: 2-year before FD for IBC companies

Classification Table								
Observed		Predicted						
		Selected Cases			Holdout Sample			
		Type		Correct percentage	Type		Correct percentage
		0	1		0	1	
Type	0	79	26	75.2	38	6	86.4
	1	18	87	82.9	11	33	75
Overall %ge				79			80.7

Source: Author 's calculations

5.7.2 Assessing Fitness of Model

The financial distress prediction model developed correctly classifies 75.2% of healthy firms & 82.9% of sampled financially distressed firms and 86.4% of healthy firms & 75% of financially distressed firms for the holdout sample. In table 5.39, the development of the model predicts a total of two hundred ten samples. The forecast includes one hundred sixty-six accurate samples and forty-four incorrect samples. The precise estimate is 79%. For the holdout sample, the model predicts a total of eighty-eight samples. The forecast includes seventy-one accurate samples and seventeen incorrect samples. The precise estimate is 80.7%. The overall logistic model forecasts correctly 79% of the cases for the development of the model and 80.7% of the cases in the holdout sample.

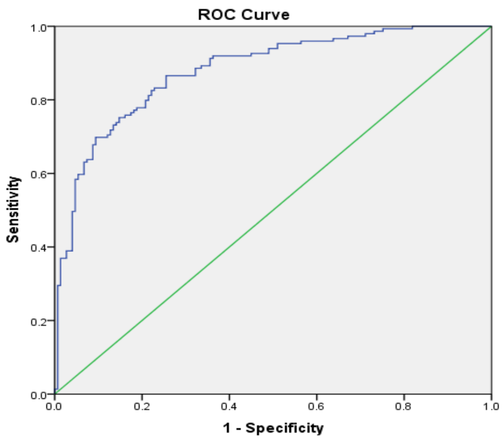
Table 5.40 : Variables in the model to predict FD using financial & market variables: 2- year before for IBC companies

Equation variables						
	b	**S.E.**	**wald**	**df**	**sig.**	**exp (b)**
MVSF	-0.456	0.129	12.441	1	0.000	0.634
STDEV	0.472	0.163	8.414	1	0.002	1.603
DE	0.781	0.177	19.506	1	0.000	2.184
CPM	-0.060	0.019	9.890	1	0.000	0.942
CFOINT	-0.135	0.042	10.211	1	0.000	0.874
Constant	-1.159	0.665	9.037	1	0.000	0.314

Source: Author ‘s calculations

5.7.3 Interpreting the Fitted Logistic Regression Model

In the above table 5.40, value of Wald test for each predictor indicates that Debt-to-equity ratio, (Adjusted net profit + depreciation) / sales * 100 (CPM) & Cash flow from operations/ Interest (CFOINT), Market value to shareholder funds (MVSF) and Standard Deviation (STDEV) significantly predict financial distress ($p<0.05$). The values of exp (b) of 2.184 for the (debt)-to-(equity) ratio indicates that if the percentage of (debt)-to-(equity) ratio goes up by one, then odds of financial distress will also increase. As exp (b) is greater than one, which means with every unit increase in this ratio, the likelihood of distress will increase by 2.184. The values of exp (b) of 0.942 for (Adjusted net profit + depreciation) / sales * 100 (CPM) indicates that if the percentage of (Adjusted net profit + depreciation) / sales * 100 (CPM) goes up by one, then odds of financial distress will decrease; as exp (b) is less than one, which means with every unit increase in (Adjusted net profit + depreciation) / sales * 100 (CPM), the likelihood of distress will decline by 0.942 times. Exp (b) value of 0.874 for (Cash flow from operations)/ (Interest) (CFOINT) indicates that if the percentage of (Cash flow from operations)/ (Interest) (CFOINT) goes up by one, then odds of financial distress will decrease, as exp (b) is less than one, which means with every unit increase in (Cash flow from operations)/ (Interest) (CFOINT), the probability of distress will decline by 0.874 times. Values of exp (b) of 0.634 for Market value to shareholder funds (MVSF) indicates that if the percentage of Market value to shareholder funds (MVSF) goes up by one, then odds of financial distress will decrease. As exp (b) is less than one, which means with every unit increase in Market value to shareholder funds (MVSF), the likelihood of distress will decline by 0.634 times. The values of exp (b) of 1.063 for Standard Deviation (STDEV) indicates that if the percentage of Standard Deviation (STDEV) goes up by one, then odds of financial distress will also increase. As exp (b) is greater than one, which means with every unit increase in Standard Deviation (STDEV), the likelihood of distress will increase by 1.063 times than firms that do not experience an increase in this ratio.



Source: Author 's calculations

Figure 5.5: ROC curve: 2- year before FD for IBC companies using financial & market variables

Table 5.41 : Area under the Curve: 2- year before FD for IBC companies using financial & market variables

AUC				
Test result variable(s)	Predicted probability			
Area	SE.	Asymptotic sig.	Asymptotic 95% confidence interval	
			Lower bound	Upper bound
0.880	0.020	0.000	0.841	0.918

Source: Author 's calculations

As per table 5.41, AUC is 0.880, indicating that for a randomly selected distress company and randomly selected healthy company, there is a 0.880 likelihood that for a financial distress company, the model estimated the likelihood of distress would be more than for a healthy company. The AUC ranges from 0.841 to 0.918 at a 95% confidence interval. As per the general rule of Hosmer and Lemeshow (2000), two years before financial distress model presents outstanding in-sample discrimination using both financial and market variables for IBC firms.

5.8 THREE-YEAR BEFORE FINANCIAL DISTRESS USING FINANCIAL & MARKET VARIABLES: FOR IBC COMPANIES

This section estimates three-year before to financial distress model based on financial & market variables of financially distressed and healthy companies in the year t-3, i.e., three years before the year in which a financial distressed incident happened for a listed company referred to IBC, matching with a healthy company in the same year. It summarizes the findings of the three-year prior financially distressed model, including Pseudo R-squares, Model Classification table, Wald statistic, p-values, Odds ratios, ROC curve, and Area under the curve.

Table 5.42 : Correlation Statistics: 3-year before FD using financial & market variables for IBC and Healthy companies

	MVSF	STDEV	DE	CPM	CFOINT
MVSF	1.000	.060	-.237	-.022	.069
STDEV	.060	1.000	.207	.037	.015
DE	-.237	.207	1.000	-.118	-.173
CPM	-.022	.037	-.118	1.000	.033
CFOINT	.069	.015	-.173	.033	1.000

Values are significant at 1% level

Source: Author ‘s calculations

Table 5.43 : Multicollinearity Statistics: 3-year before FD using financial & market variables for IBC and Healthy companies

		DE	CFOINT	CPM	MVSF	STDEV
Collinearity Statistics	Tolerance	0.944	0.946	0.921	0.948	0.926
	VIF	1.060	1.057	1.085	1.055	1.080

Source: Author 's calculations

The above table 5.42 provides a matrix of correlations of all covariates. In all categories, the observed correlations are statistically significant. Correlations among the covariates are generally small, indicating that the covariates give different and unique details. Variance Inflation (VIF) and its inverse, Tolerance Value (TOL), is calculated to identify the presence of multicollinearity. A value of VIF of more than 10 indicates significant collinearity. As per table 5.43, VIF are near to 1, with VIF values of 1.060, 1.057, 1.085, 1.055 and 1.080 for Debt-to-equity, Cash flow from operations/ Interest (CFOINT), (Adjusted net profit + depreciation) / sales * 100 (CPM), Market value to shareholder funds(MVSF) and Standard Deviation (STDEV), respectively, which mean that the collinearity between the regressors has not affected the level of the coefficients & the model does not have multicollinearity, and therefore, the model is capable of reliable performance.

Table 5.44 : Omnibus Tests for the financial & market variables: 3-year before FD for IBC companies

Omnibus Tests			
	Chi-square	df	sig.
Step	205.567	5	0.000
Block	205.567	5	0.000
Model	205.567	5	0.000

Source: Author 's calculations

Table 5.45 : Model Summary: 3-year before FD for IBC companies using financial & market variables

Summary of the model		
-2 log likelihood	Cox & Snell $R^{\wedge 2}$	Nagelkerke $R\wedge^{2}$
171.109	0.387	0.516

Source: Author ‘s calculations

Table 5.46 : Hosmer and Lemeshow Test using financial & market variables: 3-year before FD for IBC companies

Hosmer & Lemeshow test		
Chi-square	df	sig.
10.902	8	0.207

Source: Author ‘s calculations

5.8.1 Testing for the Significance of the Model

The result of the Omnibus test is shown in Table 5.44. The null hypothesis for the test is intercept, as well as all the coefficients are zero. A p-value (sig) below 0.05 suggests that the model is statistically significant. The pseudo-R-squares value for Nagelkerke R^2 is 0.516 (in table 5.45), which shows higher goodness of fit for the predictive model. The result of the Hosmer and Lemeshow test (Table 5.46) depicts the model is a good fit as p equal to 0.207 (> 0.05).

Table 5.47 : Classification Table of the model using financial & market variables: 3-year before FD for IBC companies

Classification Table							
Observed		Predicted					
		Selected Cases			Holdout Sample		
		Type		Correct percentage	Type		Correct percentage
		0	1		0	1	
Type	0	76	24	76	30	14	68.2
	1	19	81	81	10	34	77.3
Overall %ge				78.5			72.7

Source: Author ‘s calculations

5.8.2 Assessing Fitness of Model

The financial distress prediction model developed correctly classifies 77% of healthy firms & 82 % of sampled financially distressed firms and 68.2% of healthy firms & 77.3 % of financially distressed firms for the holdout sample. In table 5.47, the development of the model predicts a total of two hundred samples. The forecast includes one hundred fifty-seven accurate samples and forty-three incorrect samples. The precise estimate is 78.5%. The outcome of the experiment was shown to be preferable. For the holdout sample, the model predicts a total of eighty-eight samples. The forecast includes sixty-four accurate samples and twenty-four incorrect samples. The precise estimate is 72.7%. The overall logistic model forecasts correctly 78.5% of the cases for the development of the model and 72.7% of the cases in the holdout sample.

Table 5.48 : Variables in the model to predict FD using financial & market variables: 3- year before for IBC companies

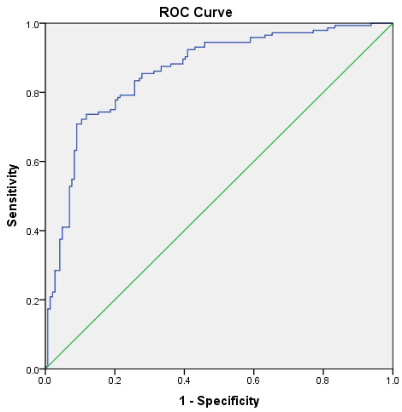
Equation variables						
	b	**S.E.**	**wald**	**df**	**sig.**	**exp (b)**
MVSF	-0.538	0.202	7.11	1	0.008	0.584
STDEV	0.505	0.217	5.398	1	0.020	1.657
DE	1.637	0.327	24.994	1	0.000	5.141
CPM	-0.095	0.034	7.721	1	0.005	0.909
CFOINT	-0.255	0.069	13.854	1	0.000	0.775
Constant	-1.696	0.471	12.966	1	0.000	0.183

Source: Author ‘s calculations

5.8.3 Interpreting the Fitted Logistic Regression Model

In the above table 5.48, the Wald test for each predictor indicates that Debt-to-equity ratio, (Adjusted net profit + depreciation) / sales * 100 (CPM), Cash flow from operations/ Interest (CFOINT), Market value to shareholder funds (MVSF) and Standard Deviation (STDEV) significantly predict financial distress ($p<0.05$). The values of exp (b) of 5.141 for (debt)-to-(equity) ratio indicates that if the percentage of (debt)-to-(equity) ratio goes up by one, then odds of financial distress will also increase. As exp (b) is greater than one, which means with every unit increase in this ratio, the likelihood of distress will increase by 5.141 times. The values of exp (b) of 0.909 for (Adjusted net profit + depreciation) / sales * 100 (CPM) indicates that if the percentage of (Adjusted net profit + depreciation) / sales * 100 (CPM) goes up by one, then odds of financial distre

ss will decrease, as exp (b) is less than one, which means with every unit increase in (Adjusted net profit + depreciation) / sales * 100 (CPM), the likelihood of distress will decline by 0.909 times. The values of exp (b) of 0.775 for (Cash flow from operations)/(Interest)(CFOINT) indicates that if the percentage of (Cash flow from operations)/(Interest)(CFOINT) goes up by one, then odds of financial distress will decrease, as exp (b) is less than one, which means with every unit increase in (Cash flow from operations)/(Interest) (CFOINT), the likelihood of distress will decline by 0.775 times. Values of exp (b) of 0.584 for Market value to shareholder funds (MVSF) indicates that if the percentage of Market value to shareholder funds (MVSF) goes up by one, then odds of financial distress will decrease. As exp (b) is less than one, which means with every unit increase in Market value to shareholder funds (MVSF), the likelihood of distress will decline by 0.584 times. The values of exp (b) of 1.657 for Standard Deviation (STDEV) indicates that if the percentage of Standard Deviation (STDEV) goes up by one, then odds of financial distress will also increase, as exp (b) is greater than one, which means with every unit increase in Standard Deviation (STDEV) likelihood of distress will increase by 1.657 times than firms that do not experience an increase in this ratio.



Source: Author 's calculations

Figure 5.6 ROC curve: 3- year before FD for IBC companies using financial & market variables

Table 5.49 : Area under the Curve: 3- year before FD for IBC companies using financial & market variables

AUC				
Test result variable(s)	Predicted probability			
Area	SE.	Asymptotic sig.	Asymptotic 95% confidence interval	
			Lower bound	Upper bound
0.861	0.022	0.000	0.818	0.904

Source: Author 's calculations

As per table 5.49, AUC is 0.861, indicating that for a randomly selected distress company and randomly selected healthy company, there is a 0.861 likelihood that for a financial distress company, the model estimated the likelihood of distress would be more than for a healthy company. The AUC ranges from 0.818 to 0.904 at a 95% confidence interval. As per the general rule of Hosmer and Lemeshow (2000), three years before financial distress model presents outstanding in-sample discrimination using financial and market variables for IBC firms.

Table 5.50 :Result of the logistic regression for IBC companies using financial & market variables

Year before financial distress	Pseudo R-squares	AUC	Classification accuracy Model development	Classification accuracy Holdout Sample
1	0.655	0.907	87.6%	80%
2	0.547	0.880	79%	80.7%
3	0.516	0.861	78.5%	72.7%

Source: Author 's calculations

5.9 OVERALL FINDINGS OF THE STUDY

In this section, the logistic regression statistical technique helped forecast financial distress over one to three years, using financial and market variables. The derived models are significantly relevant to predicting financial distress companies over time frames of one to three years.

