POST-REVIVAL PERFORMANCE ANALYSIS OF FINANCIALLY DISTRESSED INDIAN COMPANIES

A Thesis Submitted

In Partial Fulfilment of the Requirements
for the Degree of

DOCTOR OF PHILOSOPHY

By

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CANDIDATE'S DECLARATION

I, Pallavi Sethi, hereby certify that the work which is being presented in the thesis entitled **"Post-Revival Performance Analysis Of Financially Distressed Indian Companies"** in partial fulfillment of the requirements for the award of the Degree of Doctor of Philosophy, submitted in the Department of Management, Delhi Technological University, is an authentic record of my own work carried out during the period from January 2021 to May 2025 under the supervision of Dr. Archana Singh and Dr. Vikas Gupta.

The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other Institute.

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CERTIFICATE BY THE SUPERVISORS

Certified that **Pallavi Sethi (**2K20/PHDDSM/503) has carried out her research work presented in this thesis entitled **"Post-Revival Performance Analysis Of Financially Distressed Indian Companies"** for the award of Doctor of Philosophy from Delhi School of Management, Delhi Technological University, Delhi, under our supervision. The thesis embodies results of original work, and studies are carried out by the student herself and the contents of the thesis do not form the basis for the award of any other degree to the candidate or to anybody else from this or any other University.

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Dedicated to My Parents

Smt. Meenakshi
and
Sh. Anil Kumar Kalra

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Pallavi Sethi

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LIST OF ABBREVIATIONS

Abbreviation	Full Form
PSB	Public Sector Bank
NPA	Non-Performing Asset
AQR	Asset Quality Review
IBBI	Insolvency and Bankruptcy Board of India
GoI	Government of India
RBI	Reserve Bank of India
IBC	Insolvency and Bankruptcy Code
NCLT	National Company Law Tribunal
CIRP	Corporate Insolvency Resolution Process
DRT	Debt Recovery Tribunal
LLP	Limited Liability Partnership
CD	Corporate Debtor
DEA	Data Envelopment Analysis
MI	Malquimist index
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
ESG	Environmental, Social and Governance
MSME	Micro, Small and Medium Enterprises
DMU	Decision-making Unit
GNP	Gross National Product
SFA	Stochastic Frontier Analysis
GDM	Global DEA Model
DA	Discriminant Analysis
ADD	Additive Model

Abbreviation	Full Form
AI	Artificial Intelligence
ANN	Artificial Neural Network
AR	Accuracy ratio
AUC	Area under Curve
AUROC	Area under ROC Curve
AVE	Average Variance Extracted
BIFR	Board for Industrial and Financial Reconstruction
CAR	Capital Adequacy ratio
CART	Classification and Regression Tree
CB-SEM	Co-Variance based Structural equation modelling
CDR	Capital Deposit ratio
CDR	Corporate Debt Restructuring
CPI	Consumer Price Index
CRS	Constant Returns to Scale
DV	Dependent Variable
EBITDA	Earnings before Interest, Tax, Depreciation, and Amortisation
EC	Efficiency Change
ED	External Debt
FXR	Foreign Exchange Reserve
GA	Gross Advances
GDP	Gross Domestic Product
GFD	Gross Fiscal Deficiet
GIGO	Garbage In Garbage Out
GNPA	Gross Non-Performing Assets
GST	Goods and Services Tax
HTMT	Heterotrait-Monotrait

Abbreviation	Full Form
IV	Independent Variable
k-NN	K-Nearest Neighbour
ML	Machine Learning
MPI	Malmquist Productivity Index
NFDI	Net Foreign Direct Investment
NFPI	Net Foreign Portfolio Investment
NNPA	Net Non-Performing Assets
PLS-SEM	Partial Least Squares-Structural Equation Modelling
ROA	Return on Assets
ROC	Receiver Operating Characteristics
ROE	Return on Equity
SARFAESI	Securitization and Reconstruction of Financial Assets and Enforcement of Security Interest Act
SDR	Strategic Debt Restructuring
SICA	Sick Industrial Companies Act
TC	Technical Change
TDR	Troubled Debt Restructuring
VRS	Variable Returns to Scale

CHAPTER 1
INTRODUCTION

1.1 Background

Financial distress is a critical concern in the corporate sector. It is characterised by a firm's inability to meet its financial obligations, which may lead to insolvency or bankruptcy if corrective measures are not implemented promptly. Financial distress arises from a complex interplay of internal and external factors, including suboptimal financial management, excessive leverage, macroeconomic fluctuations, and industry-specific challenges. Firms experiencing financial distress often exhibit declining profitability, liquidity constraints, and deteriorating market confidence, adversely affecting their long-term viability and stakeholder value.

The global financial crisis of 2007-08 accentuated the vulnerabilities of firms across various sectors, underscoring the need for robust mechanisms to predict and mitigate financial distress. The crisis revealed systemic weaknesses in financial systems and corporate governance structures, highlighting the imperative for comprehensive risk assessment frameworks.

The Indian corporate sector witnessed a significant rise in financial distress over these two decades, attributed to both structural inefficiencies and external economic pressures. The increasing exposure to competition and fluctuating economic conditions posed substantial challenges for firms operating in various sectors.

Over the past two decades, the banking sector has experienced two distinct phases in terms of regulatory and legal frameworks.

The first phase, which began in 2007-2008 and went on up to 2008-2014, can be characterised as a 'lending regime without accountability'. During this period, there was a significant increase in the loans outstanding in the banking sector, particularly within public sector banks (PSBs), where the amount surged from ₹18 lakh crore in March 2008 to an astounding ₹52 lakh crore in March 2014 (Figure 1.1). Aggressive lending practices and a notable laxity in the credit appraisal system marked this phase.

Aggressive but careful lending could have driven substantial economic growth. However, the absence of proper evaluation and a robust credit appraisal system resulted in a significant increase in loan outstanding amounts and, subsequently, in non-performing assets (NPAs). The issue of NPAs was further exacerbated by the neglect of the Asset Quality Review (AQR) and the frequent restructuring of loans.

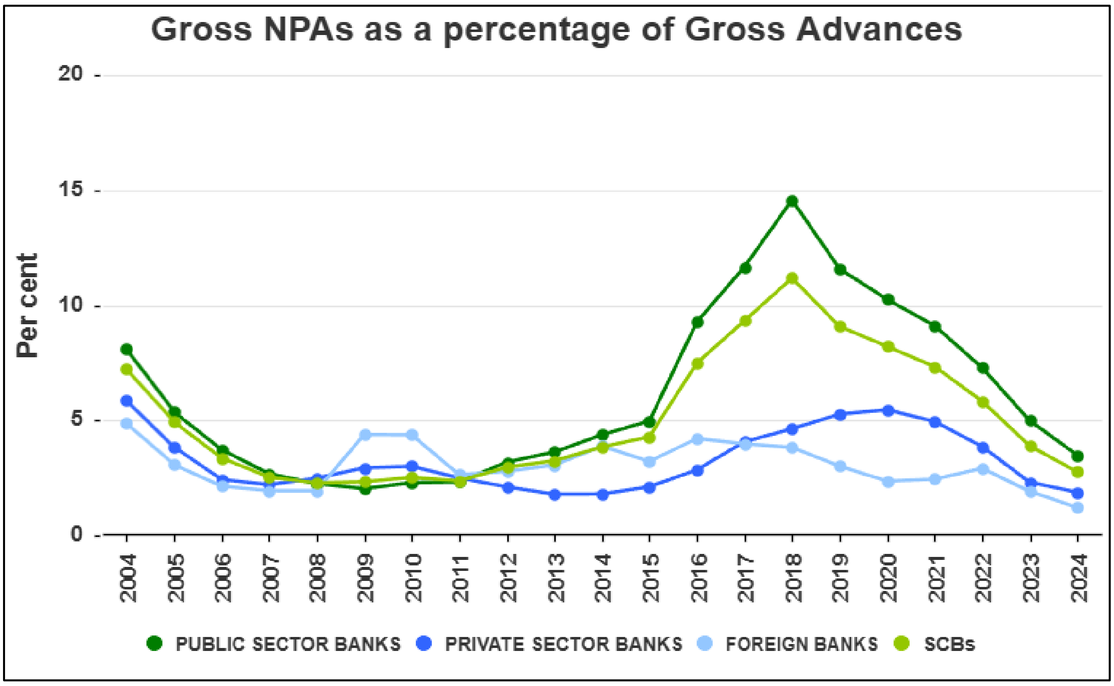

Figure 1.1: NPAs of various banks

This practice of recurrent loan restructuring created an illusion of growth within the banking sector. In reality, it masked the underlying growth of NPAs. Consequently, by 2014, the banking sector was burdened with many non-performing and poorly appraised loans, resulting in reckless and unsustainable loan advances. This situation eroded the debtors' capacity to service their loans, pushing them towards a situation of financial distress, leading to a sector plagued by wilful defaulters and inefficiently allocated resources.

1.2 Rising NPAs and the Issue of Financial Distress

In 2014, a paradigm shift occurred as the government began addressing the growing issue of non-performing assets (NPAs). The Government of India (GoI) initiated the process of recognising stressed assets and identifying NPAs by implementing an Asset

Quality Review (AQR) led by the Reserve Bank of India (RBI) in 2015. This exercise uncovered NPA masked by relaxed, flexible loan reclassification and frequent loan restructurings.

The impact of this reclassification and transparent AQR is evident from the increase in NPAs of public sector banks (PSBs), which rose from ₹1.01 lakh crore in March 2012 to ₹2.42 lakh crore in March 2015 (Figure 1.2). On one hand, the tightening regulations revealed the extent of the problem. On the other hand, the absence of an effective insolvency and bankruptcy mechanism allowed wilful defaulters to restructure their loans flexibly and conceal them without classification as stressed assets or NPAs.

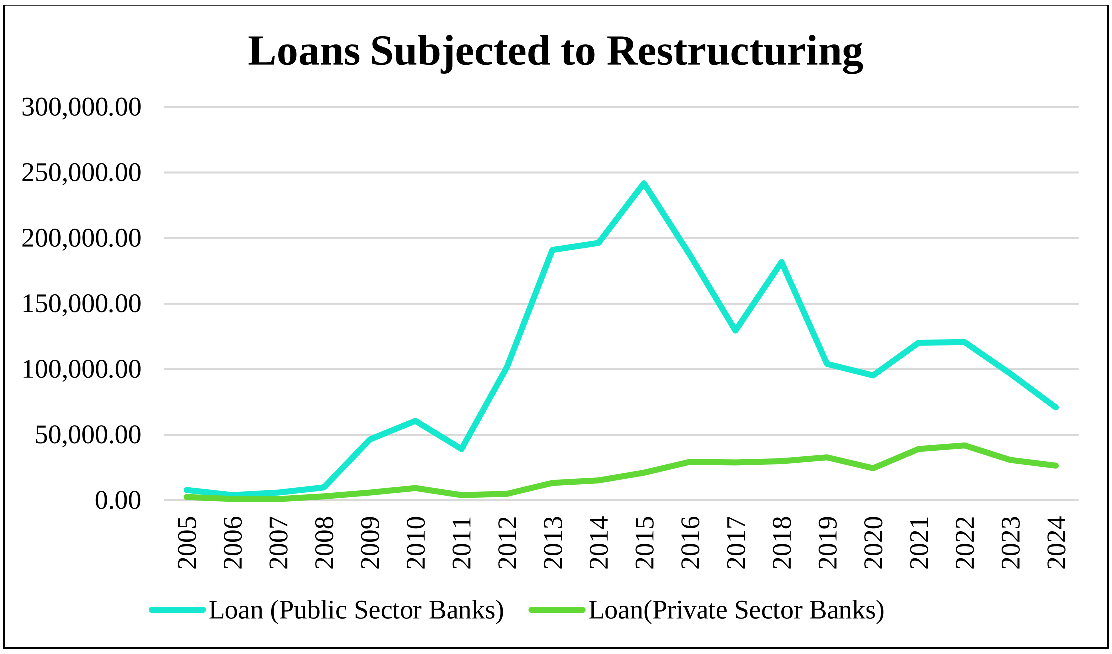

Figure 1.2: Gross NPAs as a percentage of gross advances; Source RBI

Sector-specific challenges in industries such as infrastructure, power, steel, and telecommunications further exacerbated the financial distress landscape in India. Many firms struggled to manage their debt obligations efficiently, leading to rising instances of default and insolvency. Several corporate defaults, including high-profile cases in the infrastructure and manufacturing sectors, highlighted the inadequacy of existing mechanisms to address financial distress. The banking system's accumulation of non-performing assets (NPAs) underscored the urgent need for effective corporate restructuring and debt resolution mechanisms.

1.2.1 Insolvency and Bankruptcy Code 2016

"Markets need freedom broadly at three stages of a business - to start a business (free entry), to continue the business (free competition), and to discontinue the business (free exit). This enables new firms to emerge continuously, and they do business when they remain efficient and vacate the space when they are no longer efficient. This ensures free flow of resources from inefficient uses to efficient uses," M.S. Sahoo, Chairman, IBBI (Insolvency and Bankruptcy Board of India)

The first stage ensures the allocation of resources to their most efficient uses, the second stage ensures the efficient use of allocated resources, and the third stage ensures the release of resources from inefficient uses, promoting the highest possible growth.

Initial reforms focused on the freedom of entry by dismantling the license-permit-quota Raj. This phase witnessed the enactment of laws such as the Securities and Exchange Board of India Act of 1992, which replaced licensing requirements with a registration-based framework. It provided the first pillar of support to the Indian market. Subsequently, reforms shifted focus to the freedom of conducting business. This led to implementing laws such as the Competition Act of 2002, the second pillar, to protect and foster competitive business environments.

Paradoxically, an economy that promoted free entry and competition did not allow free exit, resulting in prolonged inefficiencies due to numerous zombie entities. These entities, unable to exit the market despite their lack of efficiency, contributed to resource misallocation and stifled overall economic dynamism. This situation underscored the importance of establishing a balanced framework that encouraged new business formation and healthy competition and facilitated the timely exit of non-viable firms, ensuring the optimal allocation and utilisation of resources within the economy. There had always been a third pillar to support the Indian corporate ecosystem, ensuring that the markets have the much-needed freedom.

A firm may fail to deliver as planned for a variety of reasons. These reasons could include faulty conceptualisation of the business, inefficient execution of business operations, changes in the business environment, or even, in some cases, malevolent intent. Regardless of the cause, such failures impact the macroeconomy in multiple ways and must be addressed expeditiously.

Failures in business operations often manifest in defaults on repayment obligations. Default can also arise from mismatches between cash inflows and outflows, leading to insolvency. Insolvency is often a legitimate outcome of business operations and does not necessarily warrant the closure of the business, as doing so would destroy organisational capital. Instead, it is necessary to have a mechanism to resolve insolvency in an orderly manner. The absence of such a mechanism has historically denied effective recourse to lenders to recover their debts, discouraging them from lending. This, in turn, reduced the availability of finance for even genuinely viable projects. Furthermore, low and delayed recovery of debts increased the cost of lending, making fewer projects financially viable.

However, it is not always possible to resolve the financial distress amongst the firms. This is primarily because efficient firms continuously drive out inefficient firms from the market. Therefore, it is necessary to have a mechanism whereby inefficient or defunct firms can vacate the space and release idle resources for more efficient uses in an orderly manner. Without such a mechanism, numerous firms are stuck in unsustainable business practices or with no business activities and idle assets.

The Economic Survey 2015-16 compares this situation to the ‘Chakravyuha’ of the Mahabharata and has documented the costs associated with such impeded exits. This situation illustrates the opportunity cost of not allowing ‘creative destruction’ in an otherwise dynamic economy.

The third pillar was erected in the form of the Insolvency and Bankruptcy Code, 2016. This Code offers a market-directed, time-bound mechanism for resolving insolvency, wherever possible, or exit, wherever required, thereby ensuring freedom to exit.

One of the most significant steps the GoI took was the introduction of the Insolvency and Bankruptcy Code (IBC) in May 2016. The IBC aimed to resolve the insolvency of corporate persons, partnership firms, and individuals in a time-bound manner to maximise the value of assets. This was followed by institutionalising the entire regulatory framework, creating a more structured approach to addressing insolvency and improving the overall financial health of the banking sector.

The enactment of the Insolvency and Bankruptcy Code (IBC) in 2016 represented a landmark reform in India's insolvency resolution landscape. The IBC provides a unified legal framework for identifying, resolving, and liquidating distressed firms within a time-bound manner. The code aims to balance the interests of various stakeholders, including creditors, debtors, and investors, while ensuring the continuity of economically viable firms.

A core feature of the IBC is the Corporate Insolvency Resolution Process (CIRP), which allows financial and operational creditors to initiate insolvency proceedings against defaulting firms. The Insolvency and Bankruptcy Board (IBBI) oversees the implementation of the IBC, and the National Company Law Tribunal (NCLT) evaluates and approves resolution plans submitted by prospective investors. The introduction of the IBC had significantly improved India's rankings in the World Bank's Ease of Doing Business index by providing a transparent and predictable mechanism for resolving financial distress.

1.2.2 Insolvency and Bankruptcy Board of India (IBBI)

The IBBI is the regulatory authority responsible for overseeing the implementation of the IBC and ensuring compliance with its provisions. The board formulates guidelines, monitors insolvency professionals, and facilitates capacity building to strengthen the resolution ecosystem. The IBBI plays a pivotal role in maintaining transparency and accountability in the insolvency process.

1.2.3 National Company Law Tribunal (NCLT)

The NCLT serves as the primary adjudicatory authority under the IBC, with the mandate to oversee insolvency proceedings and facilitate the restructuring or liquidation of financially distressed firms. The tribunal is empowered to approve resolution plans, appoint insolvency professionals, and ensure compliance with regulatory provisions. The establishment of NCLT has contributed to expediting the resolution process and reducing the time to resolve distressed cases.

1.2.4 Debt Recovery Tribunal (DRT)

Debt Recovery Tribunals are meant for out-of-court negotiations between debtors and creditors. Whilst NCLT has focused on corporate entities, including Limited Liability Partnerships (LLP), DRT has been primarily dealing with the insolvency issues of individual and partnership firms.

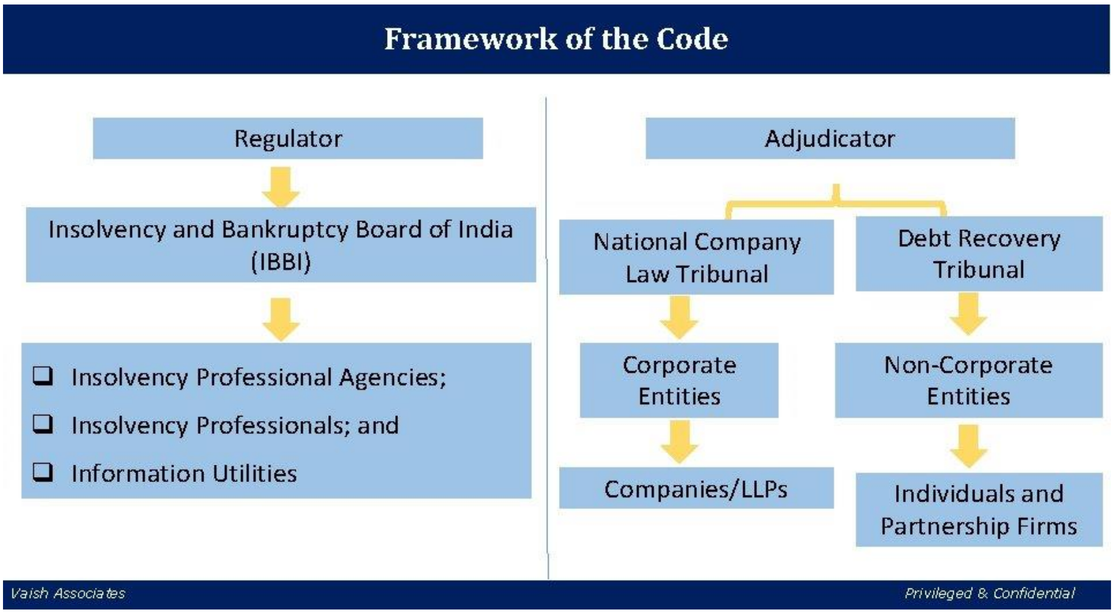

Figure 1.3: Framework of IBC 2016; Source: Vaish Associates

With the initiation of the IBBI in 2017, the number of cases admitted to NCLT has been ever-increasing, showing the confidence of the corporate stakeholders in the system (Figure 1.4)

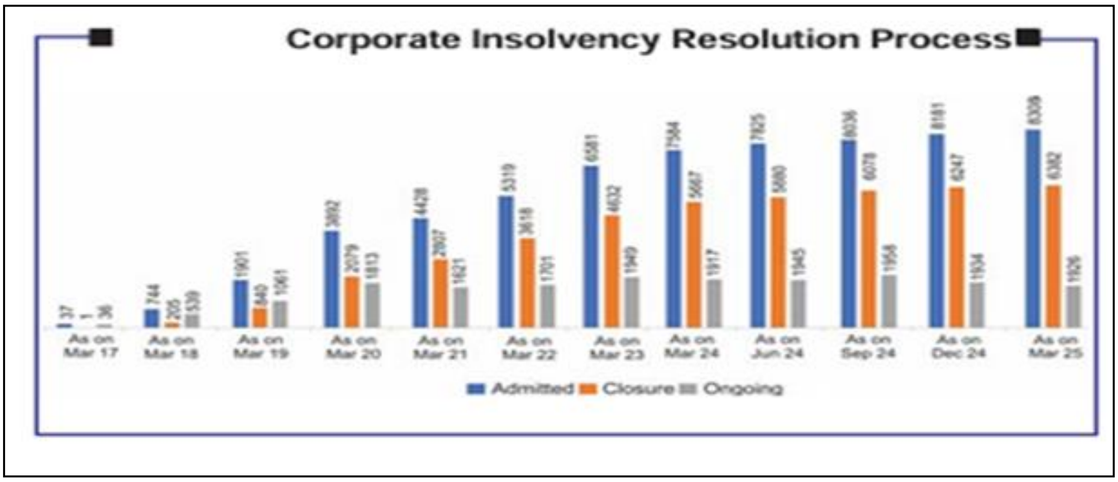

Figure 1.4: Cases admitted to NCLT; Source: IBBI Newsletter

The Insolvency and Bankruptcy Code, 2016 (IBC/ Code) primarily aims to facilitate the resolution of financially distressed companies. However, when all restructuring and revival efforts prove unsuccessful, liquidation becomes the final recourse, wherein the company's assets are sold, and the proceeds are distributed among stakeholders. Over time, the effectiveness of the IBC framework has led to an increasing number of successful corporate resolutions, thereby reducing the incidence of liquidations.

The trend in resolutions and a significant downward shift in the number of liquidations starting from 2020-21. A detailed analysis reveals a declining trend in the ratio of liquidations to resolutions over the years. As illustrated in Figure 1.5, during 2017-18, for every one Corporate Debtor (CD) successfully resolved, five CDs underwent liquidation. However, by 2024-25, this ratio has significantly improved, with only 1.89 CDs going into liquidation for every resolved case. This shift indicates a notable trend reversal, highlighting the increasing effectiveness of the resolution process under the Code in reducing corporate liquidations.

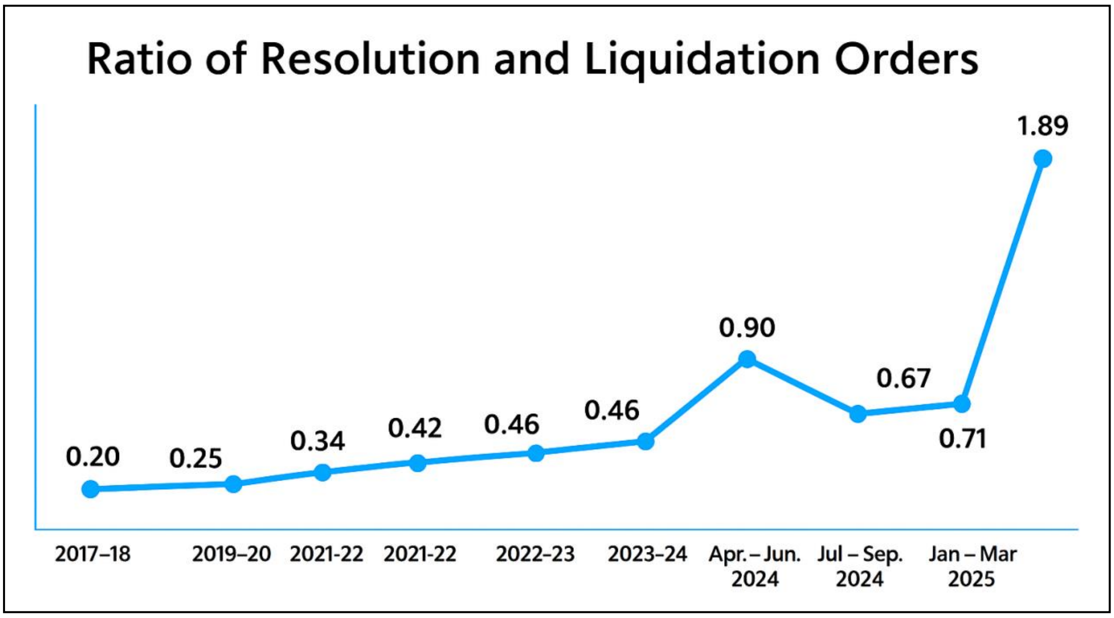

Figure 1.5: Ratio of Resolved cases to Liquidated cases; Source: IBBI Newsletter

1.3 Problem Statement

Creative destruction should continuously drive out failing, unviable firms for a market economy to function efficiently. It was not happening hitherto in the absence of an effective mechanism. Quite a few firms got stuck in 'chakravyuaha' (Economic Survey 2015-16) of unsustainable business or with idle assets and no business. Market imperfections can sometimes misjudge a firm's viability, leading to unintended consequences. A potentially sustainable firm might be mistakenly deemed unviable and forced into closure, while an unviable firm could persist longer than warranted. While rescuing an unsustainable firm may not pose a long-term concern, the premature closure of a viable business has profound implications, affecting stakeholders' livelihoods and preventing future revival. Additionally, no precise mechanism exists to ascertain a resolution applicant's credibility or a resolution plan's feasibility. A firm's default reduces available funds for creditors, restricting their ability to finance viable projects. Meanwhile, delayed and insufficient recoveries drive up lending costs, making credit more expensive, thereby rendering many otherwise viable projects unfeasible. It thus becomes imperative to identify the efficacy of the Code in terms of "ordering" for the liquidation or "restructuring" of firms and the steering of the limited finance in the right direction.

1.4 Rationale

Financial distress in firms pushes them into the inability to pay their financial creditors, thereby stressing the limited finances available in the economy. There is a need to identify the reasons for this. Apart from the financial factors like low returns, less profits, etc., there might be demographic factors like the firm's age, size, the industry it belongs to, and the macro-economic forces underplaying their role at various points of time.

The liquidated firms free up the economy's resources, making them available to other, more efficient firms. This dynamic process allows new firms to enter the market, operate efficiently during their viable phase, and exit when their efficiency declines. Meanwhile, restructured firms continue to function within the financial system, utilizing available resources to sustain their operations and drive ongoing business activity. It is essential to assess the viability of the firms to carry on their economic operations and, thus, the efficacy of the Code in making the right decision to let the firm continue its operation.

It is also essential that the firms move towards restructuring or liquidation before moving into the stage of default. It is therefore essential to predict the pre-default stage of the firm by reading the financial statements.

The current study attempts to look into the efficacy of the Code in restructuring firms and determining whether it is possible to assess the fate of firms in terms of restructuring or liquidation before they move into the default stage.

1.5 Scope of the Study

This study aims to identify the factors that lead a firm towards financial distress, which can be used to predict such distress. It further aims to evaluate the financial performance of firms that have undergone financial restructuring by the Insolvency and Bankruptcy Board of India (IBBI), thereby analysing the efficacy of the Tribunal.

This research encompasses several key areas, primarily focusing on identifying factors that serve as predictors of financial distress and subsequently utilising machine learning models to predict the stage of distress years before the firm seeks tribunal intervention for restructuring.

Given the current economic environment, it is essential to identify and allow a firm to reach the tribunal at a “pre-default” stage, thereby preventing unnecessary strain on the economy’s scarce financial resources.

Additionally, the study aims to evaluate firms’ financial and operational performance post-restructuring to assess the tribunal’s efficiency in categorising a firm as viable and permitting its restructuring.

The primary focus is on firms that either voluntarily approached the tribunal to resolve their financial distress or were recommended for liquidation by the committee of creditors.

1.6 Objectives of the Study

In light of the rationale of taking up this study, the present research aims to contribute to the understanding of financial distress and corporate restructuring by addressing the following key objectives:

- To identify and analyse macroeconomic indicators that serve as early predictors of financial distress in Indian firms.
- To assess the impact of financial restructuring on the post-reorganisation financial performance of distressed firms.
- To develop predictive models using machine learning techniques to enhance early detection of financial distress as compared to the traditional methods.

By achieving these objectives, the study seeks to provide valuable insights to policymakers, investors, and corporate managers to facilitate better decision-making and financial risk management.

1.7 Structure of the Thesis

This thesis is structured as follows:

Chapter 1: Introduction

This chapter outlines the research framework and methodologies to achieve the study's objectives. It comprehensively accounts for the research questions, hypotheses, and methodological approaches. The empirical investigations are segmented into three distinct objectives, each supported by unique models. Furthermore, it elaborates on the data sources and the study design to ensure transparency and replicability.

Chapter 2: Theoretical Underpinnings and Literature Review

This chapter establishes a theoretical foundation for the research by exploring pivotal theories such as Trade-Off, Cash Flow, and Signalling Theory. It then conducts a systematic review of the literature, highlighting various studies related to financial distress and the contributions made by researchers worldwide. The chapter concludes by identifying research gaps.,

Chapter 3: Research Methodology

This chapter outlines the research framework and methodologies to achieve the study's objectives. It comprehensively details the research questions, conceptual model, hypotheses, and methodological approaches. The empirical investigations are segmented into three distinct objectives, each supported by its respective models. Furthermore, it elaborates on the data sources, study design, and variable design to ensure transparency and replicability.

Chapter 4: Macroeconomic Determinants of Financial Distress

This chapter investigates the influence of macroeconomic factors on corporate financial distress in India. It identifies the various factors and highlights the relative contribution of each factor in a firm's financial distress

Chapter 5: Post-Revival Financial Performance Analysis of Restructured Firms

This chapter evaluates the financial performance of firms following restructuring interventions. It aims to identify the effectiveness of the restructuring process on the performance of the firm, thereby highlighting the efficacy of the Tribunal in ordering the resolution of the firm as opposed to its liquidation.

Chapter 6: Measuring Operational Efficiency of Restructured Companies: A DEA-MI Approach

This chapter examines alterations in operational efficiency through the application of Data Envelopment Analysis (DEA) techniques. It underscores the significance of analysing not only financial indicators but also operational factors that reveal firms' capacities to execute their operations both efficiently and effectively. This involves leveraging their optimal scale of operations and staying abreast of technological advancements.

Chapter 7: Financial Distress Prediction Using Machine Learning Tools

This chapter examines and contrasts statistical and machine learning models for predicting financial distress, offering a tool designed for the early detection of distress in Indian firms. It underscores the necessity of identifying early indicators to prevent the economy from succumbing to irrecoverable debts.

Chapter 8: Discussion, Conclusions and Implications

The concluding chapter synthesises the key findings of this study, aligning them with the previously outlined objectives. It delves into the research implications for policymakers, managers, corporations, investors, and leaders, providing actionable insights to improve distress prediction. Additionally, it highlights potential future research avenues, emphasising unexplored areas and proposing methodologies to predict distress signals in firms. Through a systematic analysis of financial distress and restructuring, this study aims to provide a nuanced understanding of the financial health of Indian firms and propose effective strategies to mitigate distress and enhance corporate sustainability.

The systemic failures in India's corporate credit ecosystem created the perfect storm for financial distress, prompting the launch of IBC. This chapter laid the groundwork for understanding how regulatory evolution and macroeconomic instability shape firms' financial fate—a foundation essential for analysing what follows

CHAPTER 2

THEORETICAL UNDERPINNINGS AND LITERATURE REVIEW

Having laid out the problem of rising corporate distress in India, the role of the IBC framework and the key objectives of this study, we now turn to the theoretical and empirical foundations that underpin our work. This chapter provides a comprehensive examination of financial distress, beginning with an exploration of the financial theories that form its foundation in Section 2.1. Building on these theoretical insights, the conceptual research model is developed and presented in Section 2.2. Section 2.3 offers a review of the literature, summarising key studies on financial distress. The thematic evolution of financial distress is discussed in Section 2.4, highlighting established research areas as well as emerging and unexplored dimensions within the field of financial distress and corporate restructuring. Finally, Section 2.5 identifies existing research gaps, underscoring the necessity of this study.

2.1 Financial Theories Underpinning Financial Distress

The concept of financial distress can be attributed to three fundamental financial theories:

2.1.1 Trade-Off Theory

Deciding about the optimal capital structure and what mixture of debt and equity should be appropriate has always been confusing for the management. Since Modigliani and Miller (1958), this topic has been extensively debated in the literature. According to this theory, interest is a tax-deductible expense. Therefore, companies raise debt in the capital structure to receive tax benefits. In addition, increasing their debt employment means they increase the worth of their business. However, this debt deployment is beneficial to a specific level, but if the firm goes beyond this level, it can feel a financial burden. Therefore, the trade-off theory proposes that while making capital structure choices, the company must make adjustments by considering both tax benefits and the cost of financial distress, where these factors are tradeoffs. It is known that moderate borrowings save from taxation and help to take advantage of equity trading. However, it also leads to financial distress.

The theory helps analyse how firms balance the benefits of debt, such as tax advantages, against the risks of financial distress and bankruptcy. It provides an important guideline concerning the amount of debt that the firm can incorporate into its capital structure to take advantage of trading on equity and, at the same time, maintain an optimal capital structure, thereby avoiding financial distress by not burdening itself with too much debt. It can serve as a guideline for the firms to optimise their capital structure post-revival, aiming to achieve financial stability while managing distress costs. Examining the trade-offs made during the recovery phase can provide insights into the strategic financial decisions that contribute to the long-term performance of distressed firms. Post-restructuring, firms typically re-evaluate their capital structure with the objective of determining an optimal debt–equity ratio. In many cases, the pursuit of expansion encourages firms to assume additional debt, even when their capacity to service the associated costs is limited. Such excessive leverage can exacerbate financial vulnerability and ultimately push firms into distress. Within this context, the Trade-Off Theory provides a valuable framework, enabling firms to balance the benefits of debt financing (such as tax shields) against the potential costs of financial distress. By applying this theoretical lens, firms can identify an appropriate capital structure that incorporates debt at a sustainable level, thereby minimizing risk while supporting long-term growth.

2.1.2 Cash Flow Theory

The cash flow theory suggests that a firm will be financially strong if it generates enough cash flow from its operations and will fail when it cannot generate adequate cash inflow from its operations (Wruck, 1990). The continuing imbalance between the cash outflow and cash inflow would result in financial distress in an organisation (Aziz & Dar, 2006). The imbalance in cash flows arises due to a failure in cash management. The theory believes that for firms to avoid distress, there is a need for effective and efficient utilisation of funds. Improper cash management results in an imbalance between cash inflows and outflows, frequently leading to financial distress within the firm.

Cash Flow theory offers a powerful framework for assessing the financial health of firms after their restructuring phase. By focusing on actual cash movements rather than accounting profits, the theory enables the evaluation of whether post-revival firms generate sufficient cash to meet their operational needs, repay debts, and reinvest for future growth. This approach can provide valuable insights into the sustainability of their recovery efforts, highlighting any persistent vulnerabilities in their liquidity management. It would also assist in comparing pre- and post-revival cash flow patterns to identify key factors driving successful turnarounds. In the post-restructuring phase, the availability of adequate cash flow is critical for firms to meet debt obligations in a timely manner and to sustain liquidity. Maintaining consistent liquidity is not only essential for operational stability but also for preserving the confidence of creditors and other stakeholders in the firm's recovery process. Cash Flow Theory underscores the necessity of ensuring a steady inflow of funds, thereby positioning operational liquidity as a central determinant of post-restructuring performance. Within the context of this thesis, cash flow indicators serve as key variables for evaluating the effectiveness of restructuring strategies and for predicting the financial resilience of firms in the long run.

2.1.3 Signalling Theory

Ross, Westerfield, and Jordan (2008) introduced the signalling theory. This theory argues that asymmetric information exists between management and investors. According to signalling theory, once a business implements an aggressive debt-taking approach, a good signal prevails in the marketplace that management is confident it can generate sufficient cash flows to cover both current and future debts. Hence, investors feel that the company is capable and financially strong. In contrast, if the company reduces its debt portion in capital, investors may take it as a sign that it cannot make interest payments and thereby avoid debts; eventually, the market perceives it as a negative signal. Therefore, likelihood of default is a key feature of signalling theory. Additionally, this theory is correct only when management utilises funds proficiently. On the other hand, if the firm fails to do so, then this unfavourable situation may lead the firm towards financial distress and other bankruptcy costs.

After revival, financially distressed firms often face challenges in regaining stakeholder confidence and attracting investments. In this context, signalling theory can help explain how these firms use financial decisions and actions as signals to convey their recovery strength and future growth potential to external stakeholders, such as investors, creditors, and customers. Stakeholders interpret these signals to assess the firm's viability, despite the information asymmetry about the firm's internal operations. By exploring these signalling behaviours, the effectiveness of post-revival strategies in rebuilding trust and ensuring long-term sustainability can be assessed.

2.2 Conceptual Research Model

Through the integration of these theoretical frameworks, a comprehensive evaluation of post-revival performance of restructured firms can be undertaken. It would facilitate an in-depth understanding of the financial decisions undertaken by firms, the management of liquidity strategies, and the signalling behaviours that can enhance stakeholder confidence. Thus, there is a need to identify the key factors that drive successful recoveries and ensure the long-term sustainability of financially distressed firms. It is essential to analyse the critical determinants that contribute to post-revival effectiveness. Furthermore, identifying key financial indicators is imperative to provide stakeholders with signals regarding the firm's potential trajectory towards financial distress.

The above discussion can be presented through a Conceptual Research Model as highlighted in Figure 2.1.

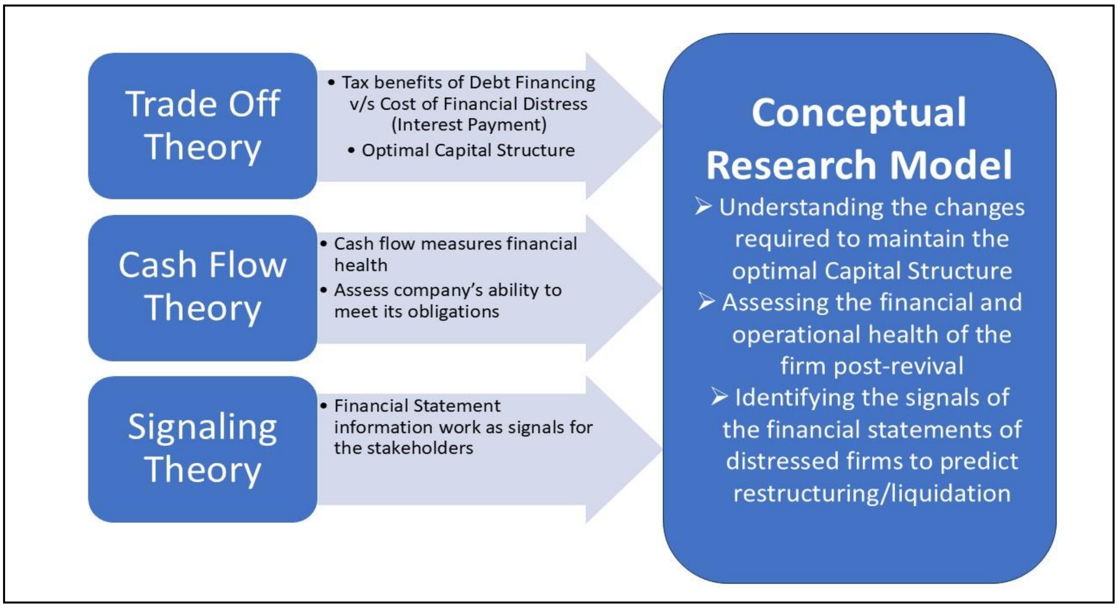

Figure 2.1: Conceptual research model

2.3 Literature Review

Financial distress is a critical challenge for the global economy, particularly in the aftermath of the 2007 financial crisis, which exacerbated systemic vulnerabilities and placed substantial strain on financial institutions worldwide (McNally, 2017). The financial health of firms within an economy serves as a key indicator of national economic performance, offering comparative insights against competing economies (Mommen & Jilberto, 2017).

In the context of increasing globalisation and intensifying competition, many firms struggle to sustain operations, often encountering difficulties in meeting their debt obligations, leading to defaults (Tandon, 2016). The incidence of financial distress among Indian firms has risen notably over the past two decades, driven by structural inefficiencies and firm-specific challenges. This issue has been further worsened by the global economic slowdown following the financial crisis (Abraham & Omkarnath, 2006). Consequently, it is imperative to examine the underlying causes of financial distress, as they play a pivotal role in shaping economic stability.

The theoretical foundation of financial distress analysis traces back to seminal works, such as those by Beaver (1966) and Altman (1968), which pioneered predictive models based on financial data. Early research primarily focused on restructuring strategies as mechanisms to restore corporate viability. Scholars from various disciplines (e.g., Cascio, 1991; John, 1992; Arthur, 1994; Delery & Doty, 1996; Hagen, Udeh, & Hassan, 2001) have proposed conceptual frameworks to elucidate the relationship between financial distress and corporate performance. Additionally, studies have examined the financial costs associated with distress (e.g., Opler, 1994; Andrade, 1998).

Further empirical investigations have explored the consequences of financial distress on firm outcomes, including survival, mergers, and corporate restructuring (e.g., Smart & Waldfogel, 1994; Chatterjee, 1996; Kahl, 2002; Jurgita, 2012). Understanding these dynamics is essential for assessing distressed firms' resilience and recovery trajectories.

Extensive research has been conducted on financial distress, underscoring its significance as a critical area of study, particularly in the context of constrained financial resources within competing economies. The study uses bibliometric analysis to explore intellectual developments and evaluate research articles in this field. This method has been frequently employed in earlier studies as a quantitative review tool (Zheng & Kouwenberg, 2019; Singh et al., 2021a; Baker et al., 2020). For the analysis, relevant documents were sourced from the Scopus database provided by Elsevier. The Scopus database has been identified as an appropriate resource for bibliometric analysis, supported by various prior studies (Aksnes & Sivertsen, 2019; Farrukh et al., 2021). Notably, it has offered extensive coverage in the social sciences since 1996 (Vieira & Gomes, 2009) and encompasses a broader selection of papers in the field of management (Aksnes & Sivertsen, 2019; Farrukh et al., 2021).

The systematic research review followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) (Figure 2.2) guidelines (Moher et al., 2009). This framework prescribes four structured steps essential for identifying and extracting data within bibliometric analysis, ensuring a methodical and transparent approach to the review process.

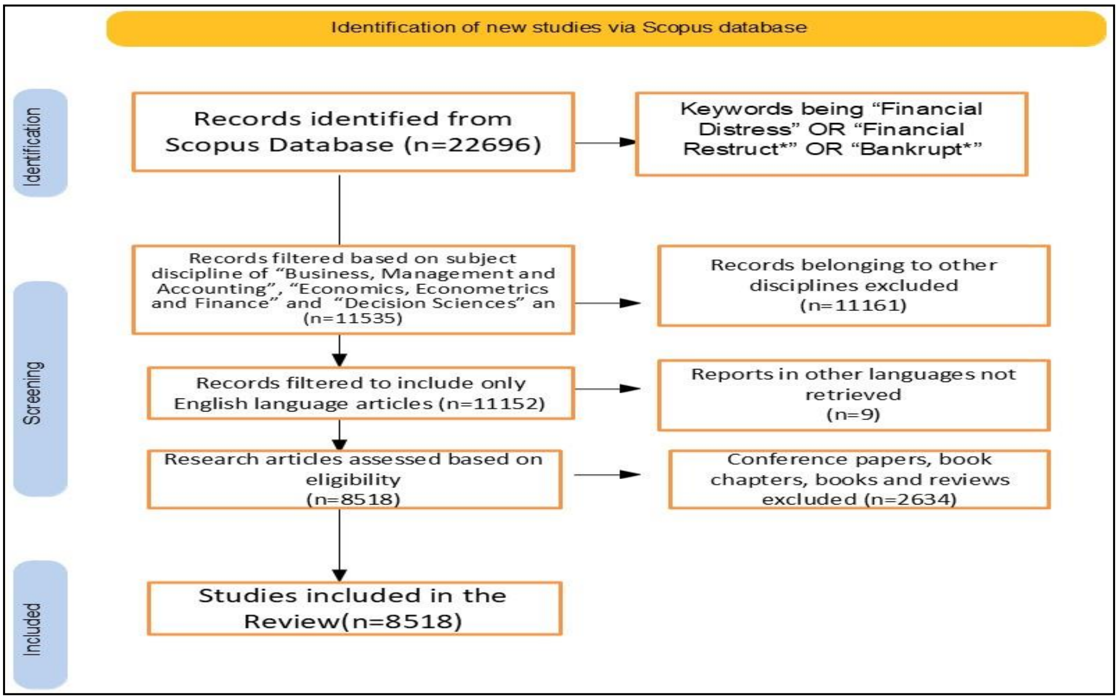

Figure 2.2: PRISMA framework for studies included in review

The bibliometric analysis commenced with identifying and extracting relevant research articles from the Scopus database. The search was conducted in four distinct stages to ensure the selection of the most comprehensive and appropriate articles for quantitative analysis. In the first stage, a search was performed in the Scopus database, utilising keyword strings such as "Financial Distress" OR "Financial Restructur*" OR "Bankrupt"

In the second stage, the search results were refined to include subjects specifically related to Social Sciences, Business Management, Finance, Economics and Decision Sciences, aligning with the premise that the literature on Financial Distress primarily pertains to these domains.

The third stage was to restrict the language to English, enabling an in-depth content analysis of the articles using relevant software tools (Van Eck & Waltman, 2011) and the fourth stage applied two filters: one restricted the publication year from 1965 to 2025, spanning 60 years, and the other limited the selection to journal articles and review papers, as these provide greater consistency in quality (Zheng & Kouwenberg, 2019). Given their widespread use in academic research, Ngai et al. (2008) utilised journals as the primary sources of knowledge and scientific discoveries. Following this rationale, the present article excludes conference proceedings, Master's or Doctoral thesis, books, and unpublished studies from its analysis.

2.4 Thematic Analysis

Thematic mapping in this section aims to identify recurring patterns within textual data. According to Aria and Cuccurullo (2017), the thematic map serves as an intuitive visualisation, enabling the analysis of themes based on their placement within specific quadrants. These themes are derived from keywords, titles, and abstracts of research papers. This two-dimensional framework categorises themes based on two key parameters: density and centrality (Figure 2.3) (Talan & Sharma, 2019).

The X-axis represents centrality, which quantifies a theme's relevance or significance in the research domain, while the Y-axis denotes density, indicating the developmental stage of a given theme. To evaluate these parameters, measures of central tendency, such as mean and median, are employed (Talan & Sharma, 2019). The bibliometric analysis was conducted using Biblioshiny in R software, facilitating a structured literature assessment. Based on this classification, thematic evolution spans several decades, covering research from 1965 to 2025, with key transition points at 2005, 2013, 2018, and 2022.

2.4.1 Early Period (1965–2005): Foundational Themes

During the early period from 1965 to 2005, financial distress research was centered around fundamental themes such as finance, bankruptcy, and financial forecasting. This phase saw the development of bankruptcy prediction models and risk assessment techniques, which laid the groundwork for understanding corporate financial instability. The research methodologies during this time were predominantly quantitative, relying on economic modeling and statistical forecasting to predict financial distress and evaluate firm survival probabilities. These foundational studies established key theoretical frameworks that would later evolve with advancements in data analytics and global financial dynamics.