The result of the goodness of fit for three models shown by Hosmer and Lemeshow test found low chi-square static <15 and a high p-value >0.05 for all three models. Thus, all three models are successful in predicting the outcome and fitted models are quite effective to be used for predicting the outcome. As per earlier studies, the analysis found that the predictive capacity of the models is diminishing with the increase in the time period of financial distress, with deteriorating Pseudo R-squares, AUC values and accuracy level of classification matrix. Tables 5.50 contain Nagelkerke's R square for relative evaluation of all three models and have only been used for making comparisons for different models. As anticipated, the value of Nagelkerke R square decreases for models from years 1 to 3. But the decrease is small, suggesting predictors are stable and the overall ability to predict is satisfactory. Greater the AUC, the higher a model's predictive accuracy. The AUC reflects the possibility that a randomly selected failing company is more suspect of failure than a randomly chosen successful company. Area under curve value near to 1 for all three models shows their higher ability in classification. As per table 5.50, the value of AUC decreases from 0.907 to 0.861 for models from years 1 to 3. But the decrease in magnitude is only small, which suggests that reasonable discrimination of the predictive models. It can be observed in all three models, coefficient values for all three financial variables & two market variables; Debt-to-equity ratio, (Adjusted net profit + depreciation) / sales * 100 (CPM), Cash flow from operations/ Interest (CFOINT) & Market value to shareholder funds (MVSF), Standard Deviation (STDEV) are significant at five -percent level with likely positive and negative signs. Debt-to-equity ratio has a positive value of the coefficient in all three models, which suggest that increase in this ratio will further increase the likelihood of distress of companies and is the most important ratio for predicting distress given its higher odds ratios in all three models. Standard Deviation (STDEV) is the second most important variable after debt-to-equity. It has a positive coefficient value in all three models, which suggests that an increase in Standard Deviation (STDEV) will further increase the probability of financial distress of companies. (Adjusted net profit + depreciation) / sales * 100 (CPM) has a negative coefficient value in all three models, which suggests that an increase in CPM value will decrease the likelihood of distress of firms. Cash flow from operations/ Interest (CFOINT) has a negative coefficient value in all three models, which suggests that an increase in its value will decrease the probability of distress. Market value to shareholder funds (MVSF) has a negative coefficient value in all three models, which suggests that an increase in its value will decrease the likelihood of distress. Predictive accuracy, highest in case of one -year before financial distress model with 87.6% of the cases for the development of model followed by two- year model with 79% of the cases for the development of model & three- year model has 78.5% of the cases for the development of model respectively. Overall, one- year before financial distress model has the best predictive accuracy using financial and market variables for various firms followed by two years and three-year models, respectively.

5.10 MACROECONOMIC VARIABLES FOR PREDICTING FINANCIAL DISTRESS

The main focus of this study is to test macroeconomic variables as control variables to help forecast the condition of the economy to boost the accuracy of the model. The purpose of the study is to evaluate the usefulness of macroeconomic variables in enhancing the accuracy and prediction power of financial distress models along with accounting and market variables**.**

5.11 ONE-YEAR BEFORE FINANCIAL DISTRESS USING FINANCIAL, MARKET & MACROECONOMIC VARIABLES: FOR BIFR COMPANIES

This section estimates one -year before to financial distress model based on financial variables & market variables along with macroeconomic variables in the year t-1, i.e., one year before the year in which a financial distressed incident happened for a listed company referred to BIFR, matching with a healthy company in the same year.

It summarizes the findings of the one-year prior financially distressed model, including Pseudo R-squares, Model Classification table, Wald statistic, p-values, Odds ratios, ROC curve, and Area under the curve.

Table 5.51 : Correlation Statistics: 1-year before FD using financial, market & macroeconomic variables for BIFR and Healthy companies

	DE	PBIDTM	NSTA	ER	EX
DE	1.000	-.011	-.013	.008	.110
PBIDTM	-.011	1.000	.596	.225	.119
NSTA	-.013	.596	1.000	-.138	.027
ER	.008	.225	-.138	1.000	.277
EX	.110	.119	.027	.277	1.000

Values are significant at 1% level

Source: Author 's calculations

Table 5.52 : Multicollinearity Statistics: 1-year before FD using financial, market & macroeconomic variables for BIFR and Healthy companies

		DE	PBIDTM	NSTA	ER	EX
Collinearity Statistics	Tolerance	.944	.973	.908	.826	.918
	VIF	1.059	1.028	1.101	1.211	1.090

Source: Author 's calculations

Matrices of correlation and multicollinearity were measured to make sure there was no multicollinearity between all the variables. Table 5.51 provides a matrix of correlations of all covariates. In all categories, the observed correlations are statistically significant. Correlations among the covariates are generally small, indicating that the covariates give different and unique details. Variance Inflation (VIF) and its inverse, Tolerance Value (TOL), is calculated to identify the presence of multicollinearity. A value of VIF of more than 10 indicates significant collinearity. As per table 5.52, analyses of all the regressors obtained show, they all have VIF's near to 1, with VIF values of 1.059, 1.028, 1.101, 1.211 and 1.090 for Debt-to-equity ratio, (Adjusted gross profit + interest)/sales * 100 (PBIDTM), Net Sales / Total Assets (NSTA), Excess Return (ER) and Exchange Rate(EX), respectively, which mean that the collinearity between the regressors has not affected the level of the coefficients & the model does not have multicollinearity, and therefore, the model is capable of reliable performance.

Table 5.53 : Omnibus Tests for the financial, market & macroeconomic variables: 1-year before FD for BIFR companies

Omnibus Tests			
	Chi-square	**df**	**sig.**
Step	168.378	5	0.000
Block	168.378	5	0.000
Model	168.378	5	0.000

Source: Author ‘s calculations

Table 5.54 : Model Summary: 1-year before FD for BIFR companies using financial, market & macroeconomic variables

Summary of the model		
-2 Log likelihood	Cox & Snell $R^{\wedge 2}$	Nagelkerke $R^{\wedge 2}$
45.111	0.665	0.887

Source: Author ‘s calculations

Table 5.55 : Hosmer and Lemeshow Test using financial, market & macroeconomic variables: 1-year before FD for BIFR companies

Hosmer & Lemeshow test		
Chi-square	df	sig.
27.590	8	0.001

Source: Author ‘s calculations

5.11.1 Testing for the Significance of the Model

The model evaluation process can now start with the Omnibus Test.The Omnibus test in Table 5.53 checks whether this variable block is a substantial contributor to the fitness of the model. As the p-value (sig) is below 0.05, the model is statistically significant. As per table 5.54, the value for Nagelkerke R^2 is 0.887, which depicts reasonable fitness for the predictive model. The result of Hosmer and Lemeshow test (Table 5.55) indicate that the model is a poor fit as p-value is < 0.05.

Table 5.56 : Variables in the model to predict FD using financial, market & macroeconomic variables: 1-year before for BIFR companies

Equation variables						
	b	S.E.	wald	df	sig.	exp (b)
DE	0.556	0.259	4.620	1	0.032	1.744
PBIDTM	-0.437	0.106	17.001	1	0.000	0.646
NSTA	-1.666	0.630	6.990	1	0.009	0.189
ER	-1.531	0.716	4.573	1	0.032	0.216
EX	-1.978	5.085	0.151	1	0.697	0.138
Constant	4.129	1.761	5.499	1	0.019	62.107

Source: Author ‘s calculations

5.11.2 Interpreting the Fitted Logistic Regression Model

The Independent variable's slope coefficient measures how much logit varies with the unit change in an independent variable. Positive coefficients indicate a greater likelihood of distress as the ratio value increases; however, negative coefficients mean conversely. As per the above table 5.56, all the financial ratios and market variables maintain their statistical significance in this model except the exchange rate.

5.12 TWO-YEAR BEFORE FINANCIAL DISTRESS USING FINANCIAL, MARKET & MACROECONOMIC VARIABLES: FOR BIFR COMPANIES

This section estimates two-year before to financial distress model based on financial variables & market variables along with macroeconomic variables in the year t-2, i.e., 2- years prior to the year, in which a financial distressed incident happened for a listed company referred to BIFR, matching with a healthy company in the same year.

It summarizes the findings of the two-year prior financially distressed model, including Pseudo R-squares, Model Classification table, Wald statistic, p-values, Odds ratios, ROC curve, and Area under the curve.

Table 5.57 : Correlation Statistics: 2-year before FD using financial, market & macroeconomic variables for BIFR and Healthy companies

	DE	**PBIDTM**	**NSTA**	**ER**	**EX**
DE	1.000	-.237	-.259	-.208	-.018
PBIDTM	-.237	1.000	.517	.159	-.054
NSTA	-.259	.517	1.000	.124	-.226
ER	-.208	.159	.124	1.000	-.184
EX	-.018	-.054	-.226	-.184	1.000

Values are significant at 1% level

Source: Author ‘s calculations

Table 5.58 : Multicollinearity Statistics: 2-year before FD using financial, market & macroeconomic variables for BIFR and Healthy companies

		DE	PBIDTM	NSTA	ER	EX
Collinearity Statistics	Tolerance	.940	.909	.901	.860	.992
	VIF	1.064	1.101	1.110	1.163	1.008

Source: Author ‘s calculations

The above table 5.57 provides a matrix of correlations of all covariates. In all categories, the observed correlations are statistically significant. Correlations among the covariates are generally small, indicating that the covariates give different and unique details. Variance Inflation (VIF) and its inverse, Tolerance Value (TOL), is calculated to identify the presence of multicollinearity. A value of VIF of more than 10 indicates significant collinearity. As per table 5.58, analysis show they all have VIF's near to 1, with VIF values of 1.064, 1.101, 1.110,1.163 and 1.008 for Debt-to-equity ratio(DE), (Adjusted gross profit + interest)/sales * 100 (PBIDTM), Net Sales / Total Assets (NSTA), Excess Return(ER) & Exchange Rate(EX) respectively, which mean that the collinearity between the regressors has not affected the level of the coefficients & the model does not have multicollinearity, and therefore, the model is capable of reliable performance.

Table 5.59 : Omnibus Tests for the financial, market & macroeconomic variables: 2-year before FD for BIFR companies

Omnibus Tests			
	Chi-square	**df**	**sig.**
Step	54.523	5	0.000
Block	54.523	5	0.000
Model	54.523	5	0.000

Source: Author ‘s calculations

Table 5.60 : Model Summary: 2-year before FD for BIFR companies using financial, market & macroeconomic variables

Summary of the model		
-2 log likelihood	Cox & Snell $R^{\wedge 2}$	Nagelkerke $R^{\wedge 2}$
39.723	0.552	0.736

Source: Author ‘s calculations

Table 5.61 : Hosmer and Lemeshow Test using financial, market & macroeconomic variables: 2-year before FD for BIFR companies

Hosmer & Lemeshow test		
Chi-square	**df**	**sig.**
10.376	8	0.240

Source: Author ‘s calculations

5.12.1 Testing for the Significance of the Model

The result of the Omnibus test is shown in Table 5.59. The null hypothesis for the test is intercept, as well as all the coefficients are zero. A p-value (sig) below 0.05 suggests that the model is statistically significant. As per table 5.60, the value for Nagelkerke R^2 is 0.736 that depicts reasonable fitness for the predictive model. The result of Hosmer and Lemeshow test (Table 5.61) depicts the model is a good fit as p equal to 0.240 (> 0.05)

Table 5.62 : Classification Table of the model using financial, market & macroeconomic variables: 2-year before FD for BIFR companies

<table>
<tr><th colspan="8">Classification Table</th></tr>
<tr><td colspan="2" rowspan="4">Observed</td><td colspan="6">Predicted</td></tr>
<tr><td colspan="3">Selected Cases</td><td colspan="3">Holdout Sample</td></tr>
<tr><td colspan="2">Type</td><td rowspan="2">Correct percentage</td><td colspan="2">Type</td><td rowspan="2">Correct percentage</td></tr>
<tr><td>0</td><td>1</td><td>0</td><td>1</td></tr>
<tr><td rowspan="2">Type</td><td>0</td><td>79</td><td>6</td><td>92.9</td><td>34</td><td>3</td><td>91.9</td></tr>
<tr><td>1</td><td>12</td><td>73</td><td>85.9</td><td>5</td><td>32</td><td>86.5</td></tr>
<tr><td colspan="2">Overall %ge</td><td></td><td></td><td>89.4</td><td></td><td></td><td>89.2</td></tr>
</table>

Source: Author ‘s calculations

5.12.2 Assessing Fitness of Model

This section refers to how well the result attribute, often referred to as its fitness, is projected in the model via a classification matrix. The value of the cut-off is 0.5. If the company's calculated probability of financial distress is > 0.5, the firm is expected to be financially distressed. Table 5.62 shows the classification of the cross-classification matrix of the outcome variable with dichotomized variable; if the estimated likelihood exceeds the cut-off point, then the computed variable is equal to one; otherwise, it is equal to zero. If the estimated probability value is 0.5 or more, it will predict financial distress (as financial distress = 1) and healthy if it is lesser than 0.5 (as Healthy =0). Two years before the financial distress model was framed based on the 70% observations, the remaining 30% observations (holdout sample) can be used to verify its goodness of fit. The explanation for this product performance evaluation is that an appropriate model. Typically performs on an approximation study in an optimistic way. The financial distress prediction model developed correctly classifies 92.9% of healthy firms & 85.9% of sampled financially distressed firms and 91.9% of healthy firms & 86.5% of financially distressed firms for the holdout sample. The overall logistic model forecasts correctly 89.4% of the cases for the model development and 89.2% of the cases in the holdout sample.

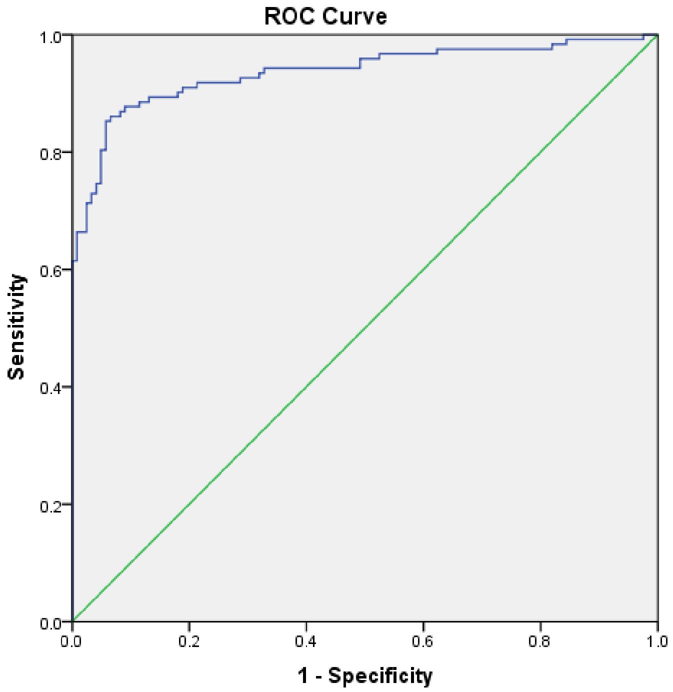
Table 5.63 : Variables in the model to predict FD using financial, market & macroeconomic variables: 2-year before for BIFR companies

Equation variables						
	b	**S.E.**	**wald**	**df**	**sig.**	**exp (b)**
DE	0.860	0.337	17.527	1	0.000	2.364
PBIDTM	-0.090	0.028	10.555	1	0.000	0.914
NSTA	-1.337	0.563	7.637	1	0.010	0.263
ER	-2.109	0.939	6.041	1	0.025	0.121
EX	-1.943	1.416	1.882	1	0.081	0.143
Constant	0.794	0.254	15.771	1	0.004	2.212

Source: Author 's calculations

5.12.3 Interpreting the Fitted Logistic Regression Model

Independent variable's slope coefficient measures how much logit vary with the unit change in an independent variable. Positive coefficients indicate a greater likelihood of distress as the ratio value increases; however, negative coefficients mean conversely. As per the above Table 5.63, all the financial ratios and market variable maintain their statistical significance in this model. In the above Table 5.63, the value of Wald test for each predictor indicates that Debt-to-equity ratio, (Adjusted gross profit + interest)/sales * 100, Net Sales / Total Assets and Excess Return significantly predict financial distress ($p<0.05$) but the exchange rate is significant at 10% level. The values of exp (b) of 2.364 for (debt)-to-(equity) ratio indicates that if the percentage of debt-to-equity ratio goes up by one, then odds of financial distress will also increase, as exp (b) is greater than one, which means with every unit increase in this ratio, likelihood of distress will increase by 2.364 times. Values of exp (b) of 0.914 for Adjusted gross profit + interest/sales * 100 (PBIDTM) indicates that if the percentage of Adjusted gross profit + interest/sales * 100 goes up by one, then odds of financial distress will decrease. As exp (b) is less than one, which means with every unit increase in Adjusted gross profit + interest/sales * 100, the likelihood of distress will decline by 0.914 times. Values of exp (b) of 0.263 for Net Sales / Total Assets indicates that if the percentage of Net Sales / Total Assets goes up by one, then odds of financial distress will decrease, as exp (b) is less than one, which means with every unit increase in Net Sales / Total Assets, the likelihood of distress will decline by 0.263 times. Values of exp (b) of 0.121 for Excess Return indicates that if the percentage of Excess Return goes up by one, then odds of financial distress will decrease, as exp (b) is less than one, which means with every unit increase in Excess Return, the likelihood of distress will decline by 0.121 times. Values of exp (b) of 0.143 for Exchange rate indicates that if the percentage of Exchange rate goes up by one, then odds of financial distress will decrease. As exp (b) is less than one, which means with every unit increase in Exchange rate, the likelihood of distress will decline by 0.143 times.