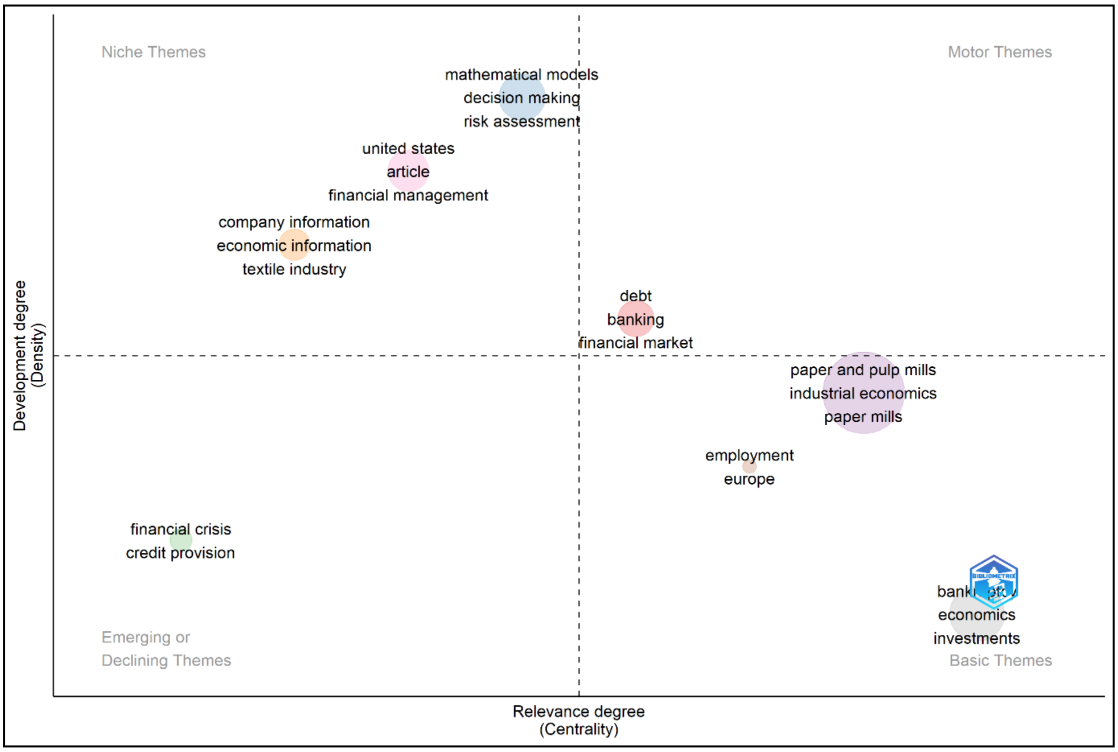

Figure 2.3: Thematic evolution 1965-2005

The early period thematic map (Figure 2.3) illustrates the structural relationships among key financial distress research themes, categorizing them based on their development degree (density) and relevance degree (centrality). Central themes such as finance, bankruptcy, and financial distress occupy highly developed positions, indicating their foundational role in the literature. Meanwhile, forecasting and risk assessment emerge as motor themes, reflecting the increasing importance of predictive analytics in financial stability studies. Interestingly, financial crisis and banking appear within emerging or declining themes, suggesting a shift in research focus, potentially due to changing global economic conditions or policy developments. The absence of a strong cluster in niche themes implies a concentration of studies on well-established financial theories rather than exploratory or highly specialized discussions. Overall, this thematic map highlights a progression toward data-driven forecasting and industry-specific risk management, signalling an evolving landscape where financial distress studies integrate quantitative modelling, AI-driven predictions, and macroeconomic influences.

2.4.2 Transition Period (2005–2013): Expansion & Global Influences

Between 2005 and 2013, financial distress research expanded significantly, driven largely by the 2008 global financial crisis, which heightened scholarly discussions on economic instability. During this period, debt management, banking instability, and corporate risk emerged as central themes, reflecting an increased focus on understanding financial vulnerabilities and institutional fragility. Additionally, regional analyses gained prominence, with studies examining financial distress across significant economies such as the United States, China, and Europe, highlighting the distinct impact of economic fluctuations and policy interventions in different financial systems. This phase marked a shift toward a globalised perspective, where financial distress was analysed within the broader context of international market interdependencies and macroeconomic policies.

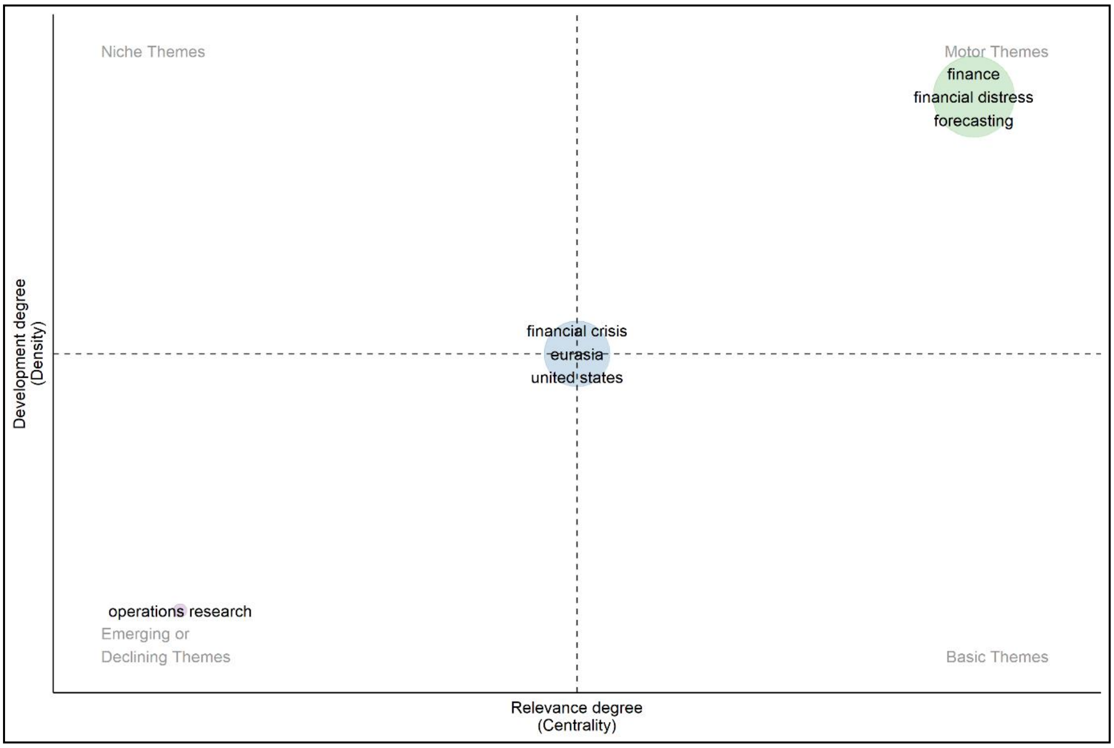

Figure 2.4: Thematic map 2005-2013

The thematic map (Figure 2.4) about the transition period presents an evolved structure of financial distress research, illustrating a progression in both development and relevance. Foundational themes such as finance, bankruptcy, and financial distress remain central, reflecting their continued prominence in academic discussions.

However, new emergent themes, including corporate governance and risk modelling, suggest an increasing emphasis on predictive analytics and strategic financial management to mitigate distress. The thematic distribution indicates a shift toward policy-driven research, particularly within the banking sector, highlighting regulatory frameworks and their role in financial stability. Additionally, economic shocks and crisis management are positioned within emerging or declining themes, indicating an adaptive response to global economic volatility. The structural evolution observed within this map suggests that contemporary financial distress research is broadening its analytical scope, integrating quantitative methodologies, macroeconomic influences, and governance mechanisms to enhance predictive and preventive strategies.

2.4.3 Recent Growth (2013–2018): Emerging Theories & Sectoral Studies

Between 2013 and 2018, financial distress research witnessed a significant shift toward industry-specific analyses, with increasing attention to distress patterns within manufacturing, banking, and commerce sectors. Risk assessment models evolved substantially during this period, incorporating machine learning and AI-driven forecasting techniques to enhance predictive accuracy and decision-making processes. Additionally, scholarly discussions expanded to regulatory frameworks, emphasising the role of governance and policy interventions in mitigating financial distress and ensuring market stability. This phase marked a critical transition wherein traditional financial analysis was increasingly complemented by technological advancements and policy-driven approaches, broadening the scope of financial distress research.

The third thematic map for 2013-2018 (Figure 2.5) reflects a continued refinement in financial distress research, showcasing the integration of quantitative forecasting methods, policy implications, and economic stability. Key themes such as finance, bankruptcy, and financial risk maintain their central positions, underscoring their enduring relevance. However, the emergence of machine learning and predictive analytics highlights a methodological shift toward data-driven approaches in financial distress assessment. The inclusion of corporate restructuring and economic recovery within the thematic framework suggests an increasing interest in firm-level adaptation strategies and regulatory intervention mechanisms. Additionally, macroeconomic instability and market volatility appear within the emerging themes quadrant, signifying a reactionary research focus influenced by global financial fluctuations. This thematic progression indicates an expanding interdisciplinary approach, wherein financial distress is examined not only through traditional economic modelling but also through technological innovations, governance frameworks, and crisis response mechanisms.

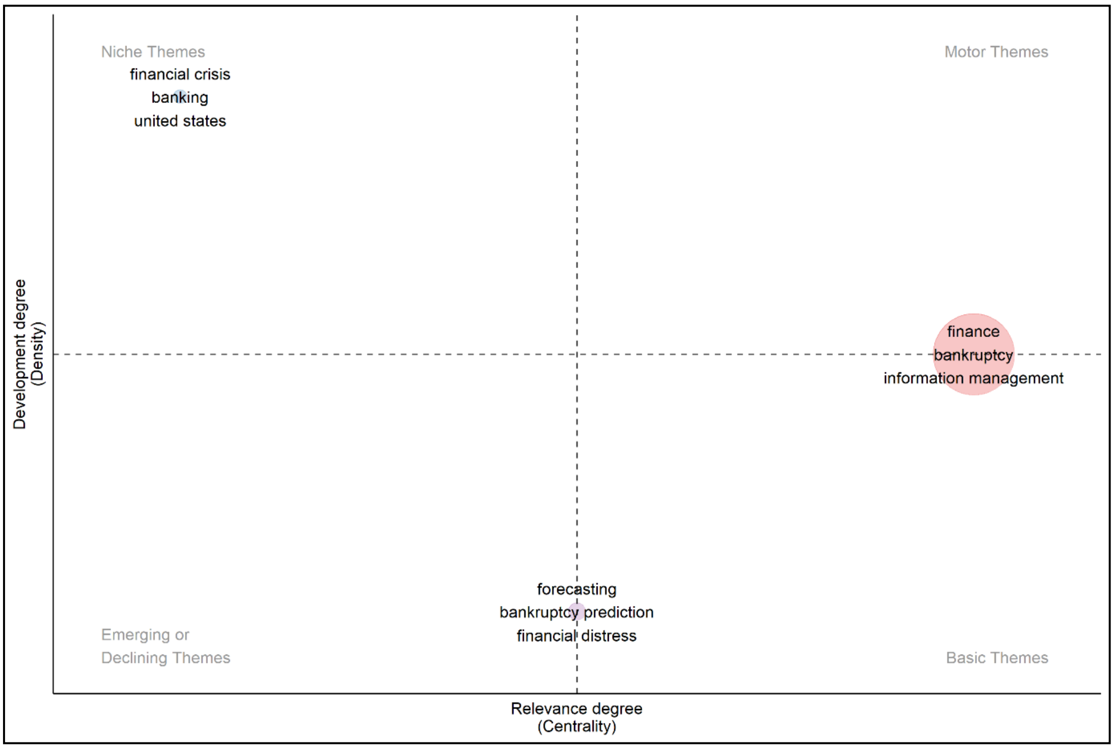

Figure 2.5: Thematic map 2013-2018

2.4.4 Latest Period (2018–2025): Modern Trends & Crisis Response

Between 2018 and 2025, financial distress research was significantly influenced by global crises, particularly the economic disruptions caused by COVID-19, which led to a surge in studies examining its impact on financial stability. During this period, sustainability and ESG (Environmental, Social and Governance) finance gained prominence, as researchers increasingly explored their role in mitigating long-term financial distress and enhancing corporate resilience. Additionally, adopting predictive analytics and AI-driven bankruptcy forecasting became a focal point, reflecting the shift toward data-driven financial risk assessment. This phase marks a growing emphasis on technological innovation and sustainability, demonstrating a broader interdisciplinary approach to financial distress research that integrates economic, social, and governance considerations.

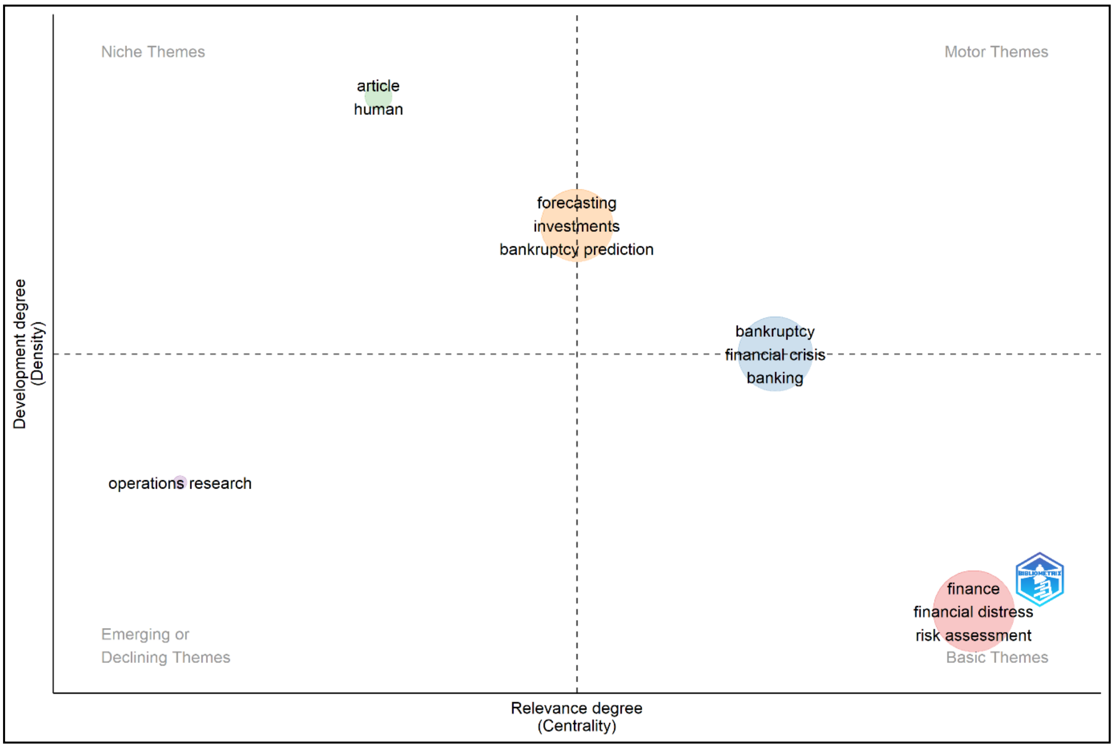

Figure 2.6: Thematic map 2018-2025

The thematic map as shown in Figure 2.6, highlights a dynamic evolution in financial distress research, showcasing an increasing emphasis on global financial stability, technological advancements, and policy-driven frameworks. Core themes like finance, bankruptcy, and financial distress remain prominent, reinforcing their foundational role. Additionally, the positioning of big data analytics and AI-based forecasting within highly relevant themes signals a methodological shift toward data-driven decision-making in financial risk assessment. Meanwhile, market shocks and debt restructuring appear in the emerging quadrant, indicating an adaptive focus on managing volatility and crisis response mechanisms. This map reflects a transition toward preventive and resilience-building strategies, highlighting the increasing role of technology, sustainability, and policy-driven interventions in mitigating financial distress.

The Thematic evolution of financial distress research highlights an increasingly complex and interdisciplinary approach. The shift from quantitative economic modelling (1965–

2005) toward predictive analytics and AI-driven forecasting (2018–2025) illustrates a remarkable transformation in financial risk assessment methodologies. The increasing regional focus (2005–2013) underscores the globalised nature of financial distress, particularly with major economic crises influencing academic discourse.

2.5 Research Gaps

The evolving landscape of financial distress research highlights several critical gaps that require further exploration.

While macroeconomic fluctuations significantly influence corporate financial stability, there is limited research on the role of macroeconomic factors—such as interest rate changes, inflationary pressures, and fiscal policies—in shaping the financial distress and recovery trajectories of firms.

Similarly, while post-COVID-19 financial distress research has provided insights into short-term crisis management, there remains a gap in examining the long-term resilience and adaptation strategies of firms beyond the initial recovery phase. Research on sustained corporate survival, including financial restructuring, operational pivots, and sector-specific recovery trends, is still underdeveloped. Additionally, post-revival performance analysis remains an underexplored domain, particularly in assessing whether firms returning from financial distress can regain pre-crisis stability or sustain long-term growth. Empirical studies evaluating factors that differentiate successful recoveries from persistent vulnerabilities are needed, incorporating governance mechanisms, financial policy shifts, and industry-specific dynamics.

Another significant area is the explainability of AI-driven financial distress prediction models, as existing studies predominantly focus on the technical accuracy of machine learning algorithms without addressing how stakeholders interpret and implement these predictions in decision-making processes. The limited understanding of AI-generated risk assessments challenges regulatory compliance, corporate strategy, and investor confidence. Furthermore, addressing these gaps through interdisciplinary research can provide a more comprehensive framework for understanding financial distress and its broader implications for corporate stability and economic resilience. This comprehensive inquiry can be further enriched by critically engaging with prior scholarly work and systematically identifying the limitations and research gaps that persist within the existing literature.

2.5.1 Factors Leading to Financial Distress

In his seminal work, “Corporate Bankruptcy in America” (1971), Edward I. Altman provided a comprehensive analysis of the factors contributing to corporate financial distress and insolvency in the United States. Altman explored the economic, legal, and managerial dimensions of bankruptcy using theoretical frameworks and empirical data. He used the first difference regression analysis to explain the number of corporate failures from quarter to quarter. The independent variables used were the change in Gross National Product, the change in the Standard and Poor’s Index of Common Stock Prices, and the change in the national money supply. The R2 in Altman’s equation was 0.19, which indicates relatively little explanatory power for economic variables (Altman, 1971).

Rose et al. (1982) incorporated variables into their study identified in prior research as correlating with cyclical fluctuations. These variables include indicators such as Share Price Indices, Gross National Product (GNP), Unemployment Rates, and Personal Income measures. Altman (1983), in another study, examined the role of macroeconomic factors, namely, price-level changes, economic growth, capital market activity and money market activity.

Wadhwani (1986) further assessed that inflation leads to higher input prices, aggravating financial distress and, therefore, the bankruptcy rate. The reasons for the liquidation of UK companies under the Thatcher government were studied by Turner et al. (1992), and the findings strongly advocated the impact of interest rates on business failures. Liu (2004) supported the role of inflation in increasing the financial distress of firms and the bankruptcy rate.

According to Gourdin (2006), a company’s external environment can be analysed from two perspectives: the business sector in which it competes and the broader macroeconomic environment. The business sector environment includes competitors, clients, and suppliers, while the macroeconomic environment encompasses a broader array of factors, namely, economic, social, demographic, political, legal, and technological aspects. To effectively implement its strategy and maintain a competitive edge, a company must closely examine the macroeconomic environment, particularly economic factors. Mackevičius (2010) noted that these economic factors are among the most influential elements affecting a specific business sector and individual companies.

In their study, Harada and Kageyama (2011) examined the macroeconomic aspects of bankruptcies in Japan, which included five economic variables alongside the bankruptcy rate. The analysis revealed dynamic relationships between economic shocks and the bankruptcy rate. A positive shock to the call rate significantly increases the overall probability of bankruptcy. In contrast, shocks to total output, the ordinary profit rate, and the quick assets ratio tend to decrease.

Bruner et al. (2013) argue that a reliable forecast of financial indicators must be grounded in assessing the external environment of the business sector. Since business growth is closely tied to a country's economic indicators, considering external factors, particularly economic ones, is essential for determining business development prospects.

According to Bhattacharjee and Han (2014), macroeconomic instability contributes to increased financial distress, with interest rate volatility being the most significant macroeconomic factor. Moreover, this adverse impact varies based on a firm's age since listing, showing statistical significance only for the youngest firms.

A study was conducted to analyse the impact of macroeconomic factors on India's airline industry by Mahtani & Garg (2018). The study revealed that macroeconomic factors, including inflation and the output growth rate, are crucial in determining the operational capacity and sustainability of airline companies in India.

Later on, Asis et al. (2021) examined the influence of global factors on corporate distress risk, finding that changes in U.S. interest rates, global liquidity fluctuations, and risk aversion significantly predict corporate distress in emerging market economies such as India.

Recently, a study by Sehgal et al. (2021) highlights the critical role of macroeconomic factors in determining financial distress. The findings indicate that higher aggregate output, more significant international fund flows, robust global demand, and increased corporate profitability are all linked to a lower probability of financial distress. However, high inflation appears unfavourable, correlating with increased financial distress. These results underscore the importance of monitoring macroeconomic and quasi-macro factors shifts to effectively track the buildup of risk or financial distress in firms' balance sheets over time. The identified indicators offer a basis for constructing effective distress prediction models.

Based on the literature study, the corporate sector's vulnerabilities must be predicted to understand the size and significance of financial distress situations and chalk out suitable policy measures in such scenarios. The credit stress of the firm, coupled with the deteriorating financial conditions, would lead to economic stress problems in the financial sector.

Thus, it becomes essential to comprehend the overall financial performance of firms, which involves examining macroeconomic variables and financial market conditions that impact the financial stress of these firms.

The evaluation of corporate competitiveness often neglects to incorporate detailed external environmental factors that elucidate temporal variations in financial indicators. A thorough analysis necessitates consideration of the unique characteristics inherent to individual business sectors and should be grounded in a targeted and comprehensive methodological approach.

The problem is that so far, significant attention has been paid to the impact of external environmental factors on the stock market and companies operating therein (Tvaronavičienė, Michailova 2006; Boreikis, Plinkus 2009; Danilenko, 2009; Plinkus, 2010; Žvirblis, Rimkevičiūtė 2012, et al.) and to the research aimed at the assessment of bankruptcy probability based on financial indicators, while efforts to assess the links between macroeconomic factors and financial performance indicators of individual economic units (companies or business sectors) were lacking.

2.5.2 Financial Performance Post-financial Restructuring

The initial criterion for a successful restructuring is that the company emerges from the process as a viable entity. A subsequent measure is to evaluate the firm's operating performance post-restructuring. A committee based on established viability benchmarks determines the firm's viability. These parameters typically include the debt-equity ratio, debt-service coverage ratio, liquidity/current ratio, and profitability ratio (Framework for Revival of Micro, Small and Medium Enterprises (MSME)). Several other variables, such as operating cash flows, economic value added, and stock performance, can predict a successful revival.

The first requirement of successful restructuring is that the company emerges from the process as a going concern. A further test is needed to assess the firm's post-restructuring operating performance. For that, the firm must operate efficiently and profit from its venture. Various measures can be adopted to assess the operating efficiency of the firm. In the past, numerous studies have been conducted to assess the corporate efficiency of firms. Most studies used financial ratios as the only measure to assess operating efficiency. The most important signals about financial distress can be received from the company's financial ratios analysis. Accounting-based indicators of financial distress are still very popular among researchers and are widely used as selection criteria. Despite the critique that financial ratios are past-oriented and cannot capture the future dynamics and prospects of the company as a going concern. They perform well in models predicting financial distress and the probability of default.

Empirical studies concerning corporate restructuring are relatively scarce in the literature. Earlier studies focused on restructuring as a mechanism or strategy to revive a struggling business. Numerous researchers across various disciplines (e.g., Cascio, 1991; John, 1992; Arthur, 1994; Delery & Doty, 1996; Hagen et al., 2001) have elucidated the relationship between restructuring and organisational outcomes. In addition, studies have concentrated on the impact of restructuring on the firm's costs (e.g., Opler, 1994; Andrade, 1998).