Source: Author 's calculations

Figure 5.7: ROC curve: 2- year before FD for BIFR companies using financial, market & macroeconomic variables

Table 5.64 : Area under the Curve: 2- year before FD for BIFR companies using financial, market & macroeconomic variables

AUC				
Test result variable(s)	Predicted probability			
Area	SE.	Asymptotic sig.	Asymptotic 95% confidence interval	
			Lower bound	Upper bound
0.936	0.017	0.000	0.904	0.969

Source: Author 's calculations

In the above figure 5.7, using logistic regression, the ROC curve was used to verify the predictive ability of the two-year financial distress model. The AUC gives a degree of discrimination that is likely to result in a failure of a financial distress enterprise being higher than a healthy one. As per table 5.64, AUC is 0.936, indicating that for a randomly selected distress company and randomly selected healthy company, there is a 0.936 likelihood that for a financial distress company, the model estimated the likelihood of distress would be more than for a healthy company. The AUC ranges from 0.904 to 0.969 at a 95% confidence interval. As per the general rule of Hosmer and Lemeshow (2000), two years before financial distress model presents outstanding discrimination.

5.13 THREE-YEAR BEFORE FINANCIAL DISTRESS USING FINANCIAL, MARKET & MACROECONOMIC VARIABLES : FOR BIFR COMPANIES

This section estimates three -years before to financial distress model based on financial variables & market variables along with macroeconomic variables of financially distressed and healthy companies in the year t-3, i.e., three years before the year in which a financial distressed incident happened for a listed company referred to BIFR, matching with a healthy company in the same year.

It summarizes the findings of the three-year prior financially distressed model, including coefficients, Pseudo R-squares, Model Classification table, Wald statistic, p-values, Odds ratios, ROC curve, and Area under the curve.

Table 5.65 :Correlation Statistics: 3-year before FD using financial, market and macroeconomic variables for BIFR and Healthy companies

	DE	PBIDTM	NSTA	ER	EX
DE	1.000	-.246	-.095	-.163	-.099
PBIDTM	-.246	1.000	.277	.125	.218
NSTA	-.095	.277	1.000	-.058	.031
ER	-.163	.125	-.058	1.000	.261
EX	-.099	.218	.031	.261	1.000

Values are significant at 1% level

Source: Author ‘s calculations

Table 5.66 : Multicollinearity Statistics: 3-year before FD using financial, market & macroeconomic variables for BIFR and Healthy companies

		DE	PBIDTM	NSTA	ER	EX
Collinearity Statistics	Tolerance	.992	.984	.975	.921	.942
	VIF	1.008	1.016	1.026	1.086	1.062

Source: Author 's calculations

The above table 5.65 provides a matrix of correlations of all covariates. In all categories, the observed correlations are statistically significant. Correlations among the covariates are generally small, indicating that the covariates give different and unique details. Variance Inflation (VIF) and its inverse, Tolerance Value (TOL), is calculated to identify the presence of multicollinearity. A value of VIF of more than 10 indicates significant collinearity. As per table 5.66, analysis shows they all have VIF's near to 1, with VIF values of 1.008, 1.016, 1.026,1.086 and 1.062 for Debt-to-equity ratio(DE), Adjusted gross profit + interest/sales * 100 (PBIDTM), Net Sales / Total Assets(NSTA), Excess Return(ER) & Exchange Rate(EX), respectively, which mean that the collinearity between the regressors has not affected the level of the coefficients & the model does not have multicollinearity, and therefore, the model is capable of reliable performance.

Table 5.67 : Omnibus Tests for the financial, market & macroeconomic variables: 3-year before FD for BIFR companies

Omnibus Tests			
	Chi-square	**df**	**sig.**
Step	54.545	5	0.000
Block	54.545	5	0.000
Model	54.545	5	0.000

Source: Author 's calculations

Table 5.68 : Model Summary: 3-year before FD for BIFR companies using financial, market & macroeconomic variables

Summary of the model		
-2 log likelihood	Cox & Snell R^2	Nagelkerke R^2
48.063	0.521	0.695

Source: Author ‘s calculations

Table 5.69 : Hosmer and Lemeshow Test using financial, market & macroeconomic variables: 3-year before FD for BIFR companies

Hosmer & Lemeshow test		
Chi-square	df	sig.
5.636	8	0.688

Source: Author ‘s calculations

5.13.1 Testing for the Significance of the Model

The result of the Omnibus test is shown in Table 5.67. The null hypothesis for the test is intercept, as well as all the coefficients are zero. A p-value (sig) below 0.05 suggests that the model is statistically significant. As per table 5.68, the value for Nagelkerke R^2 is 0.695, which depicts reasonable fitness for the predictive model. The result of Hosmer and Lemeshow test (Table 5.69) depicts the model is a good fit as p equal to 0.688 (> 0.05).

Table 5.70 : Classification Table of the model using financial, market & macroeconomic variables: 3-year before FD for BIFR companies

<table>
<tr><th colspan="9">Classification Table</th></tr>
<tr><td colspan="3" rowspan="4">Observed</td><td colspan="6">Predicted</td></tr>
<tr><td colspan="3">Selected Cases</td><td colspan="3">Holdout Sample</td></tr>
<tr><td colspan="2">Type</td><td rowspan="2">Correct percentage</td><td colspan="2">Type</td><td rowspan="2">Correct percentage</td></tr>
<tr><td>0</td><td>1</td><td>0</td><td>1</td></tr>
<tr><td rowspan="3"></td><td rowspan="2">Type</td><td>0</td><td>66</td><td>14</td><td>82.5</td><td>28</td><td>6</td><td>82.3</td></tr>
<tr><td>1</td><td>20</td><td>60</td><td>75</td><td>9</td><td>25</td><td>73.5</td></tr>
<tr><td colspan="2">Overall %ge</td><td></td><td></td><td>78.7</td><td></td><td></td><td>77.9</td></tr>
</table>

Source: Author ‘s calculations

5.13.2 Assessing Fitness of Model

As per table 5.70, the financial distress prediction model developed correctly classifies 82.5% of healthy firms & 75% of sampled financially distressed firms and 82.3% of healthy firms & 73.5% of financially distressed firms for the holdout sample. The overall logistic model forecasts correctly 78.7% of the cases for the development of the model and 77.9% of the cases in the holdout sample.

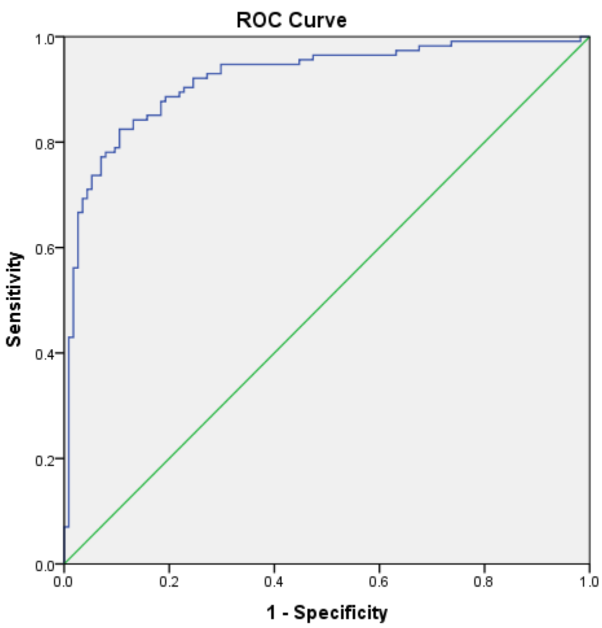
Table 5.71 : Variables in the model to predict FD using financial, market & macroeconomic variables: 3-year before for BIFR companies

Equation variables						
	b	**S.E.**	**wald**	**df**	**sig.**	**exp (b)**
DE	0.983	0.243	16.372	1	0.000	2.674
PBIDTM	-0.180	0.040	20.655	1	0.000	0.835
NSTA	-0.742	0.328	5.113	1	0.024	0.476
ER	-0.938	0.413	5.153	1	0.023	0.392
EX	-4.591	2.662	2.974	1	0.085	0.010
Constant	1.555	0.755	4.244	1	0.039	4.735

Source: Author ‘s calculations

5.13.3 Interpreting the Fitted Logistic Regression Model

As per table 5.71, the significance value of the Wald test for each predictor indicates that Debt-to-equity ratio, Adjusted gross profit + interest/sales * 100, Net Sales / Total Assets and Excess Return significantly predict financial distress ($p<0.05$) but the exchange rate is significant at 10% level. The values of exp (b) of 2.674 for debt-to-equity ratio indicates that if the percentage of debt-to-equity ratio goes up by one, then odds of financial distress will also increase, as exp (b) is greater than one, which means with every unit increase in this ratio, the likelihood of distress will increase by 2.674 times than firms that do not experience an increase in debt-to-equity ratio. The values of exp (b) of 0.835 for Adjusted gross profit + interest/sales * 100 indicates that if the percentage of Adjusted gross profit + interest/sales * 100 goes up by one, then odds of financial distress will decrease, as exp (b) is less than one, which means with every unit increase in Adjusted gross profit + interest/sales * 100, the likelihood of distress will decline by 0.835. Values of exp (b) of 0.476 for Net Sales / Total Assets indicates that if the percentage of Net Sales / Total Assets goes up by one, then odds of financial distress will decrease, as exp (b) is less than one, which means with every unit increase in Net Sales / Total Assets, the likelihood of distress will decline by 0.476 times. Values of exp (b) of 0.392 for Excess Return indicates that if the percentage of Excess Return goes up by one, then odds of financial distress will decrease, as exp (b) is less than one, which means with every unit increase in Excess Return, the likelihood of distress will decline by 0.392 times. Values of exp (b) of 0.010 for Exchange rate indicates that if the percentage of Exchange rate goes up by one, then odds of financial distress will decrease, as exp (b) is less than one, which means with every unit increase in Exchange rate, the likelihood of distress will decline by 0.010 times.



Source: Author ‘s calculations

Figure 5.8: ROC curve: 3- year before FD for BIFR companies using financial, market & macroeconomic variables

Table 5.72 : Area under the Curve: 3- year before FD for BIFR companies using financial, market & macroeconomic variables

AUC				
Test result variable(s)	Predicted probability			
Area	SE.	Asymptotic Sig.	Asymptotic 95% confidence interval	
			Lower bound	Upper bound
0.801	0.024	0.000	0.741	0.842

Source: Author 's calculations

In the above figure 5.8, using logistic regression, the ROC curve was used to verify the predictive ability of the two-year financial distress model. The AUC gives a degree of discrimination that is likely to result in a failure of a financial distress enterprise being higher than a healthy one. As per table 5.72, AUC is 0.801, indicating that for a randomly selected distress company and randomly selected healthy company, there is a 0.801 likelihood that for a financial distress company, the model estimated the likelihood of distress would be more than for a healthy company. The AUC ranges from 0.741 to 0.842 at a 95% confidence interval. As per the general rule of Hosmer and Lemeshow (2000), three years before the financial distress model presents outstanding discrimination.

Table 5.73 : Result of the logistic regression for BIFR companies using financial, market & macroeconomic variables

Year before financial distress	Pseudo R-squares	AUC	Classification accuracy Model development	Classification accuracy Holdout Sample
2	0.736	0.936	89.4%	89.2%
3	0.695	0.801	78.7%	77.9%

Source: Author 's calculations

5.14 OVERALL FINDINGS OF THE STUDY

In this section, macroeconomic variables and financial & market variables were tested to forecast financial distress over one to three years for firms referred to BIFR. The derived models are significantly relevant to predicting financial distress companies over time frames of one to three years.

It can be observed that in the one- year before financial distress model, Debt-to-equity ratio (DE), Adjusted gross profit + interest/sales * 100 (PBIDTM), Net Sales / Total Assets (NSTA), Excess return (ER) are significant at five -percent level except Exchange rate (EX). Whereas in the two & three - years before the financial distress model, Debt-to-equity ratio (DE), Adjusted gross profit + interest/sales * 100 (PBIDTM), Net Sales / Total Assets (NSTA), Excess return (ER) are significant at five -percent level but Exchange rate (EX) significant at ten -percent level. It can be observed, both in case of two–year & three years before financial distress models, coefficient values for all three financial & market variables; Debt-to-equity ratio (DE), Adjusted gross profit + interest/sales * 100 (PBIDTM), Net Sales / Total Assets (NSTA) & Excess return (ER) are significant at five -percent level with likely positive and negative signs. Debt-to-equity ratio (DE) has a positive coefficient in both models, which suggests that an increase in this ratio will further increase the likelihood of distress of companies and is the most important ratio for predicting distress given its higher odd ratios in both models. PBIDTM is the second most important variable after debt-to-equity. It has a negative coefficient value in both models, which suggests that an increase in PBIDTM value will decrease the likelihood of distress. NSTA has a negative coefficient value in both models, which indicates that an increase in its value will reduce the likelihood of distress. Similarly, Excess return has a negative coefficient value in both models, which suggests that an increase in its value will decrease companies' probability of financial distress. The exchange rate (ER) has a negative coefficient value, which indicates that an increase in its value will reduce the likelihood of distress and is the least important variable for predicting distress, given its lowest odd ratio. The result of the goodness of fit for both models shown by Hosmer and Lemeshow test found a high p-value >0.05 for both models. Thus, both models are quite effective to be used for predicting the aforementioned outcome. As per earlier studies, the analysis found that accuracy of models is diminishing, with the increase in the time period of financial distress, with deteriorating Pseudo R-squares, AUC values and accuracy level of classification matrix. The value of Nagelkerke R square slightly decreases for models from years 2 to 3, which suggests that overall ability to predict is satisfactory. As per Table 5.73, the value of AUC decreases from 0.936 to 0.801 for models from years 2 to 3, which suggests satisfactory discrimination of the predictive models. Predictive accuracy is higher in the case of two -years before the financial distress model with 89.4 % of the cases for the model development and 89.2% of the cases in the holdout sample, followed by three- year model with 78.7% of the cases for the model development and 77.9% of the cases in the holdout sample.