The studies have examined the effect of restructuring on firm performance, i.e., whether the firm survived, merged, or emerged as a separate entity (e.g., Smart and Waldfogel, 1994; Chatterjee, 1996; Kahl, 2002; Jurgita, 2012). Hotchkiss (1995) compared firms' operating performance before and after restructuring, measuring firms' operating income as net sales less cost of goods sold and other operating expenses (selling, general and administrative expenses, depreciation, and amortisation).

McHugh, Michel, and Shaked (1998) compared the cash flow projections of firms after the restructuring program with those of industry counterparts and observed that the cash flow projections needed to be more balanced. Simonetti and Rojec (2002) analysed 1200 Slovenian companies that underwent restructuring from 1994 to 1998. They examined the value-added per employee, increase/decrease in operating profit, and cash flows to support their successful transition to a revived firm. Raju Hyderabad (2014) examined the value of the firm pre-restructuring and compared it with the value created after the restructuring process.

As Table 2.1 shows, previous studies have focused only on one or two factors to assess a firm's revival. While some have focused solely on the accounting aspect by examining the ratios and operating profits, others have considered the cash flow projections. Significantly, few studies have addressed economic value added or the value created for shareholders.

Table 2.1: Indicators of operating performance analysed by previous studies

Author and year of study	**Operating performance**	**Ability to meet cash-flow projection**	**Economic-value added**
Hotchkiss(1995)	√		
Maksimovic and Philips(1998)	√		
McHugh, Michel and Shaked(1998)		√	
Alderson and Betker(1998)	√		
Betker, Ferris and Lawless(1999)		√	
Routledge and Gadenne (2000)	√		
Kruse, et.al.(2002)	√		
Simoneti and Rojec(2002)	√	√	√
Denis and Rodgers(2007)	√		
Raju Hyderabad(2014)			√
Judith Mokayain (2016)	√		

2.5.3 Operational Efficiency Post-financial Restructuring

The seminal work on DEA was done by Farrell in 1957. Farrell classified efficiency into technical efficiency and allocative efficiency. Since then, several studies have been conducted using the DEA technique to calculate the efficiency of the firms. It is an optimisation method that determines the productivity and efficiency change in the firms due to various inputs and outputs using linear programming. The basic idea behind the DEA technique is that a firm should be able to obtain maximum output using minimum inputs. It can also be interpreted as the firm receiving the same amount of production by minimising the use of its resources, i.e. the inputs. DEA is a non-parametric approach that ranks a firm, i.e., the Decision-making unit (DMU), among its peers (other DMUs in the sample). It was employed by Banker and More (1986) to analyse the efficiency based on fixed input and output variables. DEA has seen wide application in the past few years. DEA has been applied across various industries, including education, banking, agriculture, manufacturing and health. Due to the complex nature of multiple inputs and outputs used by various firms, DEA has proved to be a saviour by providing benchmarking practices. It allows for the consideration of numerous inputs and multiple outputs simultaneously.

The DEA approach has been used across various industries in India as well as across the globe.

Most studies have been in the financial sector, dealing with banks and other financial institutions. The literature dealing with the non-financial sector has been limited.

DEA methods integrate non-financial and financial factors as input/output variables and provide a standardised approach for measuring performance across industries and firms. Numerous studies have specifically employed DEA methods to assess industry performance (Destefanis & Sena, 2007; Majumdar & Chang, 1996; Sun, 2011). Siriopoulos and Tziogkidis (2009) point out that the reliance on financial ratio analysis, mainly return on equity (ROE), return on assets (ROA), and the cost/income ratio, by researchers and practitioners, often does not yield a comprehensive efficiency score when multiple inputs or outputs are considered. In contrast, the Global DEA Model (GDM), which incorporates all selected variables, provides a consolidated performance metric (Gonzalez-Bravo, 2007). For instance, Berger and Humphrey (1997) employed DEA to evaluate the efficiency of banks in the United States and Canada. They discovered that Canadian banks outperformed their American counterparts in terms of efficiency, a difference they attributed to the distinct regulatory environments in the two countries. Mester (1996) also used DEA to examine the performance of Australian banks and found a wide range of efficiency levels, which he attributed to differences in business strategies and operating environments among the banks. These studies emphasise the importance of DEA in assessing bank performance and pinpointing areas for enhancement.

Apart from the banking sector, DEA has been utilised to assess the efficiency of firms in other industries. For instance, Ozcan (1992) applied DEA to evaluate hospitals' performance in Turkey, concluding that size, location, and ownership influenced their efficiency. Zhu (2003) used DEA to evaluate the performance of Chinese manufacturing firms and found a broad spectrum of efficiency levels, which he attributed to variations in management practices and the adoption of technology among the firms. Hollingsworth (2008) applied DEA to assess hospitals' performance in the United States, noting a wide range of efficiency levels due to differences in management practices and patient demographics. Tone and Tsutsui (2010) applied DEA to evaluate Japanese manufacturing firms' performance, finding varying efficiency levels. Zhu (2000) studied Fortune 500 companies to analyse profitability and marketability. These studies collectively highlight DEA's utility and ability to evaluate performance and identify areas for improvement across various industries.

An inter-country comparison of China and Turkey manufacturing firms by Bayyurt and Duzu (2008), using DEA, revealed that the Chinese manufacturing firms were more efficient than the Turkish firms. Tahir et al. (2012) studied 14 manufacturing firms in Pakistan. They concluded that the technical efficiency of the firms was on average 0.82, with only one firm reaching an efficiency score of 1. Excess capital usage and mismanagement led to inefficiency in the Greek meat products industry, as Keramidou et al. (2011) pointed out. The technical efficiency of companies is influenced by certain factors like automation, technological innovation, and workers' training, as pointed out by Batra and Tan (2003). During the early 2000s, the DEA analysis shifted to large public sector undertakings characterised by low operating efficiency and poor performance. Bala Subrahmanya, M. H. (2004) compared the efficiency scores obtained from Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) for a sample of Indian manufacturing firms. The author found that the two methods yielded similar results, but DEA was more accessible to implement and interpret. Din et al. (2007) pointed out the same in their study of manufacturing units in Pakistan. Singh (2007) studied Haryana's private and public sector sugar mills and found the former far more efficient.

Majumdar (1994) found a high rate of inefficiencies in the pharmaceutical industry. A study by Meenakumari and Kamaraj (2008) revealed a 24% efficiency level of State-owned Electricity Companies in India.

Bhat, R., & Pandey, A. (2013) used DEA to assess the efficiency of Indian textile manufacturing firms. The authors found that the firms varied widely in terms of efficiency and suggested several strategies for improving efficiency.

Mehta et al. (2019) assigned efficiency scores and ranked the Indian Companies known for their best practices in controlling environmental carbon emissions. The authors used a hybrid model of DEA and TOPSIS to measure the efficiency and ranking of various decision-making units based on specified variables.

Sinha (2022) worked on the efficiency of fifteen Indian Insurance Companies from 2011-12 to 2016-17 and calculated the profit efficiency scores. The scores were decomposed into revenue and cost efficiency components. The study concluded that the solvency ratio is a significant explanatory variable of profit efficiency.

DEA has also been used as a technique for bankruptcy prediction. The initial concept of using the DEA method for bankruptcy prediction was introduced by Simak in 1997, who was the pioneer in comparing its outcomes with Altman's Z-score results. Other researchers who worked on bankruptcy prediction using DEA as a technique include Cielen et al. (2004). They applied the DEA radial model for bankruptcy prediction and compared the results with those from Discriminant Analysis (DA). Paradi et al. (2004) implemented additive and radial models alongside the peeling technique in the same year, achieving 100% accuracy in predicting business bankruptcy. Premachandra et al. (2009) utilised an ADD model. They compared its results with logistic regression, demonstrating a satisfactory level of accuracy in predicting business bankruptcy, though the prediction rate was less reliable for financially stable firms. Sueyoshi and Goto (2009) employed the ADD model to determine a threshold below which companies face bankruptcy, comparing the results with the DEA-DA approach. Premachandra et al. (2011) combined radial and ADD models to develop a DEA ranking index. Shetty et al. (2012) used the DEA model to evaluate their firms' bankruptcy likelihood. They examined a business sample. The outcome of their research led to the creation of measures that bankruptcy forecasters could use.

As suggested by Bryan, Fernando, and Tripathy (2013), one approach involves solving DEA problems for each period individually and constructing a panel dataset of the resulting efficiency scores. Alternatively, the Window DEA method, introduced by Charnes, Clark, Cooper, and Golany (1984), is designed to analyse efficiency changes in a time series context. This method employs a fixed observation window that shifts across the entire period, enabling the evaluation of result trends and stability within different panel subsets. However, as Cooper, Seiford, and Tone (2006) noted, a limitation of Window DEA arises in the initial and final periods, where observations may not be as comprehensively assessed.

The Malmquist DEA model is especially effective for handling panel data. The Malmquist Index (MI), originally designed to compare two economies in terms of their production technology, was incorporated into DEA by Färe, Grosskopf, Lindgren, and Roos (1992). Later, Färe, Grosskopf, Norris, and Zhang (1994) developed a DEA-based Malmquist productivity index. The disintegrated elements of the MI can identify how much of an efficiency change (increase or decrease) from period t to t + 1 is due to individual effort versus industry innovation. Efficiency change refers to the extent to which a DMU's performance improves or deteriorates over time, whereas technological change captures the shift in the efficiency frontier between two periods.

Since the introduction of the Malmquist Index (MI), numerous studies have investigated productivity changes across various sectors, including Italian manufacturing firms (Costa, 2012), Spanish government tax offices (Fuentes & Lillo-Banuls, 2015), Taiwanese banks (Shyu & Chiang, 2012), and Korean universities (Sohn & Kim, 2012). These studies primarily examined efficiency changes over time to derive managerial insights and strategic recommendations, without addressing the issue of distress prediction.

2.5.4 Predicting Financial Distress

Use of Statistical Techniques

Since the 1960s, many types of research have focused on companies that have become bankrupt. "Insolvency" refers to a company's financial situation when it finds it difficult to generate sufficient revenue to satisfy its liabilities. The companies conduct financial analyses to ensure long-term viability. The study warns about potential risk and solvency issues by analysing a company's financial performance through its liquidity, financial stability and creditworthiness. Many studies have been conducted in different fields to adapt the insolvency prediction model for businesses in other sectors. Research has been conducted to predict the solvency of various firms. The previous researchers incorporate both financial and non-financial aspects in computation. Studies mainly focus on financial ratios derived from financial reports instead of non-financial elements like a firm's age or management expertise.

In many published studies, financial ratios have been used to forecast solvency. Altman (1968) used the Z-score model to predict financial bankruptcy. The study used different variables estimated using a balance sheet and an income statement. Z-score models indicated the probability of avoiding failure. The variables considered for evaluating the firms' financial conditions were coverage, activity, leverage, profitability and liquidity (Altman et al., 2010). Altman et al. (2016) considered eight efficient predictors for evaluating solvency. William (1966) analysed thirty ratios split into six groups. The ratio was chosen from different groups, which specified various solvency problems like current ratio, total debt/ cash flow, etc. As per Ooghe (2008), lower financial independence, weaker profitability, increased expenses and lower cash flows were considered the critical solvency predictors. The study observed increased expenditure at constant turnover, which might help predict financial problems and inadequate professional competence for implementing decisions arising from various non–financial predictors. Liang et al. (2016) have used ratios like cash flow, growth, turnover, profitability, solvency, and capital structure to assess bankruptcy. The study observed profitable and solvency ratios as the most significant ratios to predict solvency. Bhimani et al. (2010) applied eleven financial ratios: financial coverage, capital/ total asset, investment ratio, days in payables and receivables, interest cost, financial coverage, solidity, gross income and return on equity. They have highlighted days and payables in receivables that determine the payment behaviour of creditors and debtors. Al-Kassar and Soileau (2014) selected specific ratios based on assets and liabilities, and there was no credit interval for failure in prediction. The study indicated that the higher the profitability and other ratios, the lower the solvency risk. When this ratio is lower, the risk of solvency is high. Mironiuc et al. (2015) indicated that the current ratio, average collection, financial leverage, liquidity, financial expenses, and other ratios indicated that these factors were statistically significant in predicting the firm's solvency position.

Hopwood *et al*. (1994) noted that financial distress is related to the probability of going bankrupt. Rather than using a multiplicity of various financial ratios used in previous research, this study is based on specific models, including logistic regression, ANN (Artificial Neural Network), etc. Some earlier studies have considered a model incorporating various ratios that helped measure liquidity, solvency, and profitability. The author selected a model based on a quantitative measure named the Zmijewski score. Zmijewski (1984) developed a weighted probit model for predicting bankruptcy.

Various research studies have indicated the use of qualitative measures of financial distress. As per evidence provided in research studies by Gajpal *et al*. (1994), Gilson *et al*. (1990), Giroux & Wiggins (1984) and Turetsky (1997), there is use of negative operating cash flow, omitting or reducing dividend payment, debt default includes default in loan payments or technical default. Troubled debt restructuring has also been used to indicate financial distress before a firm goes bankrupt. The study has used qualitative variables as dummy variables.

John (1993) suggested that financial distress could progressively result in negative operating cash flows. Giroux and Wiggins (1984) consider negative cash flows signalling a decline in corporate financial status. In the study, Foster (1986) mentions that any firm's cash flow provides vital information to investors and helps evaluate the chances of economic distress. As per the author's opinion, negative operating cash flow implies a tendency towards insufficient working capital and future cash position. This could lead to the survival of the firm in the long term.

Dielman and Oppenheimer (1984) noted that a firm's dividend decisions could be vital in identifying financially distressed firms. The authors mentioned in the study that firms generally follow a stable dividend policy when the firm is financially healthy. DeAngelo et al. (1994) contended that any firm facing financial problems could think of omitting or cutting dividends. Hence, dividend changes, mainly reductions in the amount of dividends, might predict financial distress. Dividend omissions or reductions were measured as dummy variables.

Chen and Church (1992) have mentioned that when a firm is about to fail, its financial ratios deteriorate. However, a clear indication of potential problems could lead to bankruptcy, and it becomes challenging to encounter debt obligations. It is not easy to comply with lending agreements and make scheduled payments. Additionally, when certain firms violate the debt covenants, the creditors might accelerate debt maturity and impose higher re-contracting costs on the lenders.(Anandarajan et al., 2001). Further, any technical defaults would constrain the freedom of action while operating in the firm (Smith & Warner, 1979). When the firm defaults on the debt agreements and cannot provide a remedy through re-negotiation or does not get a waiver from the creditors, there is a higher chance of becoming bankrupt when the company defaults.

Previous studies have regarded Troubled Debt Restructuring (TDR) as a distinct stage in the financial distress continuum (as mentioned by (Giroux & Wiggins, 1983; Turetsky, 1997). TDR results from various private debt renegotiations to resolve or remedy debt defaults (Anandarajan et al., 2001). As a result of TDR, current and future cash flows related to debt service might improve. TDR firms that are unsuccessful might end up in bankruptcy. TDR could be considered a clear signal about financial distress, which could indicate bankruptcy.

Using Machine Learning Models

In the current times, machine learning (ML) is considered to be a cross between Computer Science and Statistics. Artificial intelligence (AI) has been constantly improved, and big data is easily accessible in different sectors. The computation cost has been reduced, and people can use AI in the best way possible. AI's evolution directly impacts the technology market, mainly the firms related to AI (Lu et al., 2018).

Network structures with more robust mapping capacity could manage the interaction between non-linear associations and variables. Artificial neural networks (ANNs) are a solution for different Machine Learning (ML) models. They are used in the financial sector to predict exchange rates, financial distress, credit scoring, and portfolio management.

Among the early studies, Henley and Hand (1996) used the k-nearest neighbour (k-NN) algorithm to assess the customer's ability to pay loans. Galindo and Tamayo (2000) performed a comparative examination of machine learning and statistics to determine mortgage loan defaults. They concluded that the best estimates were provided by Classification and Regression Tree (CART) Decision trees, followed by neural networks and k-NN.

Anandarajan (2001) used an artificial neural network to predict the bankruptcy of financially distressed firms. They used the Zmijewski distress score, which incorporates ratios measuring profitability, liquidity, and solvency.

Yeh and Lien (2009) examined the forecasting accuracy of a few data mining techniques and observed that artificial neural networks (ANN) estimated the default more accurately than the other models.

Decision trees were used by Gepp et al. (2010) to predict business failure, and they observed that decision trees were far superior to traditional discriminant analysis. Similarly, Bhandari and Iyer (2013) used ratios on 50 failed and 50 non-failed US firms. They concluded that discriminant analysis was a better predictor than the cross-validation approach adopted under the data mining technique. Li et al. (2013) evaluated distress and the effectiveness of financial ratios using data envelopment analysis and logistic regression on a dataset of Chinese enterprises. Their results confirmed the theory that using efficiency information improves prediction ability.

Morum and Roy (2013) employed seven financial ratios to predict corporate sickness in the Indian Steel industry. They developed the model using stepwise logistic regression and cluster analysis on 40 companies classified as sick and non-sick. The authors believed that stepwise logistic regression has a better predictive ability than the other methods.

In a 2014 study, Bapat and Nagale compared the predictive powers of three distinct distress models for Indian listed companies: discriminant, logistic, and neural network. They opined that neural networks were the most accurate regarding precise classification.

Behr and Weinblat (2017) conducted another study using machine learning tools, logit regression, decision trees, and random forests. The study included German, French, Italian, British, Spanish, and Portuguese firms. They observed that distressed firms had a spiralling debt ratio, liquidity ratio, return on sales and return on assets, which were significant bankruptcy predictors.

Khemakhem and Boujelbene (2018) integrated financial and non-financial data to create a credit score model. Their research revealed that profitability ratios, repayment capability, and solvency are essential default indicators.

Addo et al. (2018) worked on binary classifiers using machine learning models to forecast loan default probabilities. They concluded that decision trees are more accurate than neural networks for predicting distress.

Shrivastava et al. (2018) predicted a corporate crisis for enterprises in India that did not have bankruptcy specifics. Based on their data, they argued that the Bayesian technique performed better in accuracy and predictive ability than the standard logistic model. In another study in the same year by Nair and Sachdeva (2018) on 574 Indian manufacturing companies classified as distressed and non-distressed, it was established that profitability and efficiency ratios were of utmost importance while predicting distress. Tang et al. (2019) used the random forest model to ascertain the credit card default risk for the firms involved in China's energy business. Their results indicated that the overdraft ratio and the amount of credit card costs significantly affect credit risk. De Paula et al. (2019) analysed data from a Brazilian credit union's loan transactions for credit risk. They established the superiority of the random forest technique in estimating credit scoring compared to logit regression. Shrivastava et al. (2020) employed logistic regression, random forest, and AdaBoost to predict bank failure. AdaBoost provided the highest level of accuracy when compared to the other approaches.

Golbayani et al. (2020) used four machine learning techniques deemed helpful in previous studies (bagged decision trees, random forest, support vector machine, and multilayer perceptron) on a dataset, and the results show that decision tree-based models perform better on the chosen datasets.

A study of 12000 small and medium enterprises concluded that the Random Forest algorithm had the highest prediction accuracy compared to Logistic regression and Artificial Neural networks.(Malakauskas & Lakštutienė, 2021)

A study was performed to predict financial distress amongst Fintech companies by employing an artificial neural network model. The study pinpointed Return on capital, current ratio, quick ratio and debt-to-equity ratio as significant predictors of financial distress. (Halteh et al., 2024)

Gupta (2022) evaluated four machine learning models on the companies under IBC and revealed that random forest outperforms the other three techniques: Support Vector Machine, Decision tree and Logit model.

Most studies employing data mining techniques opine that machine learning models outperform statistical models in terms of discriminatory power and precision. It was also discovered that machine learning algorithms for credit distribution lead to allocation to safer and larger borrowers, reducing lenders' losses.

2.6 Conclusion

Academic research on financial distress and corporate restructuring of firms after the establishment of NCLT is surprisingly thin. With some minor exceptions, it has been either institutional or descriptive. The former starts by explaining how various policy measures and financial institutions helped to solve the problem of financial distress in the past, and then proceeds to explain the design of another set of policy measures undertaken and institutions founded to cure the problem. However, in the context of India, there is a lack of literature dealing with the factors that explain the causes of bankruptcy and help in its identification. There has been little attempt to study the post-restructuring financial performance of firms that the tribunal revived. Also, the likelihood of a firm revived by NCLT, through approval of a resolution plan, falling back into NCLT due to financial distress has not been studied. By consolidating insights from a diverse range of scholarly studies, this study is a modest attempt to fill the gaps existing in the literature and strives to develop a thorough understanding of the determinants of post-revival performance while highlighting critical gaps in existing research. The conclusions derived from this review serve as a foundation for the empirical analysis presented in this study, which aims to advance the discussion on financial distress and its indicators at the firm and macroeconomic levels by contributing meaningful perspectives on the financial recovery of Indian enterprises.

CHAPTER 3

RESEARCH METHODOLOGY

With critical gaps in mind—especially around the macro drivers of distress, post-restructuring performance, operational efficiency over time, and early-warning analytics, this chapter lays out our mixed quantitative methodology. **Section 3.1** outlines the research questions, which serve as a foundation for framing the research objectives discussed in **Section 3.2**. Each research objective is examined in detail, focusing on its relevance to the study, the data requirements, and the research techniques adopted.

3.1 Research Questions

Based on the extensive literature review and the gaps highlighted therefrom, the research questions that come up are as follows:

Q.1 What Macroeconomic factors can be the predictors of bankruptcy?

Q.2 Does restructuring have an impact on:

A. The financial performance of a firm?

B. The operating efficiency of the firm?

Q.3 Can the financial distress of the firm be predicted in advance? What are the factors that help in prediction?

3.2 Research Objectives

RO1: To identify the causal macroeconomic factors that predict Financial Distress and estimate their relative importance.

RO2: To examine the impact of restructuring on the financial performance, by studying financial ratios, of the firms

RO3: To examine the impact of restructuring on the operational efficiency of the firms through NCLT and to assess the efficiency change over time.

RO4: To provide policy recommendations by exploring the potential of predictive analytics, including machine learning approaches, years before the firm is financially distressed, as compared to the traditional methods.

RO1: To identify the causal macroeconomic factors that predict financial distress and estimate their relative importance

Eighteen(18) measurable indicators have been deployed for theoretical constructs of macroeconomic indicators, including the condition of the financial market and financial distress. These indicators capture the essence of these constructs holistically.

I. Data

The dependent variable construct is financial distress. The construct is measured using three indicator variables: Total admitted claims (for the firms liquidated), Total Admitted claims (for firms restructured as per the resolution plan), and Realisation of assets (for firms going for voluntary liquidation).

The independent variable constructs are the Macroeconomic indicators and the condition of the financial market. The condition of Economic indicators is captured through the Consumer Price Index (CPI), External Debt (ED), Foreign exchange Reserves (FXR), Gross Domestic Product (GDP), Gross Fiscal Deficit (GFD), Goods and Services Tax (GST), Net Foreign Direct Investment (NFDI), Net Foreign Portfolio Investment (NFPI). On the other hand, the condition of the Financial Market is captured using continuous variables of Capital Adequacy Ratio (CAR), Credit-Deposit Ratio (CDR), Gross advances (GA), Gross Non-Performing Assets (GNPA), Net Non-Performing Assets (NNPA), Proportion of GNPA to Gross Advances (GNPA/GA) and Proportion of NNPA to Gross Advances (NNPA/GA).

Quarterly data for the 18 independent variables indicators mentioned above have been collected through various sources such as the IBBI newsletter, the Reserve Bank of India database on the Indian Economy, and final orders passed by the National Company Law Tribunal (NCLT). The data relates to 27 quarters spanning from July 2017 to March 2024

The data for the three indicators of the dependent variable have been assimilated every quarter based on the date of order of liquidation (in case of Bankruptcy), Date of Liquidation (in case of Voluntary Liquidation), and Date of approval of resolution plan (in case of CIRP).

II. Methodology

Recursive (PLS-SEM) was employed on structured time-series data to establish causal relationships between independent and dependent variable constructs. This approach enabled the identification of the significant factors contributing to the trend of corporate bankruptcy in India. The independent variables were identified from the vast literature and categorised into various constructs. The 18 measured variables were chosen for their effectiveness as indicators of the anticipated three constructs. These variables are intended to represent the relevant domains associated with the factors and exclude variables from other constructs. Recursive application of Partial Least Squares-Structural Equation Modelling (PLS-SEM) was employed to test these 18 measured variables and establish unidirectional causality through path models. The results were subsequently evaluated for construct reliability and validity, discriminant validity, and multicollinearity.