As per earlier studies, the analysis found less significance of macroeconomic variables for predicting financial distress. There is no improvement in the predictive accuracy of models compared to models including only financial variables or financial & market variables. **Asgarnezhad and Soltani (2016)** research showed that the macroeconomic variables and the likelihood of financial distress have no meaningful relationship. In other words, the macroeconomic conditions do not significantly affect corporate distress prediction **Wijaya and Anantadjaya (2014)**.

5.15 ONE-YEAR BEFORE FINANCIAL DISTRESS USING FINANCIAL, MARKET & MACROECONOMIC VARIABLES: FOR IBC COMPANIES

This section estimates one-year before to financial distress model based on financial variables & market variables along with macroeconomic variables of financially distressed and healthy companies in the year t-1, i.e., one year before the year in which a financial distressed incident happened for a listed company referred to IBC, matching with a healthy company in the same year.

It summarizes the findings of the one-year prior financially distressed model, including Pseudo R-squares, Model Classification table, Wald statistic, p-values, Odds ratios, ROC curve, and Area under the curve.

Table 5.74 : Correlation Statistics: 1-year before FD using financial, market and macroeconomic variables for IBC and Healthy companies

	DE	CPM	CFOINT	MVSF	STDEV	EX
DE	1.000	-.197	.244	.329	.203	.258
CPM	-.197	1.000	-.250	.019	.150	.037
CFOINT	.244	-.250	1.000	.069	.121	.213
MVSF	.329	.019	.069	1.000	.436	.236
STDEV	.203	.150	.121	.436	1.000	.322
EX	.258	.037	.213	.236	.322	1.000

Values are significant at 1% level

Source: Author 's calculations

Table 5.75 : Multicollinearity Statistics: 1-year before FD using financial, market & macroeconomic variables for IBC and Healthy companies

		DE	CPM	CFOINT	STDEV	MVSF	EX
Collinearity Statistics	Tolerance	.930	.878	.885	.885	.941	.861
	VIF	1.075	1.138	1.130	1.129	1.063	1.161

Source: Author 's calculations

Table 5.74 provides a matrix of correlations of all covariates. In all categories, the observed correlations are statistically significant. Correlations among the covariates are generally small, indicating that the covariates give different and unique details. Variance Inflation (VIF) and its inverse, Tolerance Value (TOL), is calculated to identify the presence of multicollinearity. A value of VIF of more than 10 indicates significant collinearity. As per table 5.75, shows they all have VIF's near to 1, with VIF value of 1.075, 1.130,1.138, 1.063, 1.129 and 1.161 for Debt-to-Equity, Cash flow from operations / Interest (CFOINT), (Adjusted net profit + depreciation) / sales * 100 (CPM), Market value to Shareholder funds (MVSF), Standard Deviation (STDEV) and Exchange Rate, respectively, which means that the collinearity between the regressors has not affected the level of the coefficients & the model does not have multicollinearity, and therefore, the model is capable of reliable performance.

Table 5.76 : Omnibus Tests for the financial, market & macroeconomic variables: 1-year before FD for IBC companies

Omnibus Tests			
	Chi-square	**df**	**sig.**
Step	60.384	6	0.000
Block	60.384	6	0.000
Model	60.384	6	0.000

Source: Author 's calculations

Table 5.77 : Model Summary: 1-year before FD for IBC companies using financial, market & macroeconomic variables

Summary of the model		
-2 Log likelihood	Cox & Snell $R^{\wedge 2}$	Nagelkerke $R^{\wedge 2}$
64.382	0.489	0.652

Source: Author 's calculations

Table 5.78 : Hosmer and Lemeshow Test using financial, market & macroeconomic variables: 1-year before FD for IBC companies

Hosmer & Lemeshow test		
Chi-square	df	sig.
27.972	8	0.000

Source: Author 's calculations

5.15.1 Testing for the Significance of the Model

The result of the Omnibus test is shown in Table 5.76. The null hypothesis for the test is intercept, as well as all the coefficients are zero. A p-value (sig) below 0.05 suggests that the model is statistically significant. The pseudo-R-squares value for Nagelkerke R^2 (in table 5.77) is 0.652, that depicts reasonable fitness for the predictive model. The result of Hosmer and Lemeshow test (Table 5.78) indicate that the model is a poor fit as p equal to 0.00 (< 0.05).

Table 5.79 : Variables in the model to predict FD using financial, market & macroeconomic variables: 1-year before for IBC companies

Equation variables						
	b	S.E.	wald	df	sig.	exp (b)
DE	1.011	0.474	4.547	1	0.033	2.749
CPM	-0.143	0.050	8.101	1	0.004	0.867
CFOINT	-0.049	0.033	2.180	1	0.140	0.952
MVSF	0.003	0.096	0.001	1	0.975	1.003
STDEV	0.391	0.375	1.083	1	0.298	1.478
EX	-1.957	7.827	0.063	1	0.803	0.141
Constant	-0.829	1.709	0.235	1	0.628	0.436

Source: Author ‘s calculations

5.15.2 Interpreting the Fitted Logistic Regression Model

The Independent variable's slope coefficient measures how much logit varies with an independent variable's unit change. Positive coefficients indicate a greater likelihood of distress as the ratio value increases; however, negative coefficients mean conversely. As per the above table 5.79, only Debt-to-equity & (Adjusted net profit + depreciation) / sales * 100(CPM) is significant, and all other financial, market & macroeconomic variables (Cash flow from operations/ Interest (CFOINT), Market value to shareholder funds (MVSF), Standard Deviation (STDEV) & exchange rate) are not significant at five -percent level.

5.16 TWO-YEAR BEFORE FINANCIAL DISTRESS USING FINANCIAL, MARKET & MACROECONOMIC VARIABLES: FOR IBC COMPANIES

This section estimates distress model using financial variables & market variables along with macroeconomic variables in the year t-2, i.e., two years prior to the year in which a financial distressed incident happened for a listed company referred to IBC, matching with a healthy company in the same year.

It summarizes the findings of the two-year prior financially distressed model, including Pseudo R-squares, Model Classification table, Wald statistic, Odds ratios, ROC curve, and Area under the curve.

Table 5.80 : Correlation Statistics: 2-year before FD using financial, market and macroeconomic variables for IBC and Healthy companies

	DE	CPM	CFOINT	STDEV	MVSF	EX
DE	1.000	.064	.174	.161	-.216	-.172
CPM	.064	1.000	-.094	.216	-.074	.056
CFOINT	.174	-.094	1.000	-.233	-.266	-.233
STDEV	.161	.216	-.233	1.000	.113	.337
MVSF	-.216	-.074	-.266	.113	1.000	.283
EX	-.172	.056	-.233	.337	.283	1.000

Values are significant at 1% level

Source: Author ‘s calculations

Table 5.81 : Multicollinearity Statistics: 2-year before FD using financial, market & macroeconomic variables for IBC and Healthy companies

		DE	CPM	CFOINT	STDEV	MVSF	EX
Collinearity Statistics	Tolerance	.920	.846	.815	.835	.901	.873
	VIF	1.087	1.182	1.228	1.198	1.110	1.145

Source: Author ‘s calculations

Table 5.80 provides a matrix of correlations of all covariates. In all categories, the observed correlations are statistically significant. Correlations among the covariates are generally small, indicating that the covariates give different and unique details. Variance Inflation (VIF) and its inverse, Tolerance Value (TOL), is calculated to identify the presence of multicollinearity. A value of VIF of more than 10 indicates significant collinearity. As per table 5.81, analyses of all the regressors obtained; show they all have VIF's near to 1, with VIF values of 1.087, 1.228, 1.182, 1.110, 1.198 & 1.145 for Debt-to-equity, Cash flow from operations/ Interest (CFOINT), (Adjusted net profit + depreciation) / sales * 100 (CPM), Market value to shareholder funds (MVSF), Standard Deviation (STDEV) and Exchange rate, respectively, which means that the collinearity between the regressors has not affected the level of the coefficients & the model does not have multicollinearity, and therefore, the model is capable of reliable performance.

Table 5.82 : Omnibus Tests for the financial, market & macroeconomic variables: 2-year before FD for IBC companies

Omnibus Tests			
	Chi-square	df	Sig.
Step	72.349	6	0.000
Block	72.349	6	0.000
Model	72.349	6	0.000

Source: Author 's calculations

Table 5.83 : Model Summary: 2-year before FD for IBC companies using financial, market & macroeconomic variables

Summary of the model		
-2 log likelihood	Cox & Snell $R^{\wedge 2}$	Nagelkerke $R^{\wedge 2}$
49.645	0.561	0.747

Source: Author 's calculations

Table 5.84 Hosmer and Lemeshow Test using financial, market & macroeconomic variables: 2-year before FD for IBC companies

Hosmer & Lemeshow test		
Chi-square	df	sig.
2.863	8	0.943

Source: Author 's calculations

5.16.1 Testing for the Significance of the Model

The result of the Omnibus test is shown in Table 5.82. The null hypothesis for the test is intercept, as well as all the coefficients are zero. A p-value (sig) below 0.05 suggests that the model is statistically significant. As per table 5.83, the pseudo-R-squares value for Nagelkerke R^2 is 0.747 that depicts reasonable fitness for the predictive model. The result of Hosmer and Lemeshow test (Table 5.84) depicts the model is a good fit as p equal to 0.943 (> 0.05).

Table 5.85 : Variables in the model to predict FD using financial, market & macroeconomic variables: 2-year before for IBC companies

Equation variables						
	b	**S.E.**	**wald**	**df**	**sig.**	**exp (b)**
DE	0.993	0.457	4.726	1	0.030	2.700
CPM	-0.036	0.023	2.388	1	0.122	0.965
CFOINT	-0.092	0.046	3.940	1	0.047	0.912
STDEV	1.089	0.448	5.918	1	0.015	2.972
MVSF	-0.333	0.373	0.800	1	0.371	0.716
EX	-5.639	11.623	0.235	1	0.628	0.004
Constant	-3.055	1.882	2.634	1	0.105	0.047

Source: Author 's calculations

5.16.2 Interpreting the Fitted Logistic Regression Model

Independent variable's slope coefficient measures how much logit vary with the unit change in an independent variable. Positive coefficients indicate a greater likelihood of distress as the ratio value increases; however, negative coefficients mean conversely. As per the above table 5.85, only Debt-to-Equity, Cash flow from operations/ Interest (CFOINT), Standard Deviation (STDEV) are significant, and all other financial, market & macroeconomic variables are not significant.

5.17 THREE-YEAR BEFORE FINANCIAL DISTRESS USING FINANCIAL, MARKET & MACROECONOMIC VARIABLES: FOR IBC COMPANIES

This section estimates three years before to financial distress model based on financial variables & market variables along with macroeconomic variables of financially distressed and healthy companies in the year t-3, i.e., three years before the year in which a financial distressed incident happened for a listed company referred to IBC, matching with a healthy company in the same year.

It summarizes the findings of the three-year prior financially distressed model, including Pseudo R-squares, Model Classification table, Wald statistic, p-values, Odds ratios, ROC curve, and Area under the curve.

Table 5.86 : Correlation Statistics: 3-year before FD using financial, market and macroeconomic variables for IBC and Healthy companies

	DE	CPM	CFOINT	MVSF	STDEV	EX
DE	1.000	-.007	.189	.117	-.026	-.071
CPM	-.007	1.000	-.137	-.087	.170	.013
CFOINT	.189	-.137	1.000	.102	-.009	-.081
MVSF	.117	-.087	.102	1.000	.027	.093
STDEV	-.026	.170	-.009	.027	1.000	.004
EX	-.071	.013	-.081	.093	.004	1.000

Values are significant at 1% level

Source: Author ‘s calculations

Table 5.87 : Multicollinearity Statistics: 3-year before FD using financial, market & macroeconomic variables for IBC and Healthy companies

		DE	CPM	CFOINT	MVSF	STDEV	EX
Collinearity Statistics	Tolerance	.944	.921	.946	.948	.926	0.864
	VIF	1.060	1.085	1.057	1.055	1.080	1.157

Source: Author ‘s calculations

Table 5.86 provides a matrix of correlations of all covariates. In all categories, the observed correlations are statistically significant. Correlations among the covariates are generally small, indicating that the covariates give different and unique details. Variance Inflation (VIF) and its inverse, Tolerance Value (TOL), is calculated to identify the presence of multicollinearity. A value of VIF of more than 10 indicates significant collinearity. As per table 5.87, analyses of all the regressors obtained; show they all have VIF's near to 1, with VIF values of 1.060, 1.057, 1.085, 1.055, 1.080 & 1.157 for Debt-to-equity, Cash flow from operations/ Interest (CFOINT), (Adjusted net profit + depreciation) / sales * 100 (CPM), Market value to shareholder funds(MVSF), Standard Deviation (STDEV) and Exchange rate, respectively, which mean that the collinearity between the regressors has not affected the level of the coefficients & the model does not have multicollinearity, and therefore, the model is capable of reliable performance.

Table 5.88 : Omnibus Tests for the financial, market & macroeconomic variables: 3-year before FD for IBC companies

Omnibus Tests			
	Chi-square	df	sig.
Step	29.832	6	0.000
Block	29.832	6	0.000
Model	29.832	6	0.000

Source: Author 's calculations

Table 5.89 : Model Summary: 3-year before FD for IBC companies using financial, market & macroeconomic variables

Summary of the Model		
-2 Log Likelihood	Cox & Snell $R^{\wedge 2}$	Nagelkerke $R^{\wedge 2}$
12.162	0.288	0.383

Source: Author 's calculations

Table 5.90 : Hosmer and Lemeshow Test using financial, market & macroeconomic variables: 3-year before FD for IBC companies

Hosmer & Lemeshow test		
Chi-square	**df**	**sig.**
9.493	8	0.302

Source: Author 's calculations

5.17.1 Testing for the Significance of the Model

The result of the Omnibus test is shown in Table 5.88. The null hypothesis for the test is intercept, as well as all the coefficients are zero. A p-value (sig) below 0.05 suggests that the model is statistically significant. As per table 5.89, the pseudo-R-squares value for Nagelkerke R^2 is 0.383 that depicts reasonable fitness for the predictive model. The result of Hosmer and Lemeshow test (Table 5.90) depicts the model is a good fit as p equal to 0.302 (> 0.05).

Table 5.91 : Classification Table of the model using financial, market & macroeconomic variables: 3-year before FD for IBC companies

<table>
<tr><th colspan="8">Classification Table</th></tr>
<tr><td colspan="2" rowspan="4">Observed</td><td colspan="6">Predicted</td></tr>
<tr><td colspan="3">Selected Cases</td><td colspan="3">Holdout Sample</td></tr>
<tr><td colspan="2">Type</td><td rowspan="2">Correct percentage</td><td colspan="2">Type</td><td rowspan="2">Correct percentage</td></tr>
<tr><td>0</td><td>1</td><td>0</td><td>1</td></tr>
<tr><td rowspan="2">Type</td><td>0</td><td>31</td><td>13</td><td>70.5</td><td>71</td><td>29</td><td>71</td></tr>
<tr><td>1</td><td>8</td><td>36</td><td>81.8</td><td>30</td><td>70</td><td>70</td></tr>
<tr><td colspan="2">Overall %ge</td><td></td><td></td><td>76.1</td><td></td><td></td><td>70.5</td></tr>
</table>

Source: Author 's calculations

5.17.2 Assessing Fitness of Model

As per table 5.91, the financial distress prediction model developed correctly classifies 70.5% of healthy firms & 81.8% of sampled financially distressed firms and 71% of healthy firms & 70% of financially distressed firms for the holdout sample. The overall logistic model forecasts correctly 76.1% of the cases for the model development and 70.5% of the cases in the holdout sample.

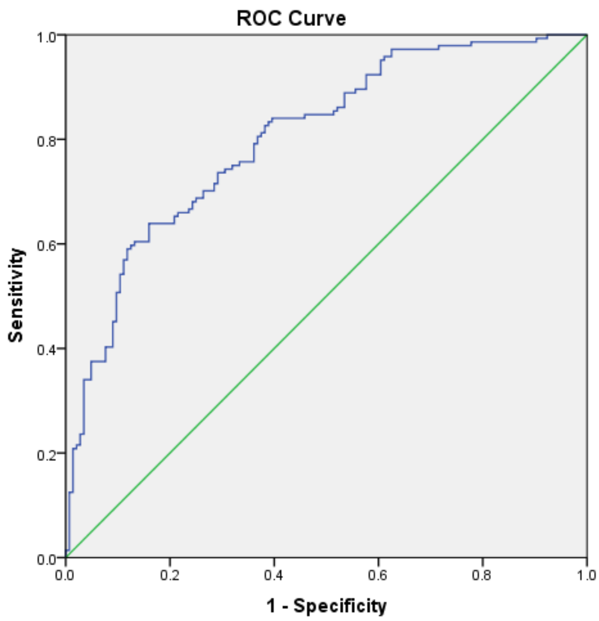
Table 5.92 : Variables in the model to predict FD using financial, market & macroeconomic variables: 3-year before for IBC companies

Equation variables						
	b	**S.E.**	**wald**	**df**	**sig.**	**exp (b)**
DE	0.220	0.061	13.007	1	0.000	1.246
CPM	-0.036	0.018	3.939	1	0.044	0.965
CFOINT	-0.074	0.035	4.380	1	0.036	0.929
MVSF	-0.285	0.112	6.475	1	0.014	0.752
STDEV	0.195	0.091	4.591	1	0.031	1.216
EX	-5.192	3.107	2.792	1	0.090	0.006
Constant	0.047	0.021	5.009	1	0.025	1.048

Source: Author's calculations

5.17.3 Interpreting the Fitted Logistic Regression Model

Above Table 5.92 indicate that all the independent variables are significant except the exchange rate, which is significant at 10%. The values of exp (b) of 1.246 for (debt)-to-(equity) ratio indicates that if the percentage of (debt)-to-(equity) ratio goes up by one, then odds of financial distress will also increase. As exp (b) is greater than one, which means with every unit increase in this value, the likelihood of distress will increase by 1.246 times. Values of exp (b) of 0.965 for (Adjusted net profit + depreciation) / sales * 100 (CPM) indicates that if the percentage of (Adjusted net profit + depreciation) / sales * 100 (CPM) goes up by one, then odds of financial distress will decrease. As exp (b) is less than one, which means with every unit increase in (Adjusted net profit + depreciation) / sales * 100 (CPM), the likelihood of distress will decrease by 0.965 times. Values of exp (b) of 0.929 for (Cash flow from operations)/(Interest)(CFOINT) indicates that if the percentage of (Cash flow from operations)/ (Interest)(CFOINT) goes up by one, then odds of financial distress will decrease. As exp (b) is less than one, which means with every unit increase in (Cash flow from operations)/ (Interest) (CFOINT), the likelihood of distress will decline by 0.929 times. Values of exp (b) of 0.752 for Market value to shareholder funds (MVSF) indicates that if the percentage of Market value to shareholder funds (MVSF) goes up by one, then odds of financial distress will decrease. As exp (b) is less than one, which means with every unit increase in Market value to shareholder funds (MVSF), the likelihood of distress will decline by 0.752 times. Values of exp (b) of 1.216 for Standard Deviation (STDEV) indicates that if the percentage of Standard Deviation (STDEV) goes up by one, then odds of financial distress will also increase. As exp (b) is greater than one, which means with every unit increase in Standard Deviation (STDEV) likelihood of distress will increase by 1.216 times. Values of exp (b) of 0.006 for Exchange rate indicates that if the percentage of Exchange rate goes up by one, then odds of financial distress will decrease. As exp (b) is less than one, which means with every unit increase in Exchange rate, the likelihood of distress will decline by 0.006 times.



Source: Author ‘s calculations

Figure 5.9: ROC curve: 3- year before FD for IBC companies using financial, market & macroeconomic variables

Table 5.93 : Area under the Curve: 3- year before FD for IBC companies using financial, market & macroeconomic variables

AUC				
Test result variable(s)	Predicted probability			
Area	SE.	Asymptotic sig.	Asymptotic 95% confidence interval	
			Lower bound	Upper bound
0.803	0.025	0.000	0.753	0.853

Source: Author ‘s calculations

In the above figure 5.9, the ROC curve was used to verify the predictive ability of the three-year financial distress model. The AUC gives a degree of discrimination that is likely to result in a failure of a financial distress enterprise being higher than a healthy one. As per table 5.93, AUC is 0.803, indicating that for a randomly selected distress company and randomly selected healthy company, there is a 0.803 likelihood that for a financial distress company, the model estimated the likelihood of distress would be more than for a healthy company. The AUC ranges from 0.753 to 0.853 at a 95% confidence interval. As per the general rule of Hosmer and Lemeshow (2000), three years before the financial distress model presents satisfactory discrimination.

5.18 OVERALL FINDINGS OF THE STUDY

In this section, macroeconomic variables were tested along with financial & market variables to forecast financial distress over one to three years for firms referred to IBC. It can be observed that in the one- year before financial distress model, coefficient values for one financial variable, two market variables and one macroeconomic variable; Cash flow from operations/ Interest (CFOINT), Market value to shareholder funds (MVSF), Standard Deviation (STDEV) and exchange rate are not significant at five -percent level. Only Debt-to-equity & (Adjusted net profit + depreciation) / sales * 100 (CPM) is significant. Similarly, in the two- years before financial distress model, coefficient values for only Debt-to-Equity, Cash flow from operations/ Interest (CFOINT), Standard Deviation (STDEV) are significant, and all other financial, market & macroeconomic variables are not significant at the five -percent level.

But in the three- years before financial distress model, coefficient values for all three financial variables, two market variables; Debt-to-equity ratio (DE), Adjusted net profit + depreciation) / sales * 100 (CPM), Cash flow from operations/ Interest (CFOINT), Market value to shareholder funds (MVSF), Standard Deviation (STDEV) are significant at five -percent level, whereas macroeconomic variable exchange rate is significant at ten -percent level. Debt-to-equity ratio (DE) has a positive coefficient in this model, which suggests that an increase in this value will increase the likelihood of distress and is the most important ratio for predicting distress given its higher odd ratio. Standard Deviation (STDEV) is the second most important variable after debt-to-equity. It has a positive coefficient value, which suggests that an increase in Standard Deviation (STDEV) will further increase the probability of financial distress of companies. Adjusted net profit + depreciation) / sales * 100 (CPM) has a negative coefficient value, which suggests that an increase in CPM value will decrease the likelihood of distress. Cash flow from operations/ Interest (CFOINT) has a negative coefficient value, which suggests that an increase in its value will reduce the likelihood of distress. Market value to shareholder funds (MVSF) has a negative coefficient value, which indicates that an increase in its value will decrease the likelihood of distress. The exchange rate (ER) has a negative coefficient value, which suggests that an increase in its value will reduce the likelihood of distress and is the least important ratio for predicting distress given its lowest odd ratio. The result shown by the Hosmer and Lemeshow test found low chi-square static <15 and a high p-value >0.05. Thus, the fitted model is quite effective to be used for predicting the outcome. Overall, only three- years before the financial distress model has been useful to predict distress using financial, market and macroeconomic variables for various firms, with a predictive accuracy of 76.1 % of the cases for the development of the model and 70.5% of the cases in the holdout sample, which is relatively less as compare to model using only financial variables or using both financial and market variables. As per earlier studies, the analysis found less significance of macroeconomic variables for predicting financial distress. **Asgarnezhad and Soltani (2016)** research showed that the macroeconomic variables and the probability of financial distress have no meaningful relationship. In other words, the macroeconomic conditions do not significantly affect corporate distress prediction **Wijaya and Anantadjaya (2014)**.

Chapter – 6

OPINION OF FINANCIAL INSTITUTIONS: A SURVEY ANALYSIS

As the Indian economy slows, several companies are experiencing financial difficulties, which has led to an increase in financial distress in recent years **Van Der Colff and Vermaak (2015)**. Businesses that are experiencing financial challenges have placed a strain on the financials of various financial institutions, including banks and non-bank financial companies (NBFCs), that have extended credit to these companies. In general, distressed assets lose their value quickly, rendering them unprofitable in the long run and putting additional strain on the financial institutions. The failure of a business has far-reaching implications for all stakeholders. Shareholders are more likely to suffer a loss if the value of their investment declines or is completely lost, creditors will get just a portion of or no return on any advance, workers are laid off from their employment. Moreover, the government earns less income from business and workplace taxes, and to make the problem worse, and the government must run social programs to assist the unemployed, affecting the rest of the taxpayers. In the last decade, business debt has been at risk of rising considerably, & in most adverse situations, it might rise much higher, which eventually poses a threat to the quality of commercial banks' loan portfolios. Therefore, the banking sector must detect the financial crisis at an early stage, take fast actions to resolve it and provide a fair recovery for creditors and investors **Norden and Weber (2010)**. India's corporate bankruptcy resolution system has several flaws in its mechanism, regulations, and weaknesses in the efficient implementation by different financial institutions, all of which have resulted in unfavourable outcomes. IBC is the most recent policy move toward resolving this issue. It is anticipated that the IBC law would fundamentally alter the entire credit environment in India **Sengupta, Sharma and Thomas (2016)**.

6.1 PURPOSE OF THE STUDY

This section explains the result of the interviews of various officials working with financial institutions in India. Most of the analysis is based on conceptual understanding and evaluating the results acquired throughout the investigation. The study considered the opinion of financial institutions on prevailing distress in India. The study attempts to determine causes of increasing distress in Indian companies, early warning signs, the effectiveness of new insolvency law, and credit rating agencies.

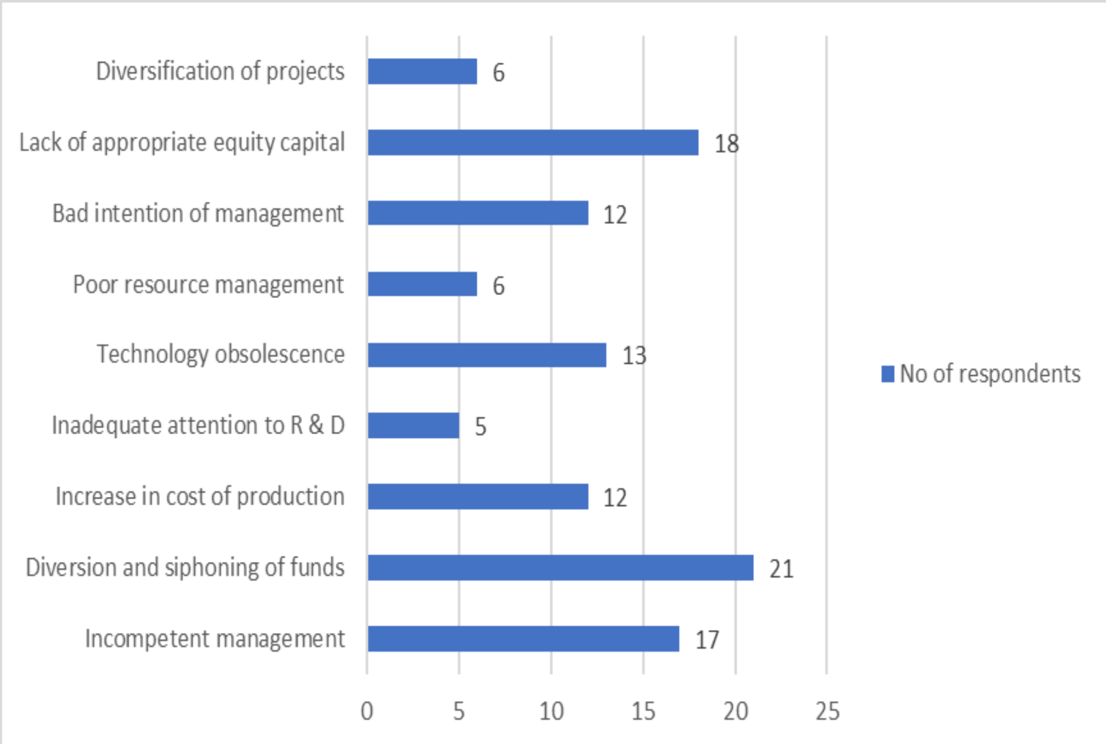
6.2 METHODOLOGICAL SUPPORT

This study analyses the opinion of financial institutions about the financial distress of Indian companies and related matters to financial distress. While the evolution of financial distress models has been broadly examined in previous studies, literature on the causes of financial distress has gotten relatively less attention. The reasons for investigating financial institutions' views are that they are most closely associated with financial distress firms. Because this study looks into financial institutions' opinions, a semi-structured interview was more beneficial because the questions were more related to respondents' perceptions of reality. This chapter explains the results of the interviews of various officials working with financial institutions in India. This study employed a qualitative design using semi-structured interviews. The interviews were conducted through a combination of telephonic and in-person interviews. According to **McIntosh** a**nd Morse (2015**), semi-structured is widely regarded as a relatively simple technique because it allows participants to spend as much time as they want to answer questions. Using open-ended questions, researchers can get detailed and precise descriptions of the topic under investigation. Each interview was intended to collect opinions on financial distress. The interview schedule comprised five main questions, and the questionnaire was pilot tested with five academicians and industry experts. With the help of this testing, various difficulties and vagueness can be eliminated. On experts' suggestions, the questionnaire was further modified regarding the language of questions, presentation of the matter, etc. Some minor changes were made mainly in the wording and order of the questions. After doing all these changes, the final interview schedule for the study has been framed. Five open-ended questions were included in the discussion. The purpose of utilising open-ended questions was to elicit critical information that may have been neglected in the prior study. A copy of the final interview schedule is attached as Appendix. The interviewees were chosen from various financial institutions working at the senior level positions like Chief Manager, Assistant General Manager. However, to maintain anonymity, their names and affiliations are not revealed in this section. The convenience sampling methodology has been applied in this study to choose sampled respondents using judgemental sampling. Different researchers have differing viewpoints about the sample size in qualitative research. There are no hard and fast rules, how many respondents one should consider in qualitative research because the purpose is to describe and interpret rather than generalize. Many researchers work with a tiny sample size as tiny as 10 or less. While presenting the "logic of small samples" in qualitative research, **Crouch and Mckenzie (2006)** state that small sample sizes, less than 20, allow the researcher to relate effectively, hence increasing the validity of findings. The number of respondents needed will vary depending on what you want to find out, the reason for doing the investigation, what will be beneficial, and what can be done within given time. Out of fifty individuals contacted, only twenty-one responded. Finally, twenty-one individual interviews with different respondents were eventually conducted, based on the researchers' assessment and time limitations. When all twenty-one interviews had been transcribed, the data was then more carefully scrutinized, considered, and analyzed using Microsoft Excel.