III. Partial Least Squares-Structural Equation Modelling (PLS-SEM)

Structural Equation Modelling (SEM) is a second-generation multivariate data analysis method, as it can test theoretically supported linear and additive causal models(Hair et al., 2021). PLS-SEM is a soft modelling approach to SEM with no assumptions about data distributions (Hair et al., 2019). PLS-SEM estimates the partial model structures by combining principal component analysis with least squares regression (Mateos-Aparicio, 2011). It computes the measurement and structural model relationships separately, enabling the analysis of composite-based path models. It is a perfect methodology over CB-SEM (Co-Variance based Structural equation modelling) as it consists of financial ratios and similar indicators; also, the research is based on secondary data and lacks comprehensive substantiation on measurement theory (Hair et al., 2019). Despite these advantages, PLS-SEM can give rise to multi-collinearity issues as it cannot model undirected correlation. This can lead to errors in estimating path coefficients and bias loadings. The results thus obtained from Smart-PLS for PLS-SEM are checked for multi-collinearity, construct reliability, validity, and discriminant validity.

Figure 3.1 depicts the measurement models and structural models of our study:

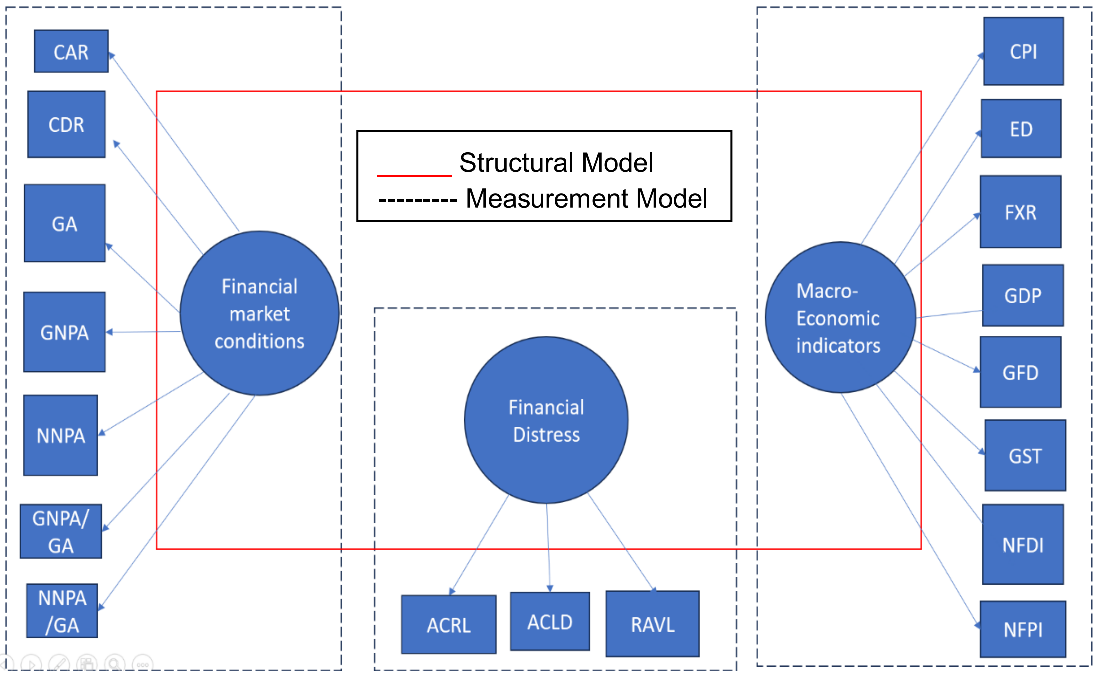

Figure 3.1: Measurement models (outer model) and structural models (inner model) in SEM

RO2: To examine the impact of restructuring on financial performance, by studying the financial ratios, of the firms

I. Data

The National Company Law Tribunal (NCLT) was established in June 2016 and initiated the restructuring process in June 2017. All firms previously referred to the Board for Industrial and Financial Reconstruction (BIFR) were overtaken by the NCLT. The study's sample includes all firms with their resolution plan approved by the NCLT from June 2017 to March 2021. This comprises 345 companies, of which the financial data is available only for 126 companies in CMIE-Prowess. After removing the outliers using Mahalanobis-D, we are left with 89 firms. Therefore, the current study pertains to the 89 firms (Annexure I) that underwent restructuring through the NCLT and had their resolution plan approved.

The study considers the long-term financial data of the firms, precisely three years before restructuring and three years after restructuring. The year of restructuring is referred to as Year 0 and excluded from the analysis to prevent data distortion. The analysis employs an event-year window, rather than a calendar-year approach, to ensure consistent measurement of performance and the impact of the Insolvency and Bankruptcy Code (IBC). For example, a firm that initiated resolution in 2018 and resolved in 2019 would be matched with another firm that filed for resolution in 2020 and resolved in 2021, allowing for a comparative analysis of resolution outcomes. Consequently, performance is tracked on an event basis, such as one, two and three years post-restructuring.

The timeline for the analysis can be represented as follows:

Year -3	Year -2	Year -1	Year R	Year +1	Year +2	Year +3

The financial performance analysis in this study employs eighteen ratios, as shown in Table 3.1.

Table 3.1: Financial Metrics for pre-post analysis

Measure	**Ratio/Metric**
Efficiency	Net Fixed Asset Utilisation Ratio Finished goods turnover ratio Debtors Turnover Ratio Creditors Turnover Ratio Return on Total Assets Return on Capital Employed Return on Net Worth
Profitability	Profit before tax as % of total Income Profit After tax as % of total Income Net profit margin Operating Profit margin Cash profit as % of Total Income
Coverage	Interest Cover Debt Service Coverage ratio
Leverage	Debt equity ratio Total Operating Liabilities to Tangible Net Worth (TOL/TNW)
Liquidity	Current ratio Quick ratio

Hotchkiss (1995) utilised the Profit Margin Ratio as a critical measure for evaluating the performance of firms that underwent restructuring through Chapter 11. The Current Ratio and Quick Ratio serve as valuable measures for assessing a firm's liquidity. Using pre-post analysis, Daddikar and Shaikh (2014) employed the Return on Equity and Profit Margin Ratio to determine the impact of mergers and acquisitions on financial performance. In this study, the Debt Ratio is used in comparison to Total Liabilities, as the capital structure plays a significant role in the restructuring of firms. All the ratios used for the analysis encompass measures of profitability, liquidity, efficiency and solvency.

II. Methodology

A two-sample paired t-test is conducted for each ratio used in the study to determine the significant differences in pre and post-restructuring. For the paired t-test, year R-1, one year before restructuring, is taken as the standard for comparison. The impact of restructuring on the financial performance of firms was analysed on an incremental yearly basis. It will help to understand the improvement in the financial performance of firms on an incremental basis. Also, it would do away with the bias that may creep in due to the averaging method. To achieve this purpose, the following pairs have been analysed

- One year before and one year after Restructuring (-1, +1)
- One Year before and two years after Restructuring(-1, +2)
- One year before and three years after restructuring (-1, +3)
- Average of two years before an average of two years after restructuring (μ_{-2}, μ_{+2})
- Average of three years prior and average of three years after restructuring (μ_{-3}, μ_{+3})

Firms' financial performance has been measured in pre- and post-restructuring years and compared using ratios. The objective is to identify whether restructuring benefits the firm financially.

RO3: To examine the impact of restructuring on the operational efficiency of the firms restructured through NCLT and to assess the efficiency change over time

I. Data

The data used in the present study is taken from the IBBI (Insolvency and Bankruptcy Board of India) website. The Law Tribunal that looks into the matters of the companies is the National Company Law Tribunal (NCLT). The NCLT (under IBBI) approved the resolution plan for the financial restructuring of 376 companies up to March 31, 2024. Out of this, only manufacturing companies that restructured till March 2021 have been taken to avoid distortion of efficiency parameters. This leaves us with 40 companies in the sample. The companies selected for the study are mentioned in Annexure II.

The overall efficiency of the 40 firms in the sample was evaluated using firm-level data for three years following their resolution. The analysis employs an event-year window, rather than a calendar-year approach, to ensure consistent measurement of performance and the impact of the Insolvency and Bankruptcy Code (IBC). For example, a firm that initiated resolution in 2018 and resolved in 2019 would be matched with another firm that filed for resolution in 2020 and resolved in 2021, allowing for a comparative analysis of resolution outcomes. Consequently, performance is tracked on an event basis, such as one and two years post-resolution.

II. Methodology

The Malmquist index scores are calculated for the 40 DMUs in the sample three years after resolution; they were then decomposed into technical efficiency and technological change.

The Technical Efficiency has been further decomposed into Pure Technical Efficiency and Scale Efficiency.

The mathematical equations used for the above analysis, as already discussed above, are:

Total Factor Productivity (MI) = Technical Efficiency Change (E) * Technological Progress Change (T) i.e. MI=E*T

Technical Efficiency Change (E) = Pure Technical Efficiency Change (PT) * Scale Efficiency (S)

i.e. E=PT*S

Therefore, MI = PT * S * T

The efficiency scores related to technical efficiency (VRS) and technical efficiency (CRS) were calculated in Excel. R software was used to calculate the Malmquist index, using both technical efficiency and scale efficiency.

RO4: To provide policy recommendations by exploring the potential of predictive analytics, including machine learning approaches, years before the firm is financially distressed, as compared to the traditional methods.

I. Data This objective focuses on analysing five years of data from 1146 companies.

Table 3.1: Year-wise data of restructured and liquidated companies

Year	No. of cases admitted in IBBI for restructuring	No. of restructured cases available in CMIE prowess	No. of cases admitted in IBBI for liquidation	No. of liquidated cases available in CMIE prowess	Total Number of distressed firms for which the data is available	Financial and Non-Financial data collected for the years
2016-17	Nil	**Nil**	23	**16**	16	2011-12 to 2015-16
2017-18	19	**7**	376	**158**	165	2012-13 to 2016-17
2018-19	75	**31**	550	**195**	226	2013-14 to 2017-18
2019-20	132	**46**	751	**214**	260	2014-15 to 2018-19
2020-21	119	**42**	161	**43**	85	2015-16 to 2019-20
2021-22	144	**46**	231	**58**	104	2016-17 to 2020-21
2022-23	189	**72**	155	**20**	92	2017-18 to 2021-22
2023-24	273	**132**	358	**66**	198	2018-19 to 2022-23

Source: IBBI

In this study, 770 companies were considered liquidated by NCLT since its inception, i.e., 2016, and 376 companies had their resolution plan approved from 2017-18 till March 2024. Table 3.1 shows the details of the companies included in the study's sample. The financial information of the selected companies has been considered for a period of five years prior to their liquidation or restructuring. We used financially stressed firms admitted to NCLT as the sample of study to ensure increased compatibility to a realistic decision-making process as adopted by Anandarajan et al., 2001. This is because the Resolution Professionals must decide to classify a financially distressed firm (rather than a financially healthy one) as a potential candidate for bankruptcy.

The observations of 1146 companies over the past five years yielded 5,730 firm observations, which were used to identify the key financial ratios that predict the outcome of economic distress.

Table 3.2 gives a snapshot of sample characteristics from various industries.

Table 3.2: Various industries to which the sample companies belong

S.No.	Industry	No. of companies restructured	No. of companies liquidated	Total
1	Mining and Quarrying	01	Nil	01
2	Manufacturing	191	362	553
3	Electricity, Gas, Steam and Air conditioning Supply	15	24	39
4	Construction	37	62	99
5	Wholesale and Retail Trade: Repair of Motor Vehicles and Motorcycles	44	164	208
6	Transportation and Storage	10	26	36
7	Accommodation and Food Services Act	8	5	13
8	Information and Communication	16	18	34
9	Financial and Insurance Activities	36	67	103
10	Professional, Scientific and Technical Activity	1	12	13
11	Administrative and Support Service Activities	13	18	31
12	Education	1	1	2
13	Human Health and Social Work Activities	3	6	9
14	Arts, Entertainment and Recreation	0	3	3
15	Other Service Activities	0	2	2

The industry classification is based on the National Industrial Classification (NIC) 2008, adopted by the Government of India to disseminate industry-wise economic data.

Table 3.3 based on an extensive literature review, the financial ratios and the independent variables employed in the study.

Table 3.3: Financial variables and firm-specific characteristics included in the study

Financial Variables	
Measure	**Ratio/Metric**
Efficiency	Total asset utilisation ratio Finished goods turnover ratio Debtors Turnover ratio Creditors Turnover Ratio Gross Fixed Asset Utilisation Ratio Return on Total Assets Return on Capital Employed Return on Net Worth
Profitability	Profit before tax as % of total Income Profit After tax as % of total Income Net profit margin Operating Profit margin Cash profit as % of Total Income
Coverage	Interest Cover Debt Service Coverage ratio
Leverage	Debt equity ratio Total Operating Liabilities to Tangible Net Worth (TOL/TNW)
Liquidity	Current ratio Quick ratio
Firm-Specific Characteristics	
Size	Size Decile
Age	Year of incorporation
Industry	Industry Group of the firm

II. Methodology

The study applies random forest, artificial neural network, and logistic regression models, which are used to predict the firm's outcome (in terms of bankruptcy or restructuring)[1] with a certain level of accuracy.

The following techniques are used for data analysis:

1. **Random Forest (Machine Learning Model):** This model is a supervised algorithm that creates a random forest. Many decision trees are combined to make a random forest. It is used in regression and classification problems. This structure is easier to understand, and its interpretation is straightforward. It has certain advantages: the tree structure is visualised, and there is no need for extensive data preparation for analysis (Aker & Karavardar, 2023). Also, the diversity is created by incorporating the benefit of double randomisation, where each tree is estimated based on a synthetic sample drawn randomly from an estimation sample (Klaus-Peter Hellwig, 2021)

2. **Artificial Neural Network (Machine Learning Model):** This model adopts the human brain system and can generalise knowledge for predicting future events. This model is used widely for optimisation support and prediction with a backpropagation algorithm (Alamsyah et al., 2021).

3. **Logistic Regression (Statistical Technique):** This model emerged as the most suitable for handling situations wherein the dependent variable is classified or categorical. It helps in determining cause-and-effect relationships with certain explanatory variables. The prediction in this model is made using equations. This model is focused on finding an equation that would minimise the difference between the dependent variable's actual value and the independent variable's predicted value (Özdamar, 2002). Cross-validation and stratified sampling techniques were adapted to conduct the modelling as specified by Japkowicz & Shah (2011).

[1] Bankruptcy and Liquidation have been used interchangeably. Restructuring and reorganisation have been used interchangeably as reorganisation is financial restructuring.

The chapter detailed a robust, multi-pronged methodology to operationalise each objective—from macroeconomic modelling to firm-level analytics and predictive machine learning. This versatile toolkit ensures a comprehensive evaluation of both causes and consequences of distress.

CHAPTER 4

MACRO-ECONOMIC DETERMINANTS FOR FINANCIAL DISTRESS

Equipped with our empirical toolkit, we now apply it to the first objective: isolating the macroeconomic and financial-market factors that precipitate distress. It examines the intricate relationship between business cycles, financial distress, and corporate recovery, focusing on identifying the factors prevalent in the macroeconomic conditions and the financial landscape in which the firms operate. The factors leading a firm to financial distress are the ones that emerge from the environment in which the firm operates, as highlighted in **Section 4.1**. **Section 4.2** examines the macroeconomic factors that shape corporate resilience, highlighting how economic downturns contribute to financial instability. **Section 4.3** explores financial market factors, examining the roles of credit availability, debt serviceability, and banking sector vulnerabilities in corporate distress. **Section 4.4** presents an empirical analysis using recursive Partial Least Squares-Structural Equation Modelling (PLS-SEM), establishing causal relationships between financial distress indicators and firm performance. Finally, **Section 4.5** synthesises the findings, drawing key conclusions on the impact of financial and macroeconomic factors in shaping corporate recovery trajectories.

4.1 Financial Distress Determinants

Business cycles have several distinct phases: expansion, contraction, and recession. During the expansion phase, economic activity increases, resulting in business prosperity. In contrast, contraction and recession are marked by financial distress faced by firms.

The issue of financial distress becomes a significant area of concern, as it leads to an increase in the number of corporate failures, which in turn contributes to market failure. Thus, the performance of businesses is closely linked to the overall performance of the economy.

Financial distress lacks a precise definition, but it generally refers to a situation in which a firm is unable to meet its financial obligations in a timely manner. It can also be interpreted as a situation where the firm's capacity is insufficient to deal with the forces causing the distress. This condition does not arise suddenly; instead, it gradually develops over time as firms struggle to make payments and default on their obligations to creditors. It, in turn, leads to the reallocation of resources, downsizing of the firm, capital structure changes, etc. (Jolly et al., 1985)

The firms' stress can also manifest from economic conditions instead of financial stress. While financial stress arises out of competition, innovation, improper organisation, inefficient management or any misconduct on the part of the firm, economic stress results from ripple effects in any sector of the economy. The other sectors that influence the economic stability of the firms can manifest from the macroeconomic or financial sector conditions.

In the globalised world, the economies are intricately connected. If a particular sector of one economy is witnessing stress, it has a domino effect on other sectors, thereby forming linkages with the economies of various world countries.(Korol, 2013). The sub-prime crisis of 2007-08 and the Eurozone crises are few that advocate the same.

Economic crises have been followed up by distortions in the financial markets, thereby leading to unsustainable economic imbalances and misaligned exchange rates. This eventually leads to the failure of financial and non-financial institutions, spiralling down to disrupted capital flows.

The vulnerabilities of the corporate sector need to be predicted in advance to understand the size and significance of such a situation and chalk out the appropriate policy measures in such cases. The credit stress of the firm, coupled with the deteriorating financial conditions, would lead to economic stress problems in the financial sector.

Thus, it becomes essential to comprehend the overall financial performance of firms, which involves examining macroeconomic variables and financial market conditions that impact the financial stress of these firms.

The evaluation of corporate competitiveness often neglects incorporating detailed external environmental factors that elucidate temporal variations in financial indicators. A thorough analysis necessitates consideration of the unique characteristics inherent to individual business sectors and should be grounded in a targeted and comprehensive methodological approach.

The problem is that so far, significant attention has been paid to the impact of external environmental factors on the stock market and companies operating therein (Tvaronavičienė, Michailova 2006; Boreikis, Plinkus 2009; Danilenko, 2009; Plinkus, 2010; Žvirblis, Rimkevičiūtė 2012, et al.) and to the researches aimed at the assessment of bankruptcy probability based on financial indicators, while efforts to assess the links between macroeconomic factors and financial performance indicators of individual economic units (companies or business sectors) were lacking.

The financial distress that a firm undergoes can lead it to the path of insolvency. To understand the reasons for the firm's bankruptcy, leading to decreased financial performance, it is imperative to understand the factors leading to such a situation. The financial performance indicators are not the reason but the result of the firm's distress. Although the firms operate through their production facilities and formulate their policies, their business outcomes are measured in terms of sales, profits, costs, and future business prospects, which are determined by the macroeconomic conditions prevalent in the domestic and world economies. A change in the macroeconomic policies leads to changes in the macroeconomic variables of the financial markets, such as interest rate, gross advances, non-performing assets, etc. Thus, the numbers on the firm's balance sheets and income statements are influenced by the macroeconomic conditions of the economy in which they are operating and the financial ecosystem around them. Thus, to understand the factors contributing to financial distress and its severity, there is a need to study and investigate the aggregate-level factors contributing to corporate bankruptcy, factors associated with the banking sector and the factors relating to the Indian Economy. This would help to analyse the cause-effect relationship of the variables interconnected in fiscal space (Halder et al., n.d.)

4.1.1 Macro-Economic Factors

Competitiveness can be the new term coined for the modern business environment. To augment their market share and future development prospects, firms must thoroughly analyse their financial position and implement strategies to enhance their performance. While assessing a firm's economic performance, specific factors of the macroeconomic environment that influence the performance of the firm should also be identified (Franceschini et al., 2014).

A company's external environment can be analysed in two aspects: the business sector where the company operates and the macroeconomic environment of the country where the firm is based. (Gourdin, 2006). The business sector's external environment where the firm operates has elements like suppliers, buyers, competitors, etc. It is usually analysed using the SWOT (strengths, weaknesses, opportunities, and threats) analysis, which reveals the opportunities and threats related to the external environment (Ginevicius & Auskalnytė, 2001). The macroeconomic environment culminates in social, political, legal, economic, cultural, and technological factors. To implement its strategy, a firm needs to focus on its financial aspect, as out of all the elements of the macroeconomic environment, they impact the firm the most (Mackevičius, 2010). A valid financial performance forecast must be based on assessing the external environment of the business sector (Bruner et al., 2013). Any positive or negative change in the external factors has implications for the firm's financial performance (Wei & Zhang, 2008). Thus, external factors of the business environment have to be considered to determine the prospects of business development that correlate with the economic indicators at the country level.

4.1.2 Financial Market Factors

Bank-based economies rely on the banking system's stability to ensure credit availability (Moradi et al., 2016). Given that the banks are the leading providers of credit to small and medium-sized enterprises, improved credit availability increases the relative borrowing from banks and solves the issue of financial constraints of firms (Behr et al., 2013). However, at the same time, the higher levels of debt increase volatility, uncertainty and retards growth due to mandatory debt serviceability and fluctuating debt service capability (Cecchetti et al., 2011).

The problem of the twin balance sheet, combined with corporate distress and the banking sector crisis, has a devastating effect on economic growth. A weak corporate balance sheet results in a rise in stressed assets within the banking sector, significantly hindering its capacity to extend credit to financially sound companies and consequently impeding economic growth.

This vicious circle must be considered to avoid a setback for the economy (Dhananjaya, 2019).

4.2 Empirical Model

Based on the available literature, we use 18 measurable indicators for theoretical constructs of Macroeconomic indicators, the condition of the financial market and financial distress. These indicators capture the essence of these constructs holistically.

The dependent variable construct is financial distress. The construct is measured using three indicator variables: Total admitted claims (for the firms liquidated), Total Admitted claims (for firms restructured as per the resolution plan), and Realisation of assets (for firms going for voluntary liquidation).

The independent variable constructs are the Macroeconomic indicators and the condition of the financial market. The condition of Economic indicators is captured through the Consumer Price Index (CPI), External Debt (ED), Foreign exchange Reserves (FXR), Gross Domestic Product (GDP), Gross Fiscal Deficit (GFD), Goods and Services Tax (GST), Net Foreign Direct Investment (NFDI), Net Foreign Portfolio Investment (NFPI). On the other hand, the condition of the Financial Market is captured using continuous variables of Capital Adequacy Ratio (CAR), Credit-Deposit Ratio (CDR), Gross advances (GA), Gross Non-Performing Assets (GNPA), Net Non-Performing Assets (NNPA), Proportion of GNPA to Gross Advances (GNPA/GA) and Proportion of NNPA to Gross Advances (NNPA/GA).

Quarterly data for the 18 independent variables indicators mentioned above was collected through various sources such as the IBBI newsletter, the Reserve Bank of India database on the Indian Economy, and final orders passed by the National Company Law Tribunal (NCLT). The data relates to 27 quarters spanning from July 2017 to March 2024.

The data for the three indicators of the dependent variable have been assimilated every quarter based on the date of order of liquidation (in case of Bankruptcy), Date of Liquidation (in case of Voluntary Liquidation), and Date of approval of resolution plan (in case of CIRP).

We utilise recursive Partial Least Squares-Structural Equation Modelling (PLS-SEM) on our structured time-series data to establish causal relationships between independent and dependent variable constructs. This approach allows us to identify the significant factors contributing to the trend of corporate bankruptcy in India. The independent variables have been identified from the vast literature and categorised into various constructs. The 18 measured variables were chosen for their effectiveness as indicators of the anticipated three constructs. These variables are intended to represent the relevant domains associated with the factors and exclude variables from other constructs. Recursive application of Partial Least Squares-Structural Equation Modelling (PLS-SEM) was employed to test these 18 measured variables and establish unidirectional causality through path models. The results were subsequently evaluated for construct reliability and validity, discriminant validity, and multicollinearity.

4.2.1 Partial least Squares-Structural Equation Modelling (PLS-SEM)

Structural Equation Modelling (SEM) is a second-generation multivariate data analysis method as it can test theoretically supported linear and additive causal models (Hair et al., 2021). PLS-SEM is a soft modelling approach to SEM with no assumptions about data distributions (Hair et al., 2019). Partial Least Squares Structural Equation Modelling (PLS-SEM) was employed instead of traditional multiple regression due to the conceptual and methodological advantages it offers. The constructs of “macroeconomic conditions” and “financial market indicators” are inherently latent and multidimensional, each represented by several observed indicators (e.g., GDP, CPI, FXR, CAR, GNPA). PLS-SEM allows for the modelling of such latent constructs while accounting for measurement error, which regression techniques typically overlook. Moreover, the recursive nature of the model aligns with the study's aim to establish unidirectional causal relationships between macro-level constructs and financial distress. Unlike regression, which assumes independence among predictors and requires strict assumptions of normality and multicollinearity, PLS-SEM is more robust in handling complex, exploratory models with smaller sample sizes and non-normal data. Thus, PLS-SEM was deemed more appropriate for capturing the structural and predictive relationships central to this objective. Despite these advantages, PLS-SEM can give rise to multi-collinearity issues as it cannot model undirected correlation. This can lead to errors in estimating path coefficients and bias loadings. The results thus obtained from Smart-PLS for PLS-SEM are checked for multi-collinearity, construct reliability, validity, and discriminant validity.

Figure 4.1 depicts the measurement models and structural models of our study.

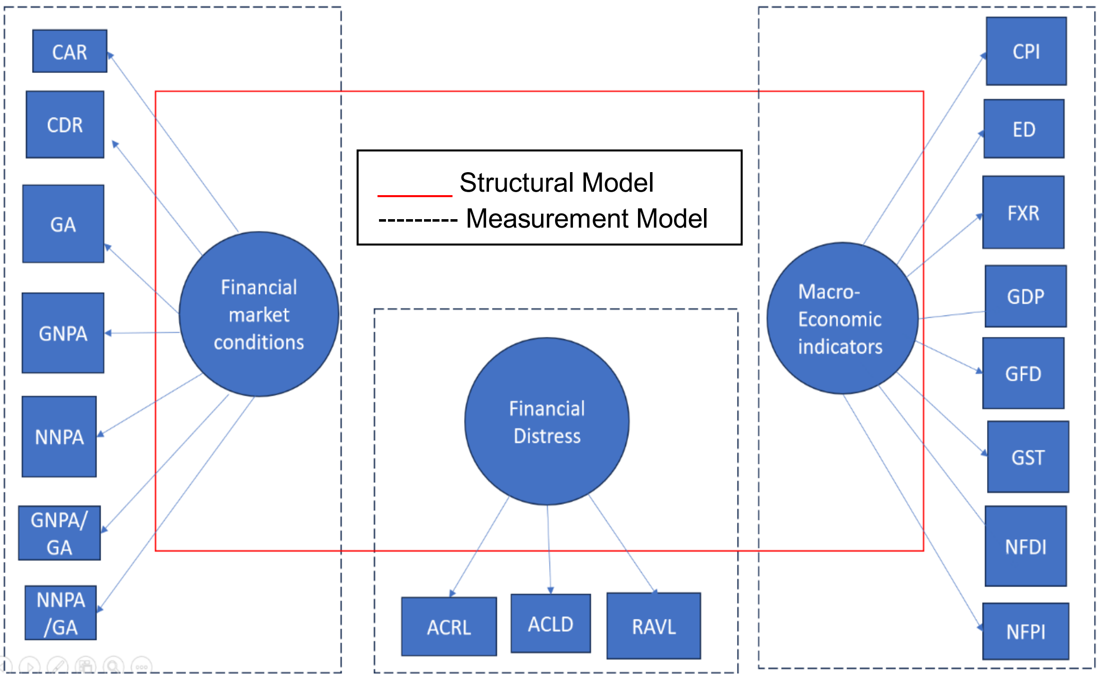

Figure 4.1: Measurement models (outer model) and structural models (inner model) in SEM

As shown in Figure 4.1, the structural model combines the dependent variable construct of corporate bankruptcy and independent variable constructs of financial market conditions and the macroeconomic indicators. The measurement model consists of the variables characterising the financial market conditions, macro-economic indicators and the financial distress situation in India. There are various types of models of PLS-SEM, namely recursive, interaction, intervening, second-order, heterogeneity and multi-group models (Hair et al., 2021). We have used the recursive model, which establishes unidirectional causality without a feedback loop.

4.3 Results and Discussion

Partial Structural Equation Modeling (PLS-SEM) determines unidirectional causality between variables through path models. The structural and measurement models are evaluated using Confirmatory Factor Analysis (CFA) and path analysis, conducted using Smart-PLS software.

The measurement models are assessed first. The structural models are assessed if the measurement model meets all the required criteria. (Hair et al., 2019). A pre-run model is shown in Figure 4.2.

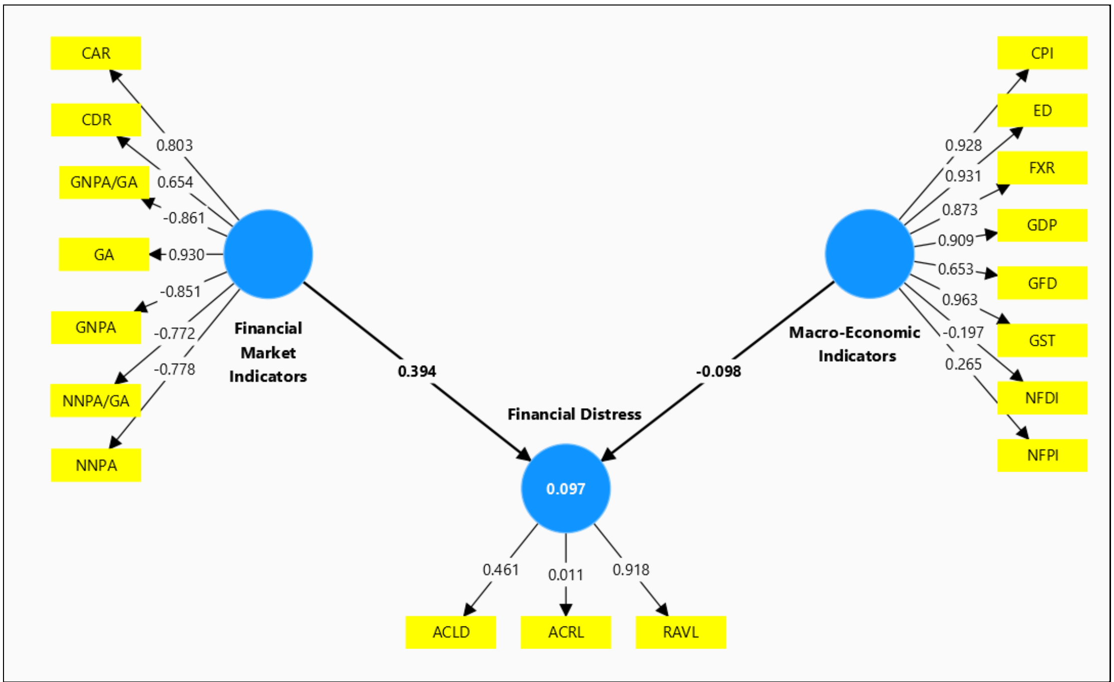

Figure 4.2: Pre-run model

We observe that financial market indicators positively impact firms' financial distress. On the other hand, macroeconomic indicators have a negative impact on the financial distress experienced in an economy.

4.3.1 First-Order Model

The negative co-variances are reflected in some indicators and are removed from the model as the first step (Hair et al., 2019). Moreover, it reduces the dimensionality of the model. The model is then re-run using Smart-PLS, and the first-order model is shown in Figure 4.3. As can be seen, the reduction in the dimensionality improved the prediction results.

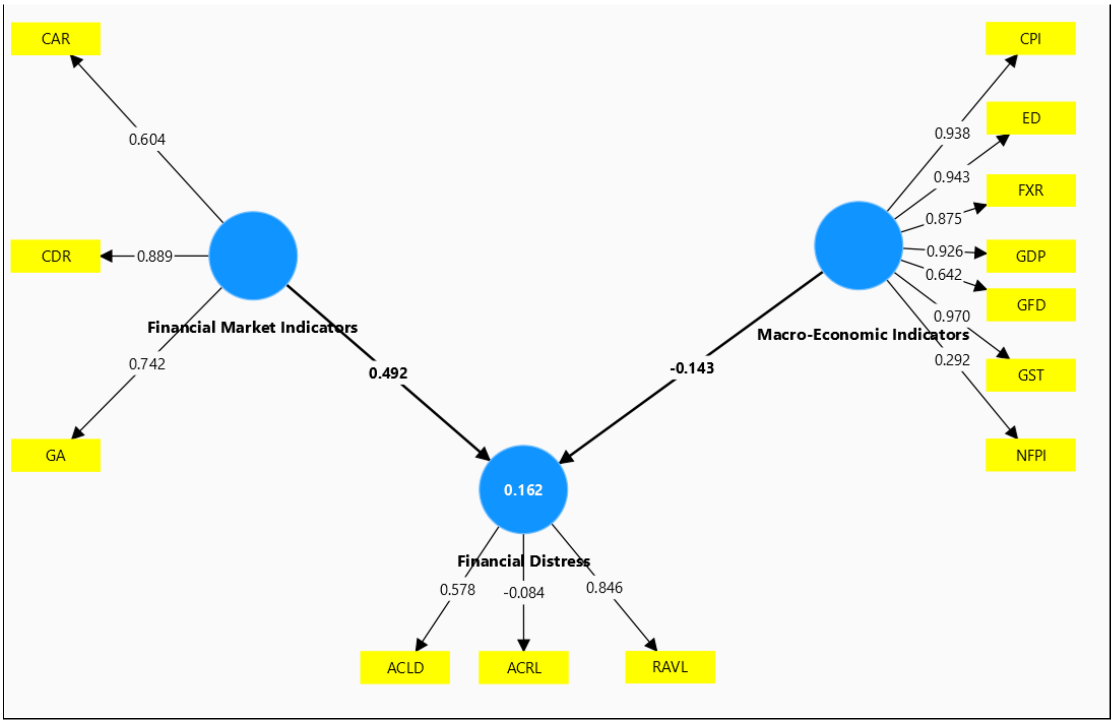

Figure 4.3: First-order model

4.3.2 Second-Order Model

The reduction in the dimensionality of the model based on negative co-variances improved the estimation results. GNPA, NNPA, GNPA/GA and NNPA/GA were removed from the Financial Markets indicators, and NFDI was removed from the Macro-Economic Indicators. Thus, in the first-order model, we were left with ten indicators of independent variable constructs and three of dependent variable constructs.

The indicator loadings in the reflective measurement model are recommended to be above 0.708 to provide acceptable item reliability. Higher values indicate higher levels of reliability. Reliability values between 0.60 and 0.70 are considered "acceptable", whereas those between 0.70 and 0.90 range from "satisfactory to good." (Hair et al., 2019). Thus, we discard all the measured variables with factor loadings of less than 0.60 and the variable reflecting negative co-variance in the Financial Distress construct and re-run the model.

The second-order model, thus obtained, is displayed in Figure 4.4.

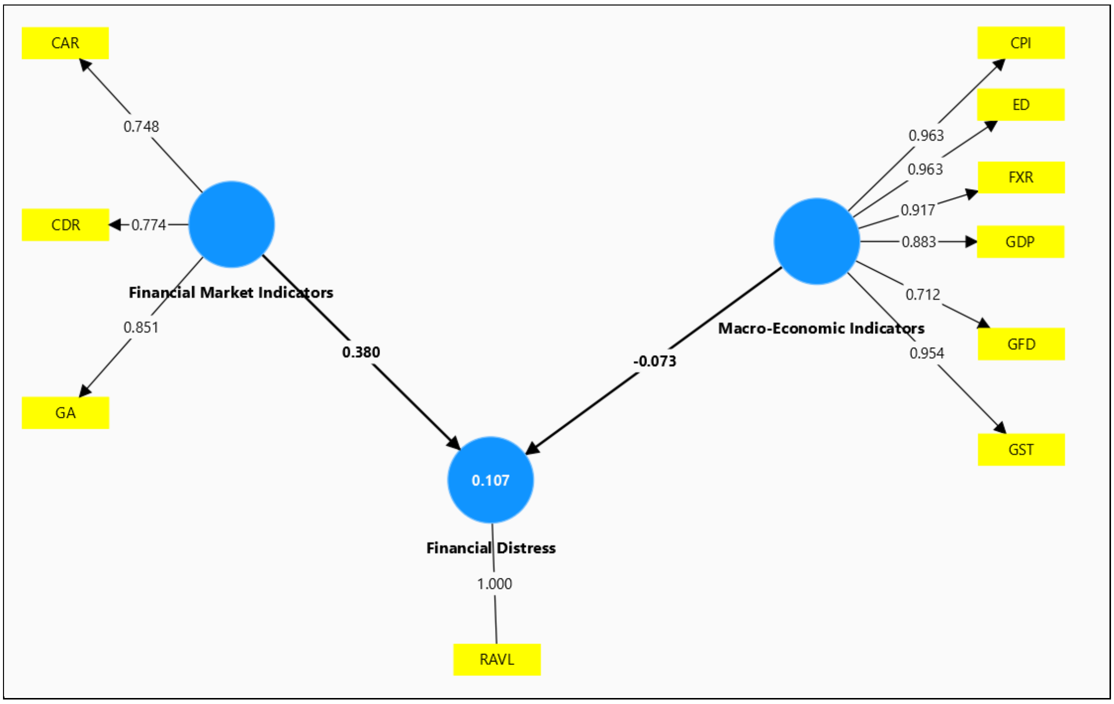

Figure 4.4: Second-order model

A close look at the model shows that the model establishes the first step of assessment of the reflective measurement model as defined by Hair et al., 2019. Moreover, it provides acceptable item reliability.

The next step of assessing the construct's internal consistency reliability is also fulfilled, measured using rho A, which usually lies between Cronbach's alpha and composite reliability. Cronbach's alpha is considered too conservative, composite reliability is too liberal, and the construct's true reliability is typically viewed as within these two extreme values.

The third step of the reflective measurement model assessment is to assess discriminant validity. Discriminant validity measures the extent to which a construct is empirically distinct from other constructs in the model. Henseler et al., 2016, proposed the Heterotrait-Monotrait (HTMT) ratio of the correlations to measure discriminant validity with a threshold of 0.90 for structural models. Any value higher than 0.90 requires a check on the cross-loadings of the individual variables to their respective constructs.

4.3.3 Third-Order Model

Based on the threshold value of 0.90 for the HTMT ratio and assessment of cross-loadings to rectify the same, a third-order model is generated, as shown in Figure 4.5.

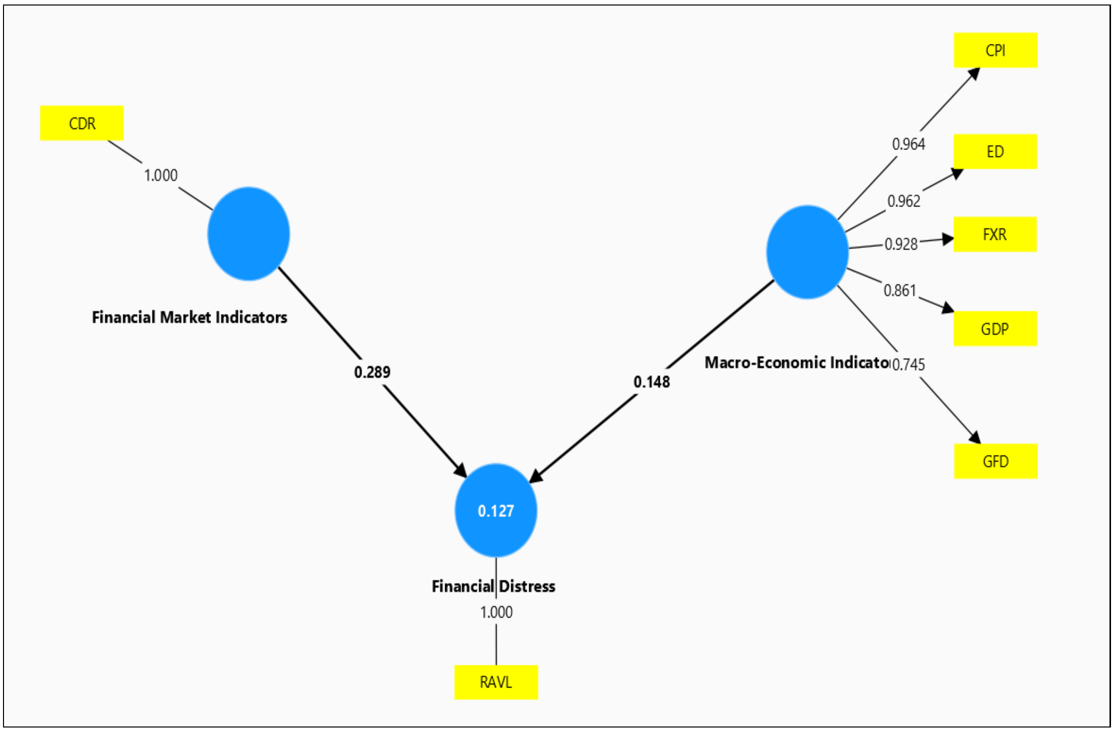

Figure 4.5: Third-order model

As shown in Figure 4.5, the third-order model emerged when running it recursively. The Credit-Deposit ratio (CDR) indicates the financial market indicators. On the other hand, CPI, ED, FXR, GDP and GFD are the variables that impact the macroeconomic indicators. Financial Distress is indicated purely by RAVL.

Table 4.1: Model fit summary

	Saturated model	Estimated model
SRMR	0.094	0.094
d_ULS	0.25	0.25
d_G	0.764	0.764
Chi-square	69.372	69.372
NFI	0.704	0.704

Table 4.1 shows the SRMR value (Standardised Root Mean Square Residual) as 0.094. A value less than 0.10 or of 0.08(in a more conservative version) is considered a good fit (Ringle, 2024). NFI values range between 0 and 1; a value closer to 1 reflects a good fit (Bentler & Bonett, 1980). Both the values suggest that the model is a good fit.

Table 4.2 shows the coefficient of determination (R-squared) and adjusted R-squared.

Table 4.2: R-squared matrix

	R-square	R-square adjusted
Financial Distress	0.127	0.054

A value of 0.127 of R-square suggests that 12.7% of the variance in financial distress is due to the conditions of financial market indicators and macroeconomic indicators. This means there would be a 12.7 variation in the financial distress state variable for a unit change in the respective independent variables. This calls for a look into other factors like management of the firm, financial factors and institutional level changes in the situation of financial distress amongst the firms.

Table 4.3: Construct reliability and validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	(AVE)
Financial distress	1.00	1.00	1.00	1.00
Financial market indicators	1.00	1.00	1.00	1.00
Macro-economic indicators	0.937	0.958	0.953	0.802

Table 4.3 reports the internal consistency of the model. The consistency of the model is established as AVE needs to be above 0.7, and all the values of Average variance Extracted (AVE), Cronbach Alpha, and those reflecting composite reliability are above 0.7.

Table 4.4 reflects the external consistency through the discriminant validity measured using the Fornell-Larcker criterion (1981).

Table 4.4: Discriminant validity through Fornell-Larcker criterion

	Financial distress	**Financial market indicators**	**Macro-economic indicators**
Financial distress	1		
Financial market indicators	0.325	1	
Macro-economic indicators	0.219	0.244	0.896

In this case, the diagonal values should be greater than those in the respective row. Our model specifies the criteria; thus, discriminant validity is established through the Fornell-Larcker Criterion.

The Fornell-Larcker criterion has failed to establish the distinctiveness between constructs (Henseler et al., 2016). Therefore, we used the Heterotrait-Monotrait (HTMT) ratio to assess the discriminant validity.

Table 4.5: Discriminant validity by Heterotrait-Monotrait (HTMT) ratio

	Financial distress	**Financial market indicators**	**Macro-economic indicators**
Financial distress	1.00		
Financial market indicators	0.325	1.00	
Macro-economic indicators	0.211	0.222	1.00

The threshold of HTMT values is 0.85 in the case of a very conservative threshold. If the HTMT value is below 0.90, discriminant validity has been established between two reflectively measured constructs (Ringle et al., 2015). The results of our study are very satisfying for this criterion, as shown in Table 4.5.

A path coefficient assesses the causal model by delineating the relationships between the constructs of the dependent variable (DV) and the independent variables (IV). It reflects the strength of the connection and the response of the DV due to a unit change in IV (Bentler & Bonett, 1980).

Table 4.6: Path coefficients

	Financial distress	Financial market indicators	Macro-economic indicators
Financial distress			
Financial market indicators	0.289		
Macro-economic indicators	0.148		

A look at Table 4.6 suggests that financial market indicators explain almost 30% of the variation in firms' financial distress, while macroeconomic indicators lead to approximately 15% of the variation. Both the constructs, Financial market and macro-economic, correlate positively with each other and with the DV, Financial distress.

4.4 Conclusion

The detailed analysis of financial distress in firms—as measured by admitted claims (in cases of restructuring or bankruptcy) and asset realisation (in cases of voluntary liquidation)—indicates that the impact of financial market and macroeconomic indicators is captured by a few specific variables. Notably, macroeconomic and financial market conditions explain only 12.7% of the variation in firms' financial distress. This limited contribution can be understood from several perspectives:

1. **Broad Aggregates with Limited Variability:** Macroeconomic variables such as GDP, inflation, and external debt, along with corresponding financial market conditions, are broad aggregates that move slowly over time. Their changes tend to affect all firms similarly across an economy, providing a uniform background environment. Consequently, while these factors set the overall economic context,

they are less effective at capturing the idiosyncratic shocks and company-specific factors that ultimately drive distress.

2. **Dominance of Firm-Specific Factors:** A significant portion of financial distress results from internal conditions—such as management practices, operational inefficiencies, and strategic decision-making—which can vary considerably among companies. Although external conditions are important, they explain only a modest share of the firm-by-firm variation because most of the distress is driven by internal factors that are not directly reflected in macroeconomic or market-level indicators.

3. **Indirect Effects and Interactions:** Macroeconomic conditions generally influence financial distress indirectly. For instance, a recession may lead to reduced cash flows, which then contributes to financial strain. The actual manifestation of distress, however, depends largely on each firm's internal resilience and its ability to cope with these external vulnerabilities. Thus, while the external environment may create conditions that foster distress, the outcome is ultimately determined by the internal responses of firms.

4. **Measurement and Model Specification:** The 12.7% figure is derived from a regression or structural model where the R^2 value indicates the proportion of variance explained by the chosen set of macroeconomic and market variables. If key internal determinants are not included in the model, the explained variation will naturally be lower. This result does not imply that macroeconomic factors are unimportant but rather that they represent just one component in a more complex interplay of factors affecting financial distress.

In addition to these general observations, the analysis identifies specific relationships within the financial market. For example, the credit-deposit ratio is the single financial market indicator that correlates positively with financial distress. A high credit-deposit ratio implies that firms maintain strained liquidity and an overstretched balance sheet, leading to an increased propensity for distress when banks extend more loans than the firms can service. Similarly, macroeconomic indicators such as GDP and CPI, while generally associated with enhanced earning capacity, may also lead firms to rely more heavily on external financing. This increased reliance can result in elevated financial liabilities, particularly when coupled with adverse factors like high external debt or currency depreciation, thereby exacerbating distress.

The finding that macroeconomic and financial market indicators explain only 12.7% of the variance in firm-level financial distress should be interpreted with caution, particularly given the dynamic nature of these variables. Macroeconomic indicators such as inflation, GDP, and fiscal deficit are broad aggregates that evolve over time and may exert lagged or nonlinear effects on firm outcomes. The recursive PLS-SEM model captures their structural influence at a macro level but does not fully account for temporal dynamics or firm-specific mediators. This modest explanatory power underscores the reality that financial distress is often driven by a complex interplay of internal financial, managerial, and sectoral factors beyond macroeconomic conditions alone. Future research could enhance explanatory depth by incorporating dynamic panel models, time-lagged variables, or interaction effects (e.g., GDP × firm size) to better capture the evolving influence of macroeconomic forces on corporate vulnerability. This limitation is further discussed in Chapter 8 under future research directions.