6.3 INTERPRETATION AND DISCUSSION: INTERVIEWS WITH EXPERTS

6.3.1 Internal Reasons for Financial Distress

The majority of the bankers cited different internal reasons for financial distress in Indian companies.



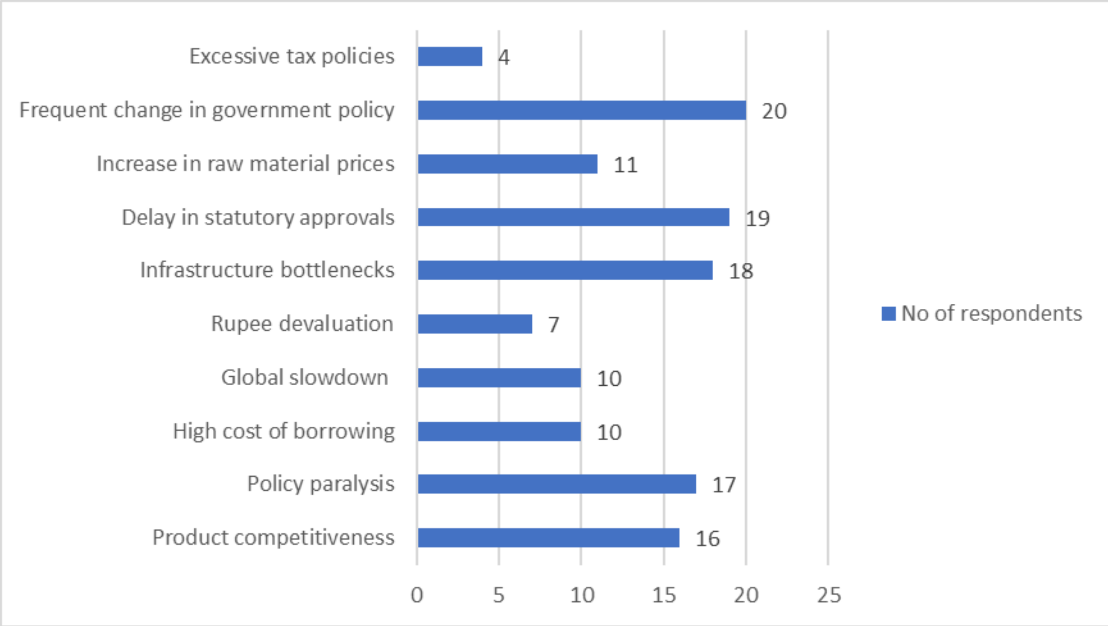
Source: Author's calculations based on interview responses

Figure 6.1 : Internal reasons for financial distress

The factors causing financial distress could be both internal and external. The internal reasons for the financial distress may vary from firm to firm. A plethora of internal reasons may have caused the financial distress. The external factors usually affect all the businesses within a group, whereas internal factors affect only a single business unit rather than the entire industry. The various experts identified nine major internal reasons for financial distress in Indian companies as per figure 6.1. Internal reasons cited by experts include fund diversion, intentionally default (or wilful default, such as purposely failing to make a payment to the bank), technology obsolescence resulting into outdated products, increase in production cost, diversification of projects (investment in multiple projects at the same time), poor resource management, improper research & development etc. Further, the most important reasons mentioned were the diversion of working capital loans for long-term funding and in some instances, promoters withdraw equity capital through unsecured loan from fraud & related companies, incompetent management due to lack of entrepreneur skills in family succession and lack of appropriate equity capital in the business due to over-pricing of project cost. 21 out of 21 respondents agreed that there was a diversion of working capital loans to long-term funding due to the lack of easy availability of long-term loans. One of them said that “The repayment of the loan was refinanced rather than made through cash flows of the company, e.g., in the majority of the cases, it was found that companies with unsustainable working capital show the same portion of working capital has been routed for long-term requirements and the companies looking to convert the working capital loan into term loan under restructuring are confident to service it.” While other stated, “Primary reason was diversion & siphoning off firm funds. One of the companies has gone for massive overseas big expansion where the probability of diversion of fund is very high”. “Also, in small companies, promoters are taking money out of the company”. The majority of the respondents, 18 out of 21, agreed that there was a lack of appropriate equity capital infusion in the companies. The feasibility study was not completed properly and promoter equity was not appropriate in the business. One of the respondents made a comment in this regard “No genuine fresh equity brought by the promoter in the company. Projects were over-priced to get 100% capital. In the case of the EPC contract, the likelihood of promoter taking the money out is very high, e.g., the inflated value comes back in the form of owner equity.” 17 out of 21 respondents cited incompetent management as a cause of distress related to the family firm succession issue. Experts cited reasons like poor managerial decisions in various functional fields. One of them stated that, “Management was incompetent because they did not understand market factors properly, for example, in the case of commodities when prices went down, the kind of equity required to absorb loss was very low." Marketing mismanagement has also impacted a large number of businesses due to their reliance on a small number of customers, low sales realization, deficient pricing policy among various firms.

6.3.2 External reasons for financial distress

The majority of the bankers cited different external reasons for financial distress in Indian companies



Source: Author's calculations based on interview responses

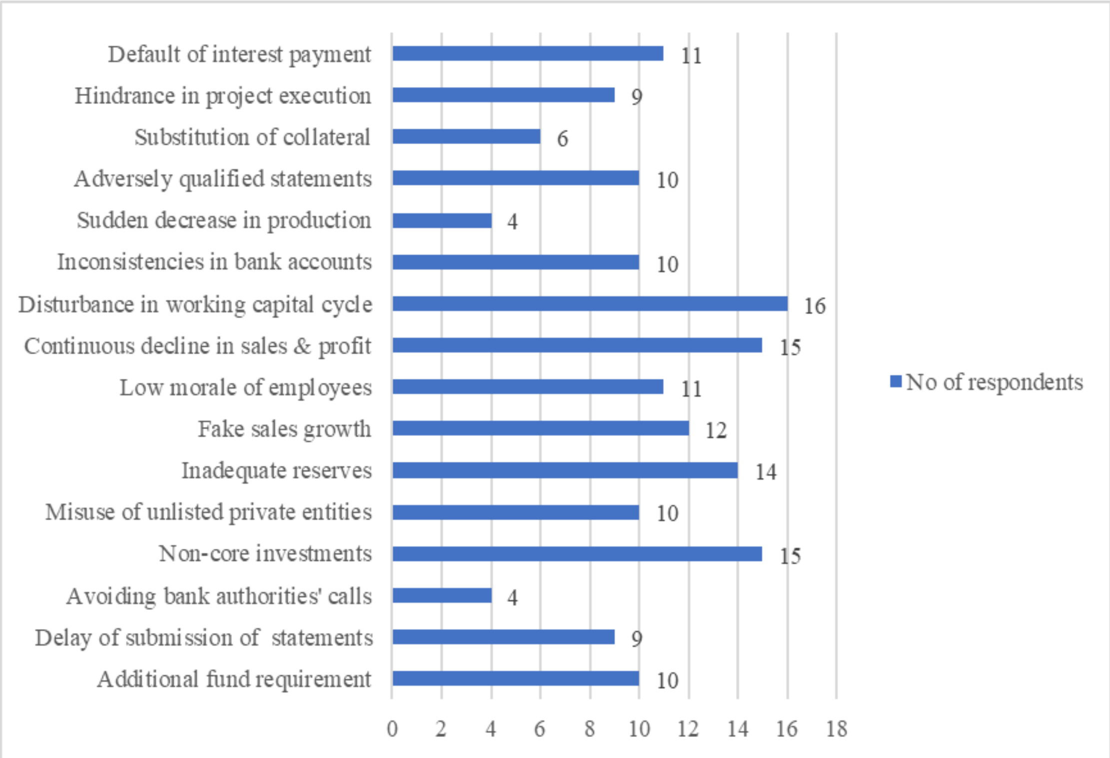
Figure 6.2 : External reasons for financial distress

A plethora of external reasons may have caused the financial distress. The external factors usually affect all the businesses in the same group. The various experts identified ten external reasons for financial distress in Indian companies as per figure 6.2. External reasons cited by experts include product competitiveness (not able to compete with the big players, competition from China),delay in statutory approvals, high cost of borrowers due to CAMEL rating, global slowdown resulting into lack of demand & decrease in exports, policy paralysis, rupee devaluation after 2009, infrastructure bottlenecks like power-related issues, rising raw material prices and frequent change in government policy as contributing factors to financial distress.

The majority of respondents (20 out of 21) agreed that frequent changes in government policies was one of the major causes of financial distress in Indian firms. One of the respondents made a remark about this, "In the power and mining sectors, the government frequently changed its coal license policy, and there was a delay in power sector projects due to land acquisition." Furthermore, changes in government regulation or policy have put businesses in financial distress. For instance, one respondent stated that "In the case of the coal block scam, companies that had previously been allocated blocks were cancelled, resulting in financial distress for related firms, particularly those in the power, steel, and mining sectors”. According to majority of respondents, (19 out of 21) delay in statutory approvals was also one of the major causes of financial distress in Indian firms. In the case of infrastructure companies, government approvals and land availability all had a significant impact. Firms faced time/cost overruns due to delayed project implementation. Delays in project implementation, according to experts, have also had a negative effect on many businesses. One of the respondents made a remark about this, “Some construction companies were unable to complete their projects on time due to issues with right-of-way acquisition for land.” It has further inflated project costs, resulting in minimal promoter equity in projects. A total of 18 out of 21 agreed infrastructure bottlenecks as a reason for distress. Some of the businesses experienced power outages. Inconsistent supply of inputs and persistent power outages are other factors that contribute to financial distress. One of the respondents made a remark about this, “In the case of textile companies, cotton prices have been highly volatile in recent years, power costs have been very high, and power cost and availability have been an issue in Tamil Nadu and problems with international repeat orders.” Many respondents mentioned (17 out of 21), policy paralysis as the cause of financial distress in Indian firms. There was policy paralysis because no decisions were made in the context of government receivables from 2009 to 2014. The pending claims of governments were critical in building the companies’ burgeoning debt. Delays in receivables from the government or entities controlled by the government may result from the government’s increased fiscal deficit or other financial constraints. One of the respondents made a comment in this regard. “Reluctance of government and government control entities to release payment on time had a cascading effect on other businesses that rely on them. Hindustan Construction Co., which entered into distress, might have repaid all debts if they had received the full amount of outstanding debts from various government entities, including NHAI, without taking any haircut during loan restructuring”. Additionally, there was a decrease in demand due to shifts in customer preferences or the availability of more affordable alternatives to traditional products. Financial distress is also a result of restrictions on bulk purchases, the government's excessive tax policies, and the slowdown in the global economy.

6.3.3 Leading indicators for financial distress

The majority of the respondents cited following leading indicators for financial distress in Indian companies



Source: Author's calculations based on interview responses

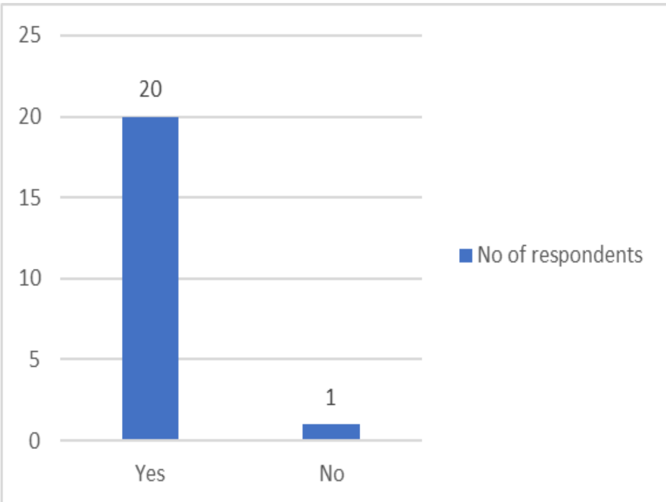
Figure 6.3 : Leading indicators for financial distress

One must be aware of financial distress as soon as possible to take appropriate action. To do so, it is necessary to examine the indicators that will assist in determining whether the company is in financial distress. It can be determined by examining the distress signals displayed by the firms. Various experts identified sixteen leading indicators of financial distress in Indian companies as per figure 6.3. Key financial distress indicators cited by experts include default of interest payment (like interest on due date not paid by firm; frequency of default in the payment increases), additional fund requirement without expansion or modernization, inconsistencies in cash credit/overdraft accounts (like failure to keep set margin or drawings beyond authorized amount from the bank or regular demand of overdraft facility from the bank or decline in number of transactions). Expert mentioned indicators like the delay of submission of statement with various statutory agencies like SEBI or publication of financial statements with a lag, unable to submit stock statement on time or wrong stock statement submission (like physical stock holding with the company not match with respect to stock statement submitted to the bank), avoiding to calls made by bank officials, substitution of collateral or property as compared to existing one, adversely qualified accounting statements, sudden decrease in production, downtrend in sales & profits margin. Increasing cost to revenues and falling income both impose financial pressure on a company. A drop in sales means, a firm has to sell its product at lower margins or even at a loss, potentially putting it in financial trouble.

Other indicators cited by experts (16 out of 21) include disturbance or increase in the working capital cycle like too much inventory on hand, massive build-up of work-in-progress and ageing debtors. Financially distressed companies experience significant hindrances in project execution due to deteriorating creditworthiness or a supplier has stopped supplying material to the company. According to some of the respondents, (15 out of 21) investment in non-core assets and speculative investments financed with debt, which are generally non-productive, as some of the leading indicators of financial distress. One of the respondents made a comment in this regard, "non-core investments during 2009-14, such as some promoters investing in real estate during the boom in this period to earn short-term profits." Further, respondents cited inadequate reserves kept by the company, fake sales growth of companies, and promoters misusing unlisted private entities or subsidiaries as leading indicators of financial distress. According to the respondents (14 out of 21), companies in financial distress do not maintain adequate reserves. According to one expert, “no reserve maintained by the promoter for contingency situation to pay term loan in case of any liquidity problem.” Others stated (12 out of 21), fake sales growth of companies as indicator for financial distress. According to one expert, “There have been many cases when the top line of the companies was increased without a corresponding increase in cash flows”; whereas in other cases, promoters have misused unlisted private entities for sales purposes. One of the respondents made a remark about this, “Listed entity funded by a bank will make front sales to these companies, which will then make sales to customers. 80% of the margin is collected by an unlisted private entity, while a bank-funded listed entity collects only 20%.” The promoters of financial distress firms provided loans to subsidiaries, and banks did not have access to the subsidiaries’ annual reports.

6.3.4 Effectiveness of IBC

The IBC is still a work in progress, five years after its implementation. According to recent reports, a quick and time-bound online auction to settle various business insolvencies may be implemented by the government. It would encourage transparency and prevent lawsuits against businesses, which are critical for an economy to optimize its resource allocation. The IBC has provided for a process by which creditors can collect their debts entirely or partially from a firm that is unable to repay so that the insolvent firm being purchased is either revitalized or disposed of to create value under new ownership. Other recovery steps (outside IBC) will waste a lot of time on legal action. The company can attempt to sell off properties, manipulate the finances, or redirect cash flows.



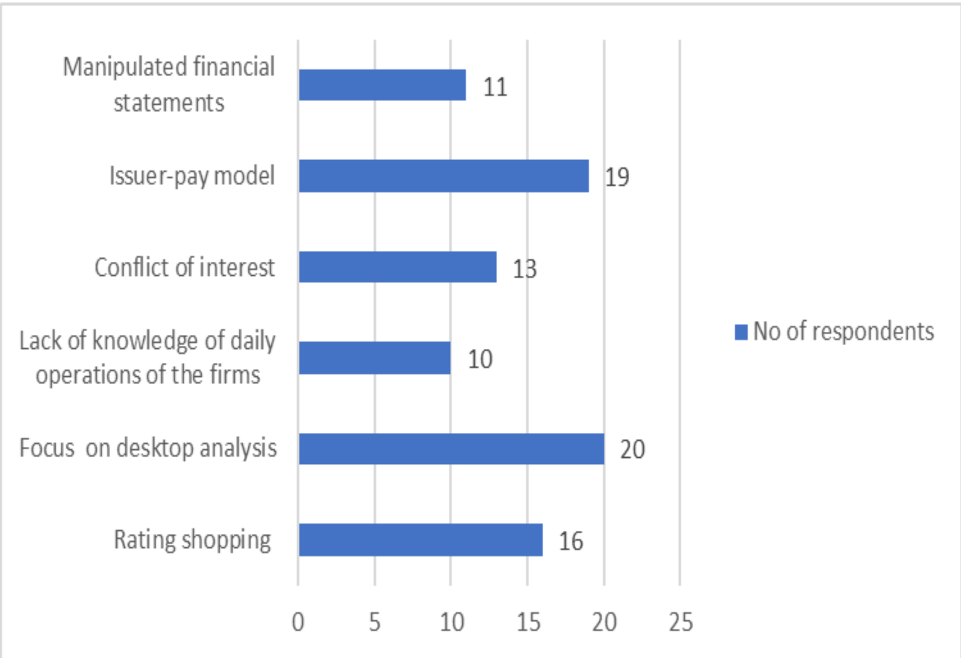
Source: Author's calculations based on interview responses

Figure 6.4 : Effectiveness of IBC law

As per the figure 6.4, most of the experts (20 out of 21) believe that IBC law will be effective in dealing with stress assets of Indian companies in a more effective manner. Prior to IBC, there was no effective resolution mechanism for recovering from distressed businesses on time, e.g., DRT was ineffective, whereas, in the case of BIFR, the businesses continue to exist even after being defaulters. As a result, there was no credit restraint among the firms, and cases had been with DRT for more than ten years with no substantive resolution. It was very challenging for the financial institutions to recover outstanding dues from companies, such as in CDR, because most firms were either not putting fresh equity in their businesses by submitting just a valid certificate from a chartered accountant & in some cases, there was a delay of up to two years. Most experts believe that there is an impact of IBC law as now management is willing to internal settle the various outstanding dues with financial institutions to stay away from NCLT. Moreover, the new law will further assist financial institutions in faster recovery for their loans. One of the respondents made a comment in this regard "Yes, IBC Law will help in early recognition of financial distress, e.g., if there are ten banks and two of them are smarter, they can refer the case in the NCLT; in case of any default by the companies rather than recognizing it later in case of previous laws." One of the respondents said "Many vendors are now filing cases against businesses rather than banks, which would further aid in the detection of financial distress at an early stage." Before IBC, banks were providing fresh term loans to distressed companies, and the loan proceeds were used to repay outstanding debts from previous loans rather than recognizing them as nonperforming assets. One of the respondents made a comment in this regard, "During 2010 to 2013, many banks injected new capital into distressed firms through debt restructuring, but these funds were not invested in the productive capacity of the firms." The IBC law has also resulted in significant behavioural changes in the management of the companies, with less leveraged projects being undertaken or additional capital being invested, which will further increase project safety and efforts to increase firm productivity. One of the experts said," When unfavourable events do occur, the CEO of the firm anticipates problems well in advance of anyone else". CEOs would be inclined to bring in more equity capital to have a larger buffer against adverse events as an early response to financial distress and take action to help increase the company's working productivity to overcome early stress, resulting in more productive companies.

Additionally, this law strengthens corporate governance by discouraging management from participating in fraudulent or extortionate transactions. The removal of wilful defaulters from the IBC mechanism resulted in a significant shift in the credit behaviour of borrowers. A more favourable business climate is created as a result of the IBC, which makes it easier for financial institutions to lend money to businesses. Obtaining low-cost funds from banks would also help to increase the productivity of businesses.

6.3.5 Issues related to Rating Agencies



Source: Author's calculations based on interview responses

Figure 6.5 : Issues related to rating agencies

There are serious concerns about the role of rating in assisting in the earlier detection of distress. Their judgments about the creditworthiness of investments are relied upon by investors. The entire system relies on them to monitor associated risks. However, rating agencies have failed to live up to various stakeholder expectations, and investors' confidence in financial ratings has been shaken by recent downgrades.

Some of the reasons given by different respondents (as per figure 6.5) on this issue include the fact that rating agencies are not familiar with the day-to-day operations of the companies, a lack of access to accurate information such as manipulated accounting data of the businesses, and a reliance on the information provided by the companies themselves. According to majority of experts (20 out of 21), rating agencies have considerable experience and analytical capability but little expertise in data verification. One of the respondents made a comment in this regard “Credit rating agencies focused exclusively on desktop analysis rather than visiting plant of the company and most of the time met only junior level employees in the companies for analysis rather than senior-level employees, with no interaction with the company's promoter." Rather than doing desktop analysis, more physical interaction with company promoters is required, as well as attendance at company meetings. Rating agencies should conduct site visits and provide opinions, rather than relying solely on secondary data from companies, as data is not always accurate. Credit rating agencies do not keep a close eye on the company's data and the various issues and events that occur within the organization. As per the respondents (19 out of 21), rating agencies adhere to an issuer-pay model, in which the issuer pays the rating agencies. One of the respondents made a comment in this regard “The firm being evaluated compensates the credit rating agency for its services. A separate fund, or even an investor protection fund, should be established to cover rating agency fees, and each financial institution should contribute to it.” In addition, according to experts (16 out of 21), there have been several instances of rating shopping by corporations. One of the respondents made the following observation "Rating shopping is taking place as a result of fees being paid by the companies, and rating agencies are also providing them with advisory issues, and some of them have even modified their rating model to attract more customers. You can get a fee estimate from three different agencies and pay it to the one that assigns you the highest rating.” In the end, it is investors and creditors who bear the brunt of the consequences of rating shopping by companies. If a firm has got ratings from multiple agencies, it must publish all of them. Further steps can be taken to increase transparency by requiring dual rating, particularly for large borrowings, and rating agencies should also disclose fees charged to clients. As per the respondents (13 out of 21), sometimes, it is possible to have a conflict of interest, as demonstrated by a comment made by one of the respondents. “It's possible that an analyst, who has been given the task of rating an instrument, has an ownership stake in the issuing firm, and therefore his rating is bound to be biased.”

When rating agencies evaluate companies, a programmatic approach should be used. One of the respondents made a comment in this regard. “Rating agencies classify one-day default as a ‘D' rating, which kills a company because sometimes a company has temporary cash flow issues, and with a ‘D' rating, the company will have even more difficulty accessing external funding from the market”. Rating agencies should give the company a reasonable amount of time to resolve the problem. Thus, there is a need to change the approach taken by rating agencies. They should not immediately downgrade the company; instead, they should speak with management and gain a better understanding of the company's issues. Further, accountability of rating agencies is required. It is desirable to implement a peer review and rotation of rating agencies for assigning ratings to companies. Since the stakeholders want assurance that credit ratings are reliable, a peer review and rotation process should be in place. Additional steps should be taken to improve the credit rating standard through increased accountability, transparency, and competitiveness. Simultaneously, credit rating agencies should tighten their self-regulation standards. In addition to conducting their internal reviews, rating assignments may be cancelled if companies requiring ratings do not provide sufficient information.

Chapter – 7

CONCLUSIONS, SUGGESTIONS & LIMITATIONS

7.1 INTRODUCTION

This study is organized into seven main sections. The introduction section has been thoroughly explored in Chapter 1. A conceptual framework and research methodology have been developed with the support of this literature for further study. Besides that, an appropriate research design has been described in Chapter 1 to accomplish the study's objectives. Following that, in Chapter 2 of the study, the literature review has been discussed. In addition, data analysis using statistical approaches has been presented in Chapters 3, 4, 5 and 6. The results of the research and the outcomes of earlier studies were also reviewed in the discussion section. The summary & conclusion, suggestions and limitations of the current study are included in Chapter 7, along with the future scope.

The following sections comprise this chapter:

Summary and Conclusions

Suggestions

Limitations & Future scope of the study

7.2 SUMMARY AND CONCLUSIONS

The present research has four objectives. The first, second and third objectives are based on secondary data, while the fourth objective is based on primary data. The following is the conclusion of the framed objectives.

With the growing financial distress risk in the listed companies in India in the past few years, various stakeholders are very much concerned about the financial health of these companies to protect their capital. In the chapter 3, an attempt has been made to do the trends and patterns analysis of financial distress prevailing in the listed companies in India. Following the global financial crisis, the number of cases referred to BIFR increased dramatically. Due to the strain on multiple corporations' balance sheets, there has been a significant surge in the number of listed firms filed under IBC law. There was also a significant impact on corporate profits following the liquidity shock of demonetization and the broader slowdown in the Indian economy and disruption created by the goods and services act. Lenders' aggressive use of the bankruptcy code, even at the minor delay in loan repayments due to a change in the insolvency code, also led to the increase in admitted cases during a period of financial stress in the corporate world. The global slowdown that began in 2008 has reduced listed companies' interest coverage ratios and their net profit margins. The percentage of listed corporations with an interest coverage ratio less than one and a debt-to-equity ratio greater than two surged following the slowdown caused by global financial crises, with a steep reduction in listed companies net profit margins. However, there has been a significant improvement in recent years, with the RBI's series of repo rate cuts beginning in 2015, companies not undertaking new investments, resulting in companies going slow on new borrowings, and many corporate deleveraging with outstanding debt and further improvements in earnings, there has been an improvement in their debt-servicing ability of listed firms. While indicators such as debt-equity, debt- market capitalization have improved, but interest coverage ratio, net profit margin & current ratio, in particular, demonstrate that the risk of unsustainable business debt remains significant, as many firms have difficulty servicing existing debt, posing concerns to lenders. It emphasizes the importance of keeping a close eye on the business environment. Various patterns were investigated among listed companies referred to BIFR and IBC with different characteristics such as sector, ownership structure, firm life cycle, and size. Maximum number of listed companies in both BIFR and under IBC are from major industrialised states of India. Textiles, steel, paper, pharmaceuticals, chemicals, sugar, packaging, consumer durables, FMCG, edible oil sector, capital goods, trading, infrastructure, construction and mining & mineral products have been identified as important sectors that have experienced financial distress in the last decade. In the textiles industry, stiff competition, changing customer demands, outdated machinery, and technologies have resulted in low efficiency and poor-quality goods. Steel companies have been severely harmed due to inadequate capital investments, high levels of debt and excess capacity.

Most companies registered with BIFR and IBC were either widely held or family-held, with only a few companies falling into the foreign-held category, indicating that corporations under the influence of foreign ownership perform better, consistent with the findings of **Pérez-González (2001);Douma, George and Kabir (2006); Lins, Volpin and Wagner (2013); Kota and Singh (2016); Hintošová and Kubíková (2016)** ; **Udin, Khan and Javid (2017); Sridharan and Joshi (2018**). Furthermore, most firms that experienced financial distress were in the maturity stage of their life cycle, but very few firms experienced distress in the growth stage of their life cycle, so growth firms are more likely to be profitable and have a lower risk, consistent with the findings of **Steyn Bruwer and Hamman (2005)**; **Koh et al. (2015); Shamsudin and Kamaluddin (2015).** Small firms have witnessed financial distress more than larger ones as both operational and funding difficulties affect smaller enterprises in a downturn, consistent with the findings of **Binti, Zeni and Ameer (2010); Nanda and Panda (2018).**

Using logistic regression, the study has developed new financial distress prediction models for companies, referred to both BIFR and IBC. Listed companies in IBC have not been researched substantially, as the law was introduced in 2016 only. Most previous studies that dealt with the financial distress of companies have focused on accounting-based variables only. The present study has tested the market and macroeconomic variables in addition to accounting variables to enhance the predictive power of the models. Further, the research assesses whether a logistic model including market and accounting data is better than models that only use accounting data. The majority of research on listed firms has used accounting ratios as explanatory variables & estimated financial distress one year in advance. The present study has estimated financial distress up to three years in advance.

In chapter 4, models using financial variables have been estimated on the estimation samples and tested on the holdout samples for up to three years prior to financial distress. For companies in BIFR, the model predicts financial distress in the future using logistic regression based on the 3 ratios after analysing a variety of existing ratios to predict distress: Debt-to-equity ratio (DE), (Adjusted gross profit + interest)/sales * 100 (PBIDTM) and Net sales-to-total assets ratio (NSTA). It is found that the ratio of debt-to-equity is consistently lower, whereas PBIDTM and the sales to total assets ratio are higher for healthy firms. Thus, healthy firms are lesser indebted and have more profitability. As per earlier studies, the analysis found that the predictive capacity of the models is diminishing with the increase in the time period of financial distress using financial variables with deteriorating Pseudo R-squares, AUC values and accuracy level of classification matrix. The value of Nagelkerke R square decreases for models from year 1 to 3 and the overall ability to predict the dependent variable based on various independent variables is satisfactory. The Area under curve value near 1 for all three models shows their higher ability in classification. The value of AUC suggests outstanding discrimination of the predictive models. It can be observed in all three models, coefficient values for all three financial ratios; Debt-to-Equity ratio, (Adjusted gross profit + Interest)/Sales * 100(PBIDTM), Net Sales / Total Assets, are significant. DE ratio has a positive coefficient in all three models, which suggests that increase in this value will further increase the likelihood of distress and is the most important ratio for predicting distress given its higher odds ratios in all three models. PBIDTM is the second most crucial variable after debt-to-equity and has a negative value of the coefficient in all three models, which suggests that increase in PBIDTM value will decrease the likelihood of distress. Net sales to total assets ratio has a negative coefficient value in all three models, which suggests that an increase in its value will decrease the likelihood of distress. Predictive accuracy is highest in the case of one -year before financial distress model with 94.8% of the cases for the development of the model and 89.4% of the cases in the holdout sample, followed by two- year model with 90% of the cases for the development of the model and 85.1% of the cases in the holdout sample & three- year model has 81.3% of the cases for the development of the model and 80.8% of the cases in the holdout sample respectively. Overall, one- year before the financial distress model for BIFR firms, has the best predictive accuracy using financial variables for various firms followed by two-year and three-year models respectively.