Our analysis confirmed that macroeconomic indicators and financial market signals, while statistically significant, explain only a fraction of firm-level distress—reinforcing the need to probe deeper into firm performance and managerial factors post-revival.

CHAPTER 5

POST-REVIVAL FINANCIAL PERFORMANCE ANALYSIS OF RESTRUCTURED FIRMS

While macro-structural forces provide meaningful context, the real test of financial recovery lies in the firm-specific performance following intervention. Chapter 5 shifts focus to post-restructuring financial metrics, dissecting whether resolution plans translate into tangible financial turnaround for distressed companies.

This chapter systematically examines the financial trajectory of firms following their restructuring, evaluating in **Section 5.1** whether restructuring leads to sustained improvements in financial stability and profitability. **Section 5.2** introduces the empirical framework underpinning the analysis, detailing the hypotheses and methodological approach used to assess pre- and post-restructuring performance. **Section 5.3** thoroughly examines financial indicators, including liquidity, solvency, and profitability ratios, with a focus on key metrics such as EBITDA margin, debt ratio, and return on assets. **Section 5.4** interprets the results, critically assessing the impact of restructuring on financial performance using paired sample t-tests. Finally, **Section 5.5** synthesises the findings, providing a comprehensive discussion on the implications of corporate recovery and the effectiveness of restructuring strategies in fostering long-term financial sustainability

5.1 Post-Revival Performance Analysis

The performance of firms within the business landscape is significantly influenced by economic and financial stress. Economic stress arises due to competition, prevailing economic conditions, and government regulations. Conversely, prolonged financial stress, which results from insufficient profits or returns, leads to financial distress among firms. Firms experiencing financial distress, characterised by poor operational performance and a sub-optimal capital structure, often employ various strategies to ameliorate their situation. These strategies include mergers, acquisitions, amalgamations, asset restructuring, and financial restructuring. To enhance their financial position and operational performance, firms implement changes in their capital structure, as well as in their operating capacity and capability. This includes the introduction of new technology and the adoption of techniques for the optimal utilisation of resources.

It becomes imperative to compare the financial performance of firms before and after their restructuring to determine whether the firm's financial performance has improved due to restructuring. To achieve this objective, financial ratios have been employed to measure firms' financial performance, given that different firms' financial performance is not directly comparable due to differences in size, asset structure, etc.

5.2 Empirical Model

The hypotheses framed for the study are as follows:

Null Hypothesis: H_0; There is no significant difference in pre- and post-restructuring financial performance

Alternate Hypothesis: H_α; There is a significant difference in pre- and post-restructuring financial performance

The study examines the long-term financial data of firms precisely three years prior to restructuring and three years after it. The year of restructuring is designated as Year 0 and is excluded from the analysis to avoid data distortion. Consequently, the study period extends from July 2017 to March 31, 2021. The analysis timeline can be represented as follows:

R-3	R-2	R-1	R	R+1	R+2	R+3

The financial performance analysis in this study employs eighteen ratios, assessing the firms on their liquidity, profitability, efficiency and coverage. Hotchkiss (1995) utilised the Profit Margin Ratio as a critical measure for evaluating the performance of firms that underwent restructuring through Chapter 11. The Current Ratio and Quick Ratio serve as valuable measures for assessing a firm's liquidity. Using pre-post analysis, Daddikar and Shaikh (2014) employed the Return on Equity and Profit Margin Ratio to determine the impact of mergers and acquisitions on financial performance. In this study, the Debt Ratio is used in comparison to Total Liabilities, as the capital structure plays a significant role in the restructuring of firms.

A two-sample paired t-test is conducted for each ratio utilised in the study to determine the significant differences pre- and post-restructuring. For the paired t-test, Year R-1, one year before restructuring, is the standard for comparison. The impact of restructuring on the financial performance of firms is analysed on an incremental yearly basis. This approach helps understand the incremental improvement in the financial performance of firms and mitigates the bias that may arise from the averaging method. To achieve this purpose, the following pairs have been analysed:

- One year before and one year after restructuring (-1, +1)
- One year before and two years after restructuring (-1, +2)
- One year before and three years after restructuring (-1, +3)
- Average of two years before and an average of two years after restructuring (-2, +2)
- Average of three years prior and average of three years after restructuring (µ-3, µ+3)

Firms' financial performance is measured in the pre- and post-restructuring years and compared using these ratios. The objective is to determine whether restructuring benefits the firm financially.

5.3 Analysis of Results

The results obtained from conducting a paired t-test for all the ratios taken up for analysis are discussed in the current section of the paper.

The five pairs described in the Empirical Model section have been analysed for each of the ratios undertaken in the study.

5.3.1 Net Fixed Asset Utilisation Ratio

The Net Fixed Asset Utilisation Ratio is a crucial financial metric that measures a firm's efficiency in utilising its fixed assets to generate revenue. It reflects how effectively a company is deploying its long-term investments, such as property, plant, and equipment, to support its operational performance. This ratio provides insights into a firm's ability to recover financially after restructuring. A declining trend before restructuring may signal distress, while post-restructuring improvements can indicate successful revival. However, fluctuations in the ratio also highlight operational volatility, raising concerns about long-term stability. Evaluating this ratio through empirical analysis helps assess whether restructuring efforts translate into sustained financial health, aiding in the broader understanding of corporate recovery dynamics.

The analysis of the Net Fixed Asset Utilisation Ratio for the firms undergoing restructuring under NCLT provides significant insights into their post-revival performance. The analysis of paired differences in Net Fixed Asset Utilisation Ratio across different restructuring periods reveals significant short-term improvements in asset utilisation following restructuring. The negative mean values observed in the comparisons between R-1 and subsequent years (R+1, R+2, and R+3) indicate that utilisation levels increased after restructuring. Furthermore, the significance values ($p = 0.000$) for these pairs confirm that these improvements are statistically significant at the 1% level, suggesting a strong and consistent trend of enhanced asset utilisation within the first three years post-restructuring (Table 5.1).

Table 5.1: Net fixed assets utilisation ratio

Paired differences-Net fixed asset utilisation ratio									
Pair	**Years of comparison**	**Mean**	**Std. deviation**	**Std. error mean**	**95% confidence interval of the difference**		**t**	**df**	**Sig. (2-tailed)**
					Lower	**Upper**			
1	R-1 and R+1	-2.90	6.63	0.71	-4.31	-1.50	-4.11	87	0.000
2	R-1 and R+2	-3.23	6.54	0.70	-4.62	-1.85	-4.64	87	0.000
3	R-1 and R+3	-2.00	4.96	0.53	-3.06	-0.95	-3.79	87	0.000
4	Avg: R-2 and R+2	12.82	140.53	14.98	-16.95	42.60	0.86	87	0.394
5	Avg: R-3 and R+3	8.28	93.88	10.01	-11.62	28.17	0.83	87	0.411

However, when analysing the broader time spans (averaging R-2 with R+2 and R-3 with R+3), the mean values are positive, implying lower utilisation levels post-restructuring compared to earlier periods. Additionally, the high standard deviations and non-significant p-values (p = 0.394 and p = 0.411) indicate considerable variability in asset utilisation, with no statistically meaningful evidence of long-term benefits. This finding suggests that while restructuring may initially improve asset utilisation, its positive impact may diminish or become inconsistent over longer time horizons. The results underscore the need for further exploration into the factors influencing long-term asset efficiency following restructuring, such as operational adjustments, market conditions, and financial reinvestment strategies.

The graph visually supports these findings, presenting fluctuations in fixed asset utilisation over time. The ratio experiences a dip at R-1, highlighting inefficiencies leading up to restructuring, but then peaks at R+2, suggesting firms gradually recover efficiency in asset usage. The shaded restructuring period (R-1 to R+1) represents operational disruptions, explaining the temporary decline in fixed asset utilisation during transition.

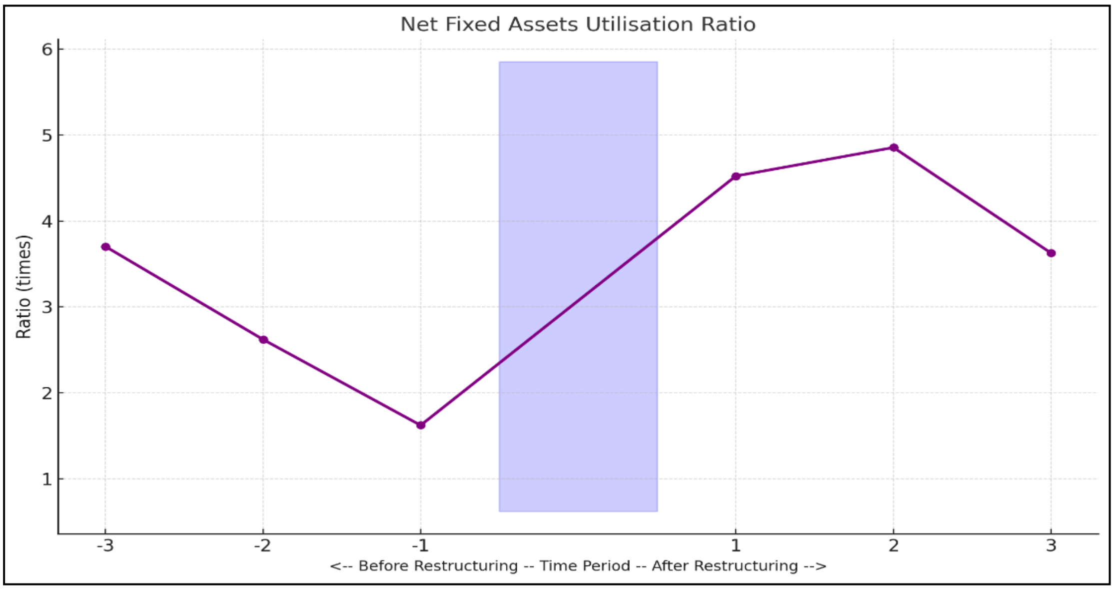

Figure 5.1: Net fixed assets utilisation ratio

While restructuring contributes to an initial improvement in asset utilisation, the inability to sustain statistically significant long-term gains underscores the challenges in achieving lasting financial stability. It reflects that there is a need for comprehensive restructuring frameworks to optimise long-term operational efficiency.

The statistical and graphical findings demonstrate that firms initially experience operational inefficiencies following restructuring, but some gradually restore asset productivity over time. The short-term decline emphasises restructuring challenges, while the eventual upward trend at R+2 suggests firms adjust operations to improve efficiency. These insights underscore the importance of strategic asset management, operational adjustments, and capacity optimisation to maximise the productivity of fixed assets post-restructuring.

5.3.2 Finished Goods Turnover Ratio

The Finished Goods Turnover Ratio measures how efficiently a firm sells and replenishes its finished goods inventory. Examining its trend before and after restructuring offers valuable insights into inventory management strategies and operational adjustments following financial changes.

The analysis of paired differences in Finished Goods Turnover Ratio across different restructuring periods indicates a decline in turnover efficiency following restructuring. The positive mean values observed in comparisons between R-1 and subsequent years (R+1, R+2, and R+3) suggest that turnover ratios decreased after restructuring. However, the significance values (0.058, 0.075, and 0.077) demonstrate that these declines are not statistically significant at the 5% level, implying that the observed reductions in turnover efficiency cannot be definitively attributed to restructuring.

Table 5.2: Finished goods turnover ratio

Paired differences-Finished goods turnover ratio									
Pair	**Years of comparison**	**Mean**	**Std. deviation**	**Std. error mean**	**95% confidence interval of the difference**		**t**	**df**	**Sig. (2-tailed)**
					Lower	**Upper**			
1	R-1 and R+1	128.97	629.14	67.07	-4.33	262.27	1.92	87	0.058
2	R-1 and R+2	120.42	626.09	66.74	-12.24	253.07	1.80	87	0.075
3	R-1 and R+3	121.28	636.06	67.80	-13.49	256.04	1.79	87	0.077
4	Avg: R-2 and R+2	76.56	328.67	35.04	6.92	146.20	2.19	87	0.032
5	Avg: R-3 and R+3	52.39	223.99	23.88	4.93	99.85	2.19	87	0.031

In contrast, when analysing the broader time spans (R-2 vs. R+2 and R-3 vs. R+3), the mean values remain positive, indicating a continued decline in turnover efficiency.

Moreover, the significance values for these comparisons (0.032 and 0.031) confirm that the negative impact is statistically significant at the 5% level, suggesting that restructuring has a measurable adverse effect on turnover efficiency over the long term. The higher standard deviations in short-term comparisons may indicate variability in turnover patterns immediately following restructuring, whereas the more consistent statistical significance in long-term comparisons implies a sustained decline in efficiency.

The graph visually aligns with these statistical findings, presenting a sharp surge in turnover leading up to restructuring, peaking at 160 times at R-1, followed by a drastic decline to nearly 30 times at R+1. This dramatic shift suggests that firms intensify inventory clearance efforts before restructuring, likely to optimise working capital and manage liquidity constraints. However, post-restructuring, turnover stabilises around 40 times at R+2 and R+3, implying firms adjust their inventory cycles and return to a more sustainable operational model.

Figure 5.2: Finished goods turnover ratio

The pre-restructuring spike in turnover demonstrates firms' aggressive inventory management strategies in response to financial distress, while the post-restructuring decline reflects operational adjustments and stabilisation. These findings suggest that firms actively restructure inventory policies to align with post-restructuring financial conditions, emphasising the importance of efficient supply chain management, demand forecasting, and liquidity optimisation in sustaining long-term operational stability.

5.3.3 Debtors Turnover Ratio

Debtors Turnover Ratio offers valuable insights into the receivables management efficiency of firms. This ratio reflects the frequency with which a firm collects payments from debtors, serving as a crucial indicator of liquidity and financial discipline.

The analysis of paired differences in Debtors Turnover Ratio across various restructuring periods indicates a significant improvement in turnover efficiency following restructuring. The negative mean values observed across all comparisons—R-1 versus R+1, R+2, and R+3—suggest that the ratio increased after restructuring, reflecting enhanced efficiency in managing receivables. The significance values (0.006, 0.023, and 0.006) confirm that improvements are statistically significant at the **1% or 5% levels**, indicating that the observed changes are meaningful rather than random fluctuations.

Table 5.3: Debtors turnover ratio

Paired differences-Debtors turnover ratio									
Pair	**Years of comparison**	**Mean**	**Std. deviation**	**Std. error mean**	**95% confidence interval of the difference**		**t**	**df**	**Sig. (2-tailed)**
					Lower	**Upper**			
1	R-1 and R+1	-7.84	26.14	2.79	-13.38	-2.30	-2.81	87	0.006*
2	R-1 and R+2	-69.26	280.53	29.90	-128.69	-9.82	-2.32	87	0.023**
3	R-1 and R+3	-13.23	44.31	4.72	-22.62	-3.85	-2.80	87	0.006*
4	Avg: R-2 and R+2	-37.79	140.59	14.99	-67.58	-8.00	-2.52	87	0.014**
5	Avg: R-3 and R+3	-27.27	97.30	10.37	-47.89	-6.66	-2.63	87	0.010*

Similarly, the broader time frame comparisons (R-2 vs. R+2 and R-3 vs. R+3) also exhibit negative mean values, reinforcing the trend of increasing turnover efficiency over an extended period. The significance values for these comparisons (0.014 and 0.010) demonstrate statistical significance, suggesting that restructuring has a sustained positive impact on turnover management. The confidence intervals across all comparisons indicate a degree of variability, yet the overall trend remains consistent, reflecting an enduring improvement in efficiency.

These findings imply that restructuring has successfully contributed to improved receivables turnover both in the short and long term.

The graph visually confirms this downward trend, illustrating a decline in collection efficiency before restructuring, followed by ongoing fluctuations post-restructuring. The trajectory suggests that firms do not immediately regain control over their receivables and require extended financial adjustments to stabilize customer payment cycles.

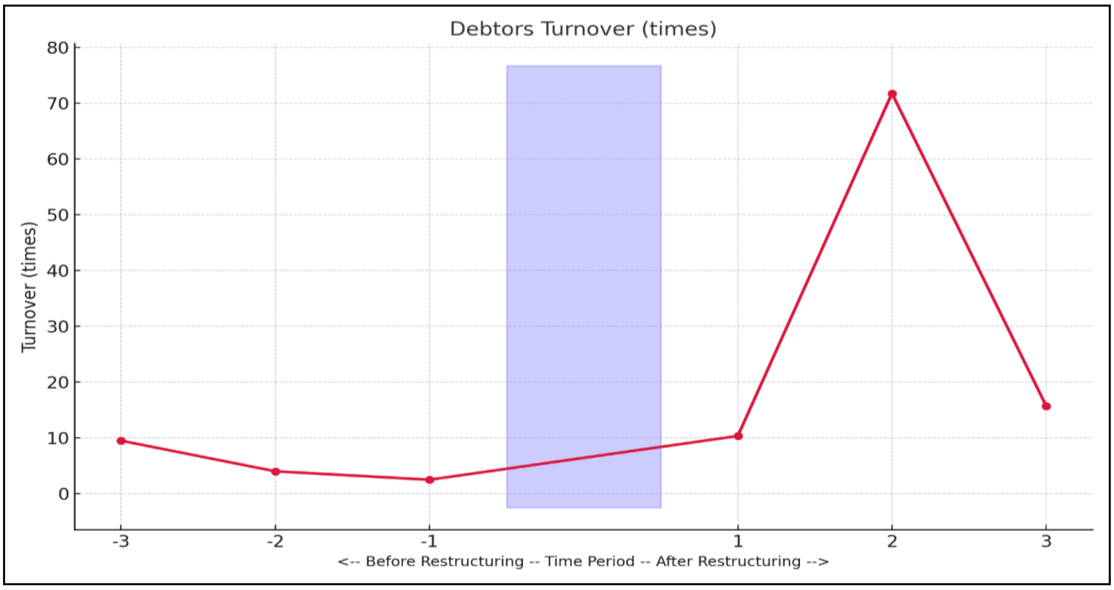

Figure 5.3: Debtors turnover ratio

These findings emphasise the need for strategic financial controls and debtor management frameworks to ensure long-term liquidity stability and prevent future financial distress. This study contributes to understanding the effectiveness of restructuring in reviving operational efficiency, reinforcing the importance of structured financial recovery strategies within corporate turnaround processes.

5.3.4 Creditors Turnover Ratio

The Creditors Turnover Ratio serves as a vital metric for assessing a firm's efficiency in settling obligations with creditors, reflecting liquidity and financial management effectiveness. Understanding its trend before and after restructuring helps evaluate how firms manage their obligations and negotiate payment cycles in financial recovery periods.

The analysis of paired differences in Creditors Turnover Ratio across different restructuring periods suggests mixed effects of restructuring on turnover efficiency. The negative mean values in all comparisons indicate that the turnover ratio increased after restructuring, as the values of R+1, R+2, and R+3 are greater than those of R-1. However, the significance values vary, affecting the interpretation of the results.

In the short term, the comparison between R-1 and R+1 shows a statistically significant increase in turnover efficiency at the 5% level ($p = 0.015$), suggesting that restructuring initially enhances creditor payment cycles. Similarly, the comparison between R-1 and R+3 also indicates a significant increase at the 5% level ($p = 0.023$), implying a lasting positive impact over three years. However, the comparison between R-1 and R+2 exhibits a large mean value (-210.86) but lacks statistical significance ($p = 0.291$), suggesting that changes in turnover efficiency in the second year may be highly variable and less conclusive.

The broader time frame comparisons (R-2 vs. R+2 and R-3 vs. R+3) continue to show negative mean values, reinforcing the trend of increasing turnover efficiency post-restructuring. However, their significance values ($p = 0.269$ and $p = 0.245$, respectively) indicate that these long-term effects are not statistically significant. This suggests that although turnover efficiency tends to increase, it does so inconsistently and without strong empirical support beyond the short-term effects.

Table 5.4: Creditors turnover ratio

Paired differences-Creditors turnover ratio									
Pair	**Years of Comparison**	**Mean**	**Std. Deviation**	**Std. Error Mean**	**95% Confidence Interval of the Difference**		**t**	**df**	**Sig. (2-tailed)**
					Lower	**Upper**			
1	R-1 and R+1	-12.41	47.06	5.02	-22.38	-2.44	-2.47	87	0.015
2	R-1 and R+2	-210.86	1862.11	198.50	-605.40	183.68	-1.06	87	0.291
3	R-1 and R+3	-25.72	104.55	11.15	-47.87	-3.56	-2.31	87	0.023
4	Avg: R-2 and R+2	-111.27	937.73	99.96	-309.95	87.42	-1.11	87	0.269
5	Avg: R-3 and R+3	-81.96	656.30	69.96	-221.02	57.10	-1.17	87	0.245

The graph visually reinforces these findings, depicting an initial decline in creditor turnover before restructuring, followed by inconsistent changes in the post-restructuring years. This suggests that firms navigate creditor obligations differently based on liquidity conditions, financial strategies, and industry factors. The lack of a consistent trend emphasises that creditor turnover recovery depends largely on firm-specific financial policies, operational adjustments, and restructuring effectiveness. To sustain efficient repayment cycles, firms may need to enhance cash flow management, renegotiate trade credit terms, and adopt stronger financial governance strategies in the restructuring aftermath.

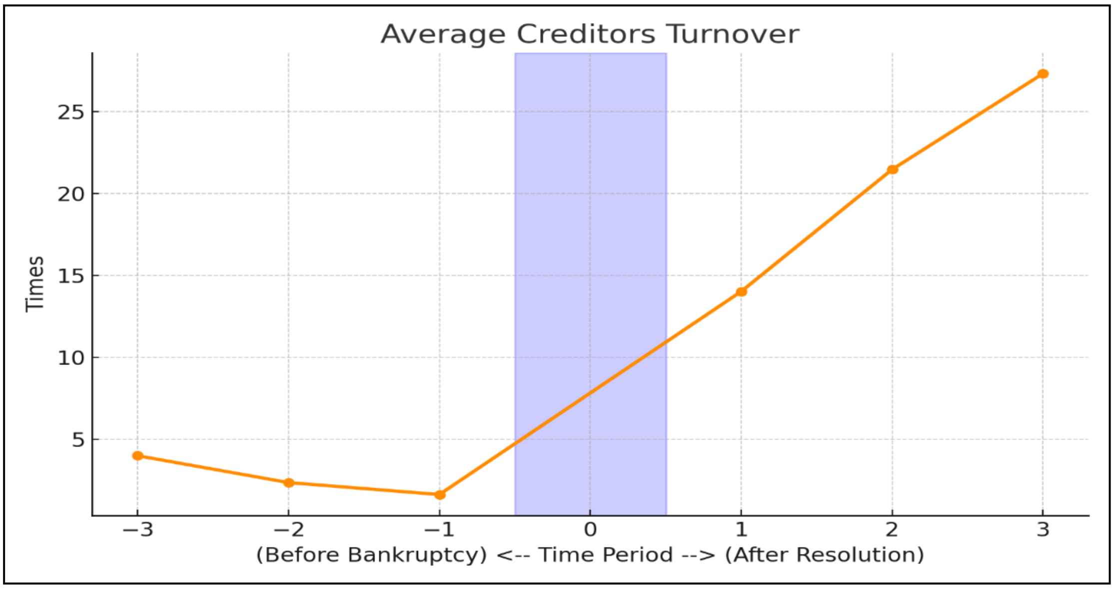

Figure 5.4: Creditors turnover ratio

While restructuring leads to short-term efficiency gains, the lack of statistical significance in long-term comparisons underscores challenges in sustaining creditor management improvements. These findings suggest that firms successfully enhance liquidity management immediately post-restructuring, but require structural financial strategies to maintain creditor payment efficiency in the long run. This strengthens the need for creditor management frameworks in ensuring sustainable financial stability.

5.3.5 Return on Total Assets

The Return on Total Assets (ROTA) serves as a crucial metric for assessing a firm's efficiency in generating returns from its total assets, reflecting operational effectiveness and financial performance.