For companies in IBC, the model predicts distress in the future using three ratios; Debt-to-Equity ratio (DE), (Adjusted net profit + Depreciation) / sales * 100 (CPM), Cash flow from operations/ Interest (CFOINT) after analysing a variety of existing ratios to predict distress. It is found that the ratio of Debt-to-Equity (DE) is consistently lower whereas Adjusted net profit + Depreciation) / Sales * 100 (CPM) & Cash flow from operations/ Interest (CFOINT) ratios are higher for non-distressed companies. So non-distressed firms are less indebted and have more profitability with higher cash flow from operations to interest obligations. As per earlier studies, the analysis found that the predictive capacity of the models is diminishing with the increase in the time period of financial distress using financial variables with deteriorating Pseudo R-squares, AUC values and accuracy level of classification matrix. As anticipated, the value of Nagelkerke R square decreases for models from year 1 to 3. The overall ability to predict the dependent variable based on various independent variables is satisfactory. The Area under curve value near 1 for all three models suggests outstanding discrimination of the predictive models. It can be observed in all three models, coefficient values for all three financial ratios; Debt-to-Equity(DE), (Adjusted net profit + depreciation) / sales * 100(CPM) & Cash flow from operations/ Interest(CFOINT) are significant. DE has a positive coefficient value in all three models, which suggests that an increase in this value will further increase the likelihood of distress and is the most important ratio for predicting distress given its higher odds ratios in all three models. (Adjusted net profit + depreciation) / sales * 100 (CPM) is the second most important variable after debt-to-equity. It has a negative coefficient value in all three models, which suggests that an increase in CPM value will decrease the possibility of distress. Cash flow from operations/ Interest (CFOINT) has a negative coefficient value in all three models, which suggests that an increase in its value will decrease the possibility of distress. Predictive accuracy is highest in case of one -year before financial distress model with 81.9% of the cases for the development of model followed by two- year model with 79% of the cases for the development of model & three- year model has 76.5% of the cases for the development of model respectively. Overall, the one-year before financial distress model for IBC firms has the best predictive accuracy using financial variables for various firms followed by the two-year and three-year models, respectively.

In chapter 5, the study tested “market & macroeconomic variables” in the “accounting models” to assess their effects for companies in BIFR and IBC. It was investigated whether “market variables & macroeconomic indicators” supplement distress forecast by providing information not found in financial statements. The market valuation serves as a supplement to the financial statement. Only one market variable, “Excess Return”, was found to be helpful in prediction along with various accounting variables for companies referred to BIFR. It has been found that the ratio of Excess Return is consistently higher for non-distressed companies. So non-distressed firms have a higher stock return as compared to the broader market. The negative value of the coefficient indicates the likelihood of distress decreases when values of ratio increase. An increased ratio means that stock return can outperform the market, which further reflects better future performance expected by the market participants from the company. Similarly, two market variables, Market value to Shareholder Funds (MVSF) & Standard-Deviation (STDEV), are found to be helpful in prediction for companies referred to IBC. It has been found that the ratio of Market value-to-Shareholder Funds (MVSF) is consistently higher for non-distressed companies. The negative value of the coefficient indicates the likelihood of distress decreases when values of ratio increase. Whereas Standard-Deviation (STDEV) is consistently lower for non-distressed companies. The positive value of the coefficient indicates the likelihood of distress increases when values of ratio increase. Only one macroeconomic variable, “exchange rate” was found to be helpful in financial distress prediction for companies referred to both BIFR and IBC.

For firms referred to BIFR, compared to models based only on ‘accounting ratios’, combining ‘accounting and market variables’ in a single model resulted in a negligible improvement in overall performance. Furthermore, classifications accuracy tables support these findings: For firms referred to BIFR, the combined ‘accounting and market variables’ yield 92.9%, 91.2% & 80.6 %, overall classification accuracy in the period t-1, t-2 and t-3, respectively, whereas the ‘accounting’ models’ yield 94.8%, 90% & 81.3%, overall classification during this period for the model developed. The accuracy of the ‘accounting and market variables’-based models reduced as anticipated for models from years 1 to 3. For firms referred to IBC, the combined ‘accounting and market variables’ yield 87.6%,79% &78.5%, overall classification accuracy in the period t-1, t-2 and t-3, respectively, whereas the ‘accounting models’ yield 81.9%, 79% &76.5%, overall classification during this period for the model developed. The results of incorporating market variables into an ‘accounting-based model’ revealed that market variables contain significant information not included in accounting statements, which is relevant to estimating the likelihood of financial distress. As a result, incorporating market variables into an ‘accounting-based model’ can improve the model’s predictive potential. A similar result has been found in **Chava and Jarrow (2004); Beaver, McNichols and Rhie (2005); Nanayakkara and Azeez (2015); Li and Faff (2019)**.

In comparison to models based on ‘accounting ratios’, combined ‘accounting and market variables’, combined ‘accounting, market & macroeconomic variables’ in a single model have not resulted in any improvement in the overall performance of models. Models with macroeconomic variables were not found significant in the period “t-1” and “t-1 & t-2” for both BIFR and IBC, respectively. Moreover, the coefficient of macroeconomic variable (exchange rate) is only significant at ten - percent level in the two & three-years before financial distress model in BIFR and three-years before financial distress model in IBC, which indicate less significance of macroeconomic variable for predicting financial distress. For firms referred to BIFR, the combined ‘accounting, market & macroeconomic variables’ yield 89.4% & 78.7 %, overall classification accuracy in the period t-2 and t-3, respectively, which is lower than both ‘accounting-based model’ and combined ‘accounting & market variables model’. Whereas for firms referred to IBC, the combined ‘accounting, market & macroeconomic variables’ yield 76.1% overall classification accuracy in the period t-3, which is marginally lower than both ‘accounting model’ and combined ‘accounting & market variables’ model. Consistent with the findings of **Wijaya and Anantadjaya (2014); Asgarnezhad and Soltani (2016),** the analysis found less significance of macroeconomic variables for predicting financial distress of the companies.

In chapter 6, survey analysis showed that factors causing financial distress could be both internal as well as external. The internal reasons for the financial distress may vary from firm to firm. The financial distress may have been caused by a plethora of internal reasons. The external factors usually affect all the businesses in the same group, and the internal factors affect a business unit only, not the entire industry. Internal reasons cited by experts were fund diversion, intentionally default, technology obsolescence resulting in outdated products, increase in production cost, investment in multiple projects at the same time, poor resource management, improper research & development etc. Further, the most important reasons mentioned were diversion of working capital loans for long-term funding, and in some instances, promoters withdraw equity capital through an unsecured loan from fraud & related companies and incompetent management due to lack of entrepreneur skills in family succession. There was a lack of proper equity capital infusion in the distressed companies due to the over-pricing of the project cost, and the repayment of the loan was refinanced instead of made through the company's cash flows. Moreover, wrong managerial decisions in different functional fields and unethical management actions such as siphoning off firm funds for own gain at the firm's expense, also contributed to financial distress. A plethora of external reasons may have caused the financial distress. External reasons cited by experts include product competitiveness, delay in statutory approvals, high cost of borrowing, policy paralysis, rupee devaluation, infrastructure bottlenecks like power-related issues, rising raw material prices as contributing factors to financial distress. Additionally, there was a decrease in demand due to shifts in customer preferences or the availability of more affordable alternatives to traditional products. Changes in government policy on a regular basis and reluctance on the part of the government and government-controlled entities to issue payments on time have a cascade effect on other enterprises that rely on them. Financial distress is also a result of restrictions on bulk purchases, the government’s excessive tax policies, and the slowdown in the global economy. The results are consistent with the findings of **Gugloth and Kumar (2011)**; **Fatoki (2014)**; **Navulla, Golla and Sunitha (2016).**

One must be aware of financial distress as soon as possible to take appropriate action. Thus, it is necessary to examine the indicators that will assist in determining whether the company is in financial distress. Various experts identified sixteen leading indicators of financial distress in Indian companies. Key financial distress indicators cited by experts include default of interest payment, additional fund requirement without expansion or modernization, inconsistencies in cash credit/overdraft accounts, delay of submission of statements with various statutory agencies like SEBI or publication of financial statements with a lag, unable to submit a stock statement on time, avoiding to calls made by bank officials, hindrances in project execution due to deteriorating creditworthiness, substitution of collateral as compared to existing one, adversely qualified accounting statements, sudden decrease in production and downtrend in sales & profits margin. Further, disturbance in the working capital cycle, investment in non-core assets, inadequate reserves, fake sales growth of companies, and promoters misusing unlisted private entities or subsidiaries for sales purposes were found as leading indicators of financial distress. There have been many cases when the companies' top line was increased without a corresponding increase in cash flows. The promoters of financial distress firms provided loans to subsidiaries, and banks did not have access to the subsidiaries' annual reports.

Most of the experts believe that IBC law will effectively deal with the stress assets of Indian companies in a more effective manner. IBC law also has made significant behavioural changes in the management of the companies with less leveraged projects being undertaken or additional capital being invested, further increasing project safety and efforts to increase firm productivity. Now management is willing to internal settle the various outstanding dues with financial institutions to stay away from NCLT and will further assist financial institutions for faster recovery for their loans. It will also help in early recognition of financial distress as now many vendors are now filing cases against businesses rather than banks. Further, CEOs would be inclined to bring in more equity capital to have a larger buffer against adverse events as an early response to financial distress. Additionally, this law strengthens corporate governance by discouraging management from participating in fraudulent or extortionate transactions.

There are serious concerns about the role of rating in assisting in the earlier detection of distress. Some of the reasons given by different respondents on this issue include the fact that rating agencies are not familiar with the companies' day-to-day operations, a lack of access to accurate information such as manipulated accounting data of the businesses, and a reliance on the information provided by the companies. Most rating agencies have considerable experience and analytical capability but little expertise in data verification. Rating agencies should conduct site visits and provide opinions, rather than relying solely on secondary data from companies, as data is not always accurate. The rating agencies adhere to an issuer-pay model, in which the issuer pays the rating agencies. Credit rating agencies do not keep a close eye on the company's data and the various issues and events within the organization. In addition, there have been several instances of rating shopping by corporations. Further, it is possible to have a conflict of interest if the analyst rating an instrument has an ownership stake in the issuing firm. The results are consistent with the findings of **Rafailov (2011)**; **Jollineau, Tanlu and Winn (2014)**. Thus, there is a need to change the approach taken by rating agencies. They should not immediately downgrade the company; instead, they should speak with management and better understand its issues.

7.3 SUGGESTIONS

A proper financial distress forewarning system, such as the models created in this study, is recommended to the creditors, shareholders, and financial intermediaries. Knowledge of financial distress predictors and proper distress prediction models assist organizations in launching turnaround initiatives and investors in making prudent investment decisions. Additionally, financial institutions can apply these models to assess the creditworthiness of borrowing enterprises. The present study suggests that models could be suitably adapted to measure the financial health of firms. These financial distress prediction models could be periodically used by the organisations to work out operations and marketing strategies to exterminate distress symptoms. The management of the company should prioritise increasing cash generation from its core business, which entails optimising the efficiency with which various revenue-generating resources are utilised. Businesses should prioritize secured debt & high-interest debt when reviewing debt repayment options and avoid unsecured debt if at all possible. Negotiate the most favourable terms possible in every loan or financing transaction.

A combination of accounting and market variables is suggested to predict distress among Indian companies, and lenders can use it in the credit analysis of borrowers to assess the probability of facing financial distress and that it would fail to repay a loan. Thus, these models can be used to categorize these borrowers into different classes based on their financial health, and therefore suitable recovery strategies could be implemented by the lenders. As investors are interested in safe and assured increasing returns from investment in securities, they are suggested to use these prediction models to periodically monitor the changes in the predictors identified in this study. It will help to safeguard their investments and prevent them from potential losses. The financial distress prediction models help lenders, including bankers and financial institutions, in the preparation of financial projections for the companies. The models developed in the study are preferably suggested for assessing the financial health of medium and large-scale companies in India.

Additional steps should be taken to improve the credit rating standard, including increased accountability, transparency, and competitiveness. Instead of relying solely on secondary data from companies, rating agencies should conduct site visits and provide opinion. Simultaneously, credit rating agencies should tighten their self-regulation standards. A separate fund, or even an investor protection fund, should be established to cover rating agency fees, and each financial institution should contribute to it. Strict penalties for promoters who divert funds and those penalties should be imposed as soon as possible. Term lenders should analyse working capital requirements and refuse to fund unproductive projects. Training in assessment skills should be provided to the credit managers on an ongoing basis. There should be no outside intervention in the evaluation of the proposal. The government should focus on deterring executives from engaging in fraudulent or extortionate transactions.

The failure of the internal inspection machinery is largely due to the incompetence of the auditors and their poor judgement. Lenders should investigate the promoters'/shareholders' equity capital sources and quality. Multiple leveraging, especially in infrastructure projects, is a matter of concern as it effectively camouflages the financial ratios such as the Debt/Equity ratio, leading to adverse selection of the borrowers. When assessing credit, lenders should ensure that the parent company's debt is not infused as equity capital of the subsidiary. To ensure proper end-use of funds and prevent borrowers from diverting or siphoning funds, lenders should always conduct their own independent and objective credit appraisals. They should not rely on credit appraisal reports prepared by outside consultants. As auditors do many things for management rather than for shareholders, so there is a need to address the role of auditors because auditors' fees are paid by management.

7.4 LIMITATIONS & FUTURE SCOPE OF THE STUDY

7.4.1 Limitations

There are few studies that are without limitations, and these limitations lead to research gaps and the need to fill them. Several challenges limit the scope of the objectives of the study. The following are some of the limitations of this study.

First, because the data have been gathered from Indian companies, the results may not apply to other world regions.

Second, while the study only looked at the financial, market, and macroeconomic variables, some other variables of financial distress prediction may need to be explored as well, which are not covered in this study.

Third, there is apprehension on the part of the respondent. Many respondents were hesitant to meet and share their thoughts during the data collection process. The respondents expressed a great deal of reluctance, as they were preoccupied with their official duties. Most respondents were unwilling to express their views on financial distress as a result of policy issues. Obtaining responses from various respondents proved to be a significant challenge.

7.4.2 Future Scope of the Study

This study makes the following recommendations for future research:

Since distressed firms' features change over time, researchers and academicians must regularly assess and improve financial distress prediction models. It is essential since the models are being applied to include: regulators examine the financial soundness of firms to ensure a sound economy; auditing companies assess the financial health of companies and measuring riskiness of portfolios.

The current study focuses on listed non-financial companies in India. India has a large section of companies in the unlisted space; factors causing financial distress in such non-listed companies may be examined and compared to the current study results.

In the present study, the variables were only limited to financial ratios, market and macroeconomic factors. For studying financial distress prediction, non-financial or qualitative factors such as a senior management profile, corporate governance and number of independent directors can also be examined.

Since the financial industry is gaining significant prominence in India, financial companies can further be investigated to learn more about the precise indicators that might be used as distress predictors.

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APPENDIX

Interview Schedule for fourth objective

PERSONAL INFORMATION

1. Name ____

2. Place of work ______________________________________

3. Designation ____

QUESTIONNAIRE:

- What are the external reasons which increase the financial distress in Indian companies?

- What are the internal reasons which increase the financial distress in Indian companies?

- What are the leading indicators for financial distress among Indian companies?

- Do you think IBC law will be effective in dealing with stress assets of Indian companies in a more effective manner?

- What is your opinion regarding credit rating agencies which are unable to forecast financial distress?

LIST OF PUBLICATIONS

Sr no.	Title of the Paper	Author's Name	ISSN	Journal Name	Indexed (WoS/ Scopus/ UGC/ NAAS)	Year	Volume No	Issue No.	Page (from-	To)
1	Financial Distress prediction of Indian companies: Future perspectives	Rohit Bansal and Dr. Hari Babu Singu	972-9380	International Journal of Economic Research	SCOPUS	2017	14	4	173	181
2	Modeling Financial Distress Prediction of Indian Companies	Dr. Suresh Kashyap and Rohit Bansal	2277-3878	International Journal of Recent Technology and Engineering (IJRTE)	SCOPUS	2019	8	1C2	112	116
3	Financial Distress Scenario in India: Recent patterns among various listed firms	Dr. Suresh Kashyap ,Rohit Bansal and Dr. Abhay Nagale	2005-4238	International Journal of Advanced Science and Technology	SCOPUS	2019	28	13	388	398