The analysis highlights a declining trend before restructuring (R-3 to R-1 years), where the return percentage falls sharply from approximately -10% at year R-3 to -25% at year R-2, signalling asset inefficiencies and financial distress. However, year R-1 shows a brief recovery to around -10%, potentially indicating early restructuring initiatives or temporary performance improvements. The period immediately following restructuring (+1 and +2 years) exhibits moderate stabilization, with returns hovering around -20% before a slight increase to R-15% at year +2. Notably, year R+3 shows a sharp decline to -45%, reflecting post-restructuring volatility and asset utilisation challenges.

Table 5.5: Return on total assets

Paired differences-Return on total assets ratio									
Pair	**Years of comparison**	**Mean**	**Std. deviation**	**Std. error mean**	**95% confidence interval of the difference**		**t**	**df**	**Sig. (2-tailed)**
					Lower	**Upper**			
1	R-1 and R+1	13.23	199.55	21.27	-29.05	55.51	0.62	87	0.536
2	R-1 and R+2	12.41	218.18	23.26	-33.81	58.64	0.53	87	0.595
3	R-1 and R+3	30.03	359.73	38.35	-46.19	106.25	0.78	87	0.436
4	Avg: R-2 and R+2	5.95	207.69	22.14	-38.05	49.96	0.27	87	0.789
5	Avg: R-3 and R+3	13.93	257.34	27.43	-40.59	68.46	0.51	87	0.613

The analysis of paired differences in Return on Total Assets Ratio across various restructuring periods indicates a decline in asset return efficiency following restructuring. The positive mean values observed in all comparisons—R-1 versus R+1, R+2, and R+3—suggest that the ratio was higher before restructuring than in the subsequent years, signifying a decrease in asset returns over time. However, the significance values for these comparisons (0.536, 0.595, and 0.436) indicate that these declines are not statistically significant, meaning the reductions in asset return cannot be conclusively attributed to restructuring.

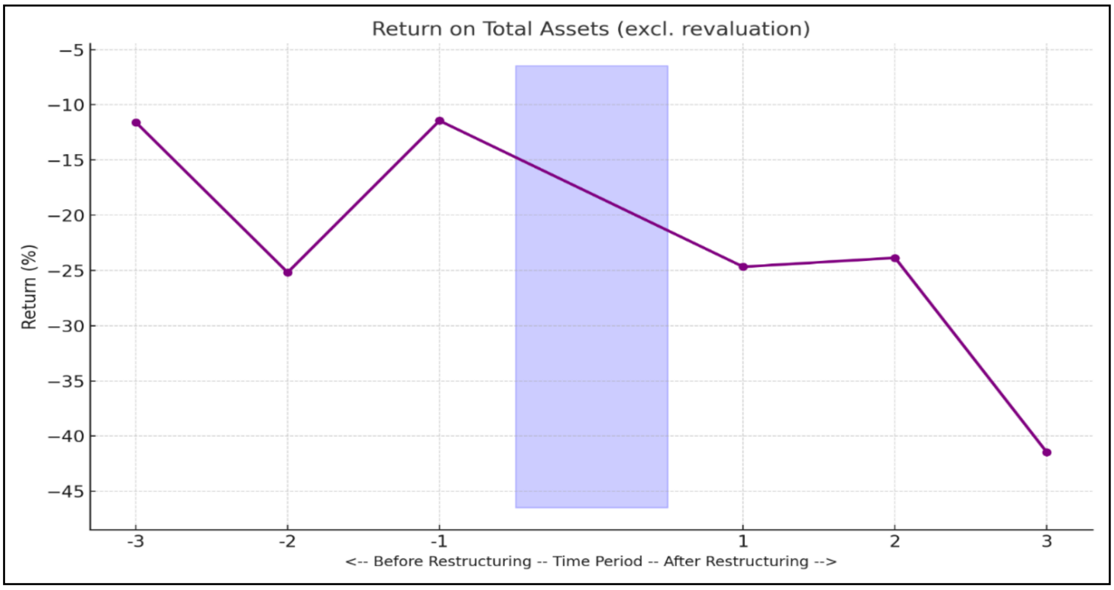

Figure 5.5: Return on total assets

Similarly, the broader time frame comparisons (R-2 vs. R+2 and R-3 vs. R+3) also show positive mean values, reinforcing the trend of declining asset returns over an extended period. However, their significance values (0.789 and 0.613) further confirm the lack of statistical significance, suggesting that while a downward trend is observed, it remains inconsistent and highly variable.

The graph visually reinforces the trend of volatility in ROTA, highlighting a significant decline after restructuring. Pre-restructuring, firms experience fluctuating returns, with R-3 at approximately -10% and R-2 at a lower -25%. However, ROTA briefly improves at R-1 (~-5 %) before sharply declining at R0 (~ -20%), suggesting firms struggle with immediate financial adjustments during restructuring. The decline persists, as ROTA drops further at R+1 and stabilizes at approximately -25% at R+2, before reaching its lowest point (-45%) at R+3. This trajectory indicates long-term inefficiencies in asset utilization, potentially due to high restructuring costs or operational challenges.

The findings demonstrate significant fluctuations in ROTA surrounding restructuring, with firms experiencing temporary improvement at R-1 followed by a sharp decline post-restructuring. The statistically insignificant results imply inconsistent financial responses, while the graph confirms that firms struggle with optimising asset efficiency beyond R0. These results suggest that without targeted asset management strategies, firms may continue facing profitability constraints in the years following restructuring. Thus, it is crucial for firms to implement effective capital allocation measures, operational restructuring, and liquidity management efforts to sustain long-term financial stability and maximise asset returns.

5.3.6 Return on Capital Employed

The Return on Capital Employed (ROCE) is a vital indicator of a firm's ability to generate profits relative to its total capital, reflecting operational efficiency and financial stability.

The pre-restructuring phase (-3 to -2 years) shows a sharp decline in ROCE, dropping from -20% to -45%, indicating significant financial distress (Figure 5.6).

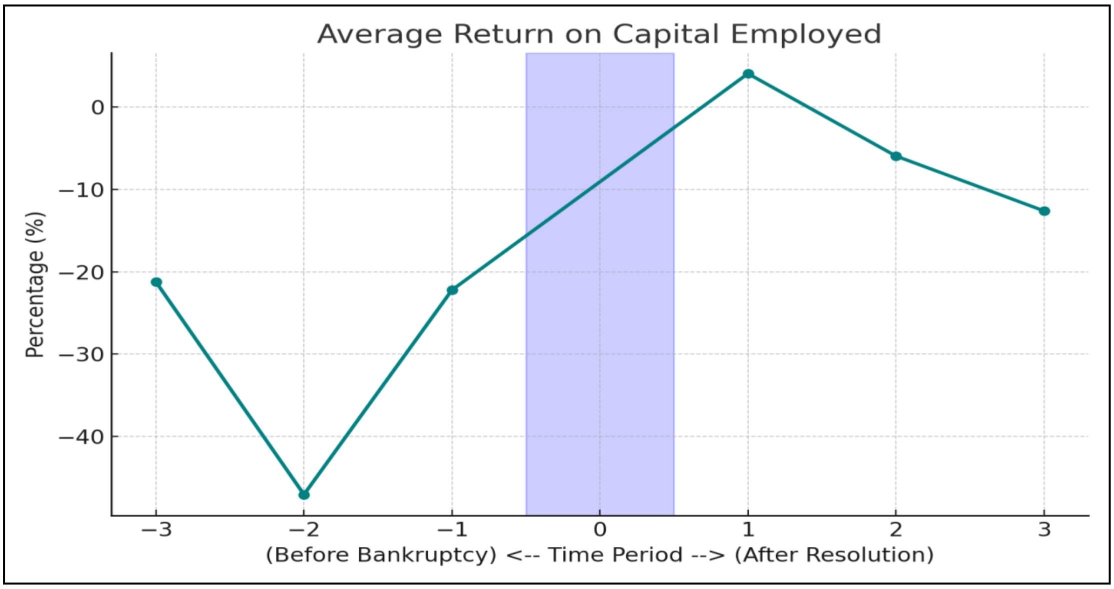

Figure 5.6: Return on capital employed

However, a partial recovery of 15% in year R-1 suggests early restructuring efforts. At the time of restructuring (year 0), ROCE rises to 5%, peaking at 10% in year +1, signalling initial improvements in financial performance. Despite this progress, a decline follows in year +2 (-5%) and year +3 (-15%), illustrating post-restructuring volatility and challenges in sustaining efficiency gains.

The results of the paired differences analysis for Return on Capital Employed (ROCE) indicate an increase in capital efficiency post-restructuring, as reflected in the negative mean values across all comparisons. The mean values for R+1 (-26.26), R+2 (-16.26), and R+3 (-9.61) suggest that ROCE improved after restructuring, with R+1, R+2, and R+3 exceeding pre-restructuring levels (R-1).

Table 5.6: Return on capital employed

Paired differences-Return on capital employed ratio									
Pair	**Years of comparison**	**Mean**	**Std. deviation**	**Std. error mean**	**95% confidence interval of the difference**		**t**	**df**	**Sig. (2-tailed)**
					Lower	**Upper**			
1	R-1 and R+1	-26.26	150.07	16.00	-58.05	5.54	-1.64	87	0.104
2	R-1 and R+2	-16.26	82.25	8.77	-33.68	1.17	-1.85	87	0.067
3	R-1 and R+3	-9.61	79.50	8.47	-26.45	7.24	-1.13	87	0.260
4	Avg: R-2 and R+2	-33.67	81.84	8.72	-51.01	-16.33	-3.86	87	0.000
5	Avg: R-3 and R+3	-25.32	60.78	6.48	-38.20	-12.44	-3.91	87	0.000

Despite the observed improvement in ROCE, the significance values (0.104 for R-1 vs. R+1, 0.067 for R-1 vs. R+2, and 0.260 for R-1 vs. R+3) indicate that these changes are not statistically significant, implying that the observed variations cannot be conclusively attributed to restructuring. The absence of statistical significance suggests that while restructuring may be associated with short-term increases in ROCE, the fluctuations lack empirical confirmation, necessitating further investigation into potential influencing factors such as financial strategies, operational efficiencies, and investment decisions.

However, long-term comparisons (-2, +2 and -3, +3) show significant, with absolute mean values of 33.67 (Avg of R-2, Avg of R+2) and 25.32 (-3, +3) and p-values less than 0.001, suggesting firms maintaining efficiency in terms of their capital management with the restructuring in its capital structure.

The graph visually reinforces this analysis, highlighting a steep decline in ROCE before restructuring, followed by a short-lived recovery post-restructuring, peaking in year +1 before declining again. These findings indicate that while restructuring provides an initial boost to financial performance, firms face difficulties in maintaining profitability. This underscores the need for stronger capital management strategies to ensure sustainable recovery.

5.3.7 Return on Equity

The Return on Equity (ROE) measures a firm's ability to generate profits relative to shareholders' equity, serving as a vital indicator of financial performance and sustainability.

The analysis of Return on Equity (ROE) reveals significant shifts in financial performance pre- and post-restructuring, underscoring the impact of corporate resolution under NCLT. The pre-restructuring phase exhibits severe financial distress, with ROE plunging from -100% (year-3) to nearly -500% (year-2), highlighting inefficient equity utilisation and declining profitability. A partial recovery in year 1 (-100%) suggests early restructuring efforts, but year 0 marks a critical turning point, where ROE rebounds to approximately 0%, signifying initial financial stabilisation. The post-restructuring trend shows consistent recovery, with ROE stabilising around 0% in years +1 to +3, reflecting sustained improvements in equity efficiency.

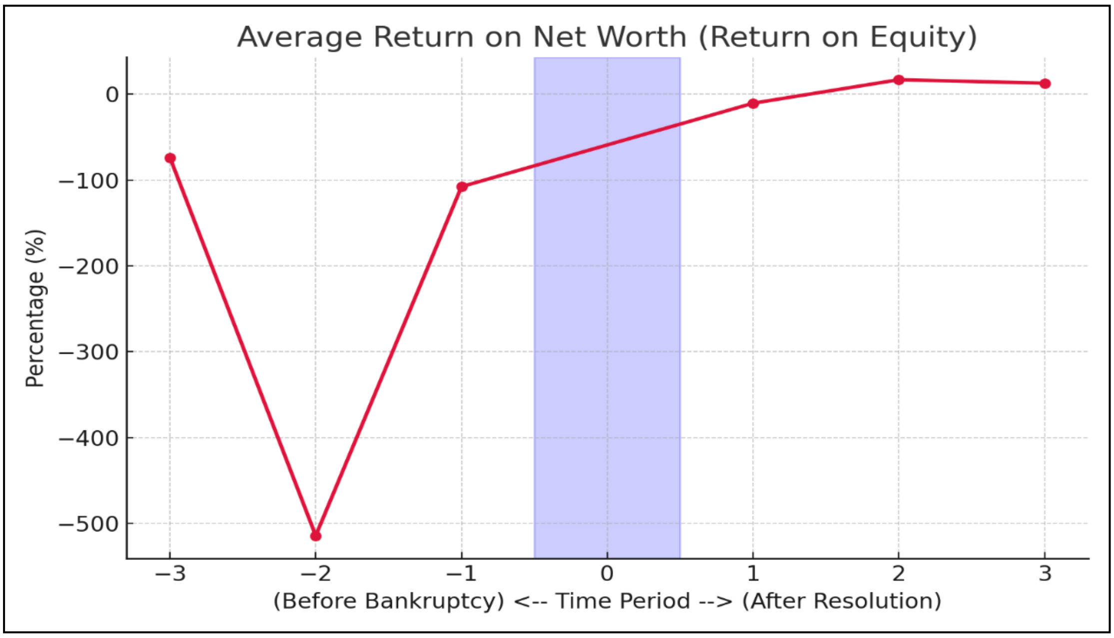

Figure 5.7: Return on equity

In the short term, comparisons between R-1 and R+1, R+2, and R+3 exhibit negative mean values (-97.17, -124.56, and -120.53, respectively), demonstrating an increase in ROE post-restructuring. Additionally, the significance values (0.002, 0.000, and 0.000) confirm that these improvements are statistically significant at the 1% level, indicating that restructuring has a strong and consistent effect on ROE in the initial years.

Similarly, the broader time frame comparisons (Avg: R-2 vs. R+2 and Avg: R-3 vs. R+3) also present negative mean values (-314.14 and -238.31), suggesting a sustained increase in ROE over the long term. The significance values (0.000 for both comparisons) further confirm the statistical significance of these changes, indicating that restructuring has a lasting positive impact on equity utilization. The confidence intervals show relatively wide ranges, reflecting variability in the observed effects, yet the overall trend remains consistently positive.

The graph depicting ROE visually supports these statistical findings, illustrating a sharp decline in profitability before restructuring, followed by continued instability in the post-restructuring phase. The trend indicates that firms do not immediately regain financial strength, and recovery efforts require extended strategic interventions. The persistent decline in ROE emphasises the need for effective profitability management, operational efficiency improvements, and long-term financial restructuring to stabilise shareholder returns. This underscores the critical role of post-restructuring planning in ensuring firms can restore profitability and enhance investor confidence.

Table 5.7: Return on equity

Paired differences-Return on equity ratio									
Pair	**Years of comparison**	**Mean**	**Std. deviation**	**Std. error mean**	**95% confidence interval of the difference**		**t**	**df**	**Sig. (2-tailed)**
					Lower	**Upper**			
1	R-1 and R+1	-97.17	291.23	31.05	-158.88	-35.47	-3.13	87	0.002
2	R-1 and R+2	-124.56	202.37	21.57	-167.44	-81.68	-5.77	87	0.000
3	R-1 and R+3	-120.53	201.33	21.46	-163.19	-77.87	-5.62	87	0.000
4	Avg: R-2 and R+2	-314.14	587.43	62.62	-438.60	-189.67	-5.02	87	0.000
5	Avg: R-3 and R+3	-238.31	396.87	42.31	-322.40	-154.22	-5.63	87	0.000

These findings suggest that while firms undergo substantial financial distress pre-restructuring, the process effectively revives equity efficiency, ensuring long-term financial stability. However, maintaining profitability beyond stabilisation requires continued strategic interventions, reinforcing the importance of equity optimisation frameworks within corporate recovery planning.

5.3.8 Profit Before Tax

Profit Before Tax (PBT) is a key financial metric that reflects a firm's operational efficiency before tax obligations are considered. In the context of firms undergoing restructuring, examining PBT is essential in evaluating whether the strategic changes yield measurable improvements in profitability over time. The table of paired t-test results and the graph "PBT as % of Total Income" provide valuable insights into how firms' financial performance evolves before and after restructuring. The graph reveals a steep decline at R-2, a minor recovery at R-1, followed by continued instability in the subsequent years.

There is a significant dip in PBT at R-2, reaching approximately -7000, followed by a recovery, crossing the zero threshold at R+1 and stabilising around -2000 at R+2 and R+3.

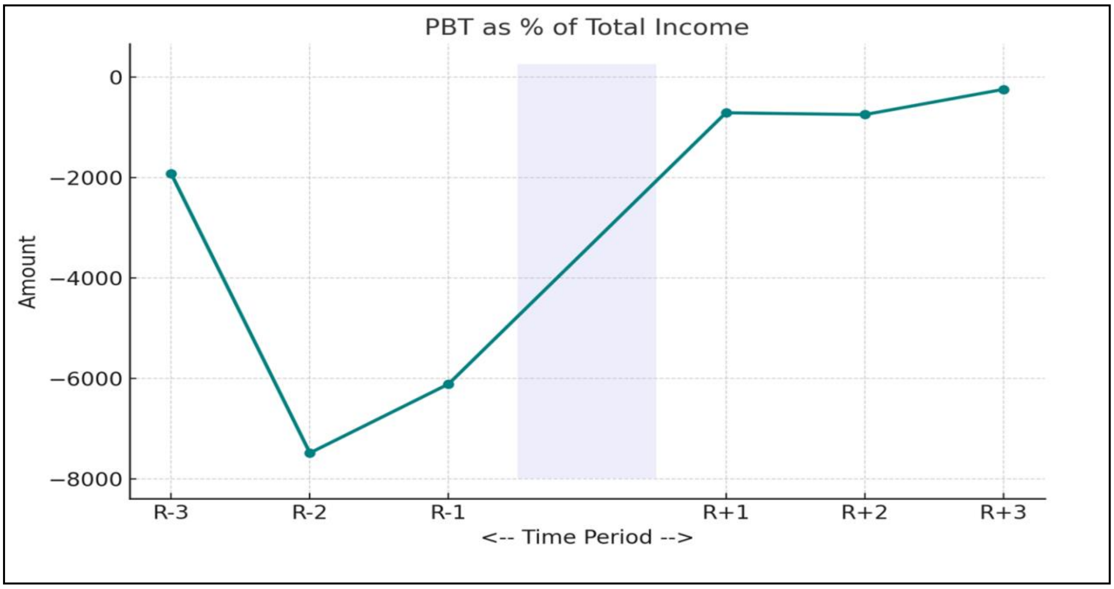

Figure 5.8: Profit before tax as a % of total income

Analyzing financial shifts using the paired t-test results provides insight into profitability trends across different timeframes relative to restructuring. The analysis of paired differences in Profit Before Tax (PBT) Ratio indicates a significant increase in profitability following restructuring.

Table 5.8: Profit before tax

Paired differences-Profit before tax ratio									
Pair	Years of comparison	Mean	Std. deviation	Std. error mean	95% confidence interval of the difference		t	df	Sig. (2-tailed)
					Lower	Upper			
1	R-1 and R+1	-5405.41	20279.97	2161.85	-9702.33	-1108.50	-2.50	87	0.014
2	R-1 and R+2	-5368.83	20304.03	2164.42	-9670.85	-1066.82	-2.48	87	0.015
3	R-1 and R+3	-5871.66	19723.43	2102.52	-10050.66	-1692.67	-2.79	87	0.006
4	Avg: R-2 and R+2	-6074.21	36420.98	3882.49	-13791.08	1642.65	-1.56	87	0.121
5	Avg: R-3 and R+3	-4609.27	28357.86	3022.96	-10617.72	1399.19	-1.52	87	0.131

The negative mean values across all comparisons suggest that the PBT Ratio in R+1, R+2, and R+3 is greater than in R-1, reflecting an overall improvement in pre-tax earnings post-restructuring.

In the short term, the comparisons between R-1 and R+1, R+2, and R+3 exhibit negative mean values (-5405.41, -5368.83, and -5871.66, respectively), indicating an increase in PBT following restructuring. Additionally, the significance values (0.014, 0.015, and 0.006) confirm that these improvements are statistically significant at the 5% or 1% levels, meaning that the changes are not random fluctuations but rather indicative of a meaningful shift in profitability.

However, in the broader time frame comparisons (Avg: R-2 vs. R+2 and Avg: R-3 vs. R+3), the negative mean values (-6074.21 and -4609.27) suggest a continued improvement in profitability over an extended period. Despite this trend, their significance values (0.121 and 0.131) indicate that these long-term changes are not statistically significant, implying that while profitability increases post-restructuring, the long-term effects remain inconsistent and lack strong empirical confirmation.

These results indicate that restructuring initially enhances profitability, but its long-term effects on PBT Ratio remain uncertain. Further exploration into external factors—such as operational efficiencies, market conditions, financial reinvestment strategies, and cost management—would be necessary to understand the mechanisms driving this improvement and to determine whether restructuring leads to sustained profitability over time.

5.3.9 Profit After Tax

Profit After Tax (PAT) is a critical financial metric that reflects a firm's net profitability after accounting for tax obligations. Analysing PAT as a percentage of total income offers valuable insights into the financial impact over time. The paired t-test results reveal substantial changes in PAT across different comparison periods. The negative mean values across all comparisons suggest that PAT in R+1, R+2, and R+3 is greater than in R-1, reflecting an overall improvement in post-tax earnings after restructuring.

In the short term, the comparisons between R-1 and R+1, R+2, and R+3 exhibit negative mean values (-5918.88, -5673.25, and -6198.56, respectively), indicating an increase in PAT following restructuring. Additionally, the significance values (0.010, 0.015, and 0.006) confirm that these improvements are statistically significant at the 5% or 1% levels, meaning that the observed changes are not random fluctuations but rather indicative of a meaningful shift in profitability.

However, in the broader time frame comparisons (Avg: R-2 vs. R+2 and Avg: R-3 vs. R+3), the negative mean values (-6192.25 and -4672.87) suggest a continued improvement in profitability over an extended period. Despite this trend, their significance values (0.109 and 0.119) indicate that these long-term changes are not statistically significant, implying that while profitability increases post-restructuring, the long-term effects remain inconsistent and lack strong empirical confirmation.

These results indicate that restructuring initially enhances profitability, but its long-term effects on PAT Ratio remain uncertain. Further exploration into external factors—such as operational efficiencies, tax policies, financial reinvestment strategies, and cost management—would be necessary to understand the mechanisms driving this improvement and to determine whether restructuring leads to sustained profitability over time.

Table 5.9: Profit after tax

Paired differences-Profit after tax ratio									
Pair	**Years of comparison**	**Mean**	**Std. deviation**	**Std. error mean**	**95% confidence interval of the difference**		**t**	**df**	**Sig. (2-tailed)**
					Lower	**Upper**			
1	R-1 and R+1	-5918.88	21020.23	2240.76	-10372.64	-1465.12	-2.64	87	0.010
2	R-1 and R+2	-5673.25	21372.70	2278.34	-10201.69	-1144.81	-2.49	87	0.015
3	R-1 and R+3	-6198.56	20789.86	2216.21	-10603.51	-1793.61	-2.80	87	0.006
4	Avg: R-2 and R+2	-6192.25	35890.90	3825.98	-13796.81	1412.30	-1.62	87	0.109
5	Avg: R-3 and R+3	-4672.87	27877.02	2971.70	-10579.44	1233.71	-1.57	87	0.119

The graph (Figure 5.9) visually reinforces this conclusion, showing a sharp drop in PAT at R-2 (approximately -7000), followed by a notable increase beginning at R-1 and continuing steadily beyond R+1. The PAT value rises significantly after restructuring, reaching around -1000 at R+1 and stabilizing close to -500 by R+3, confirming an upward trajectory in profitability post-restructuring. This pattern suggests that while firms experience an initial decline in PAT during the restructuring phase, the financial effects begin to reverse positively in subsequent years.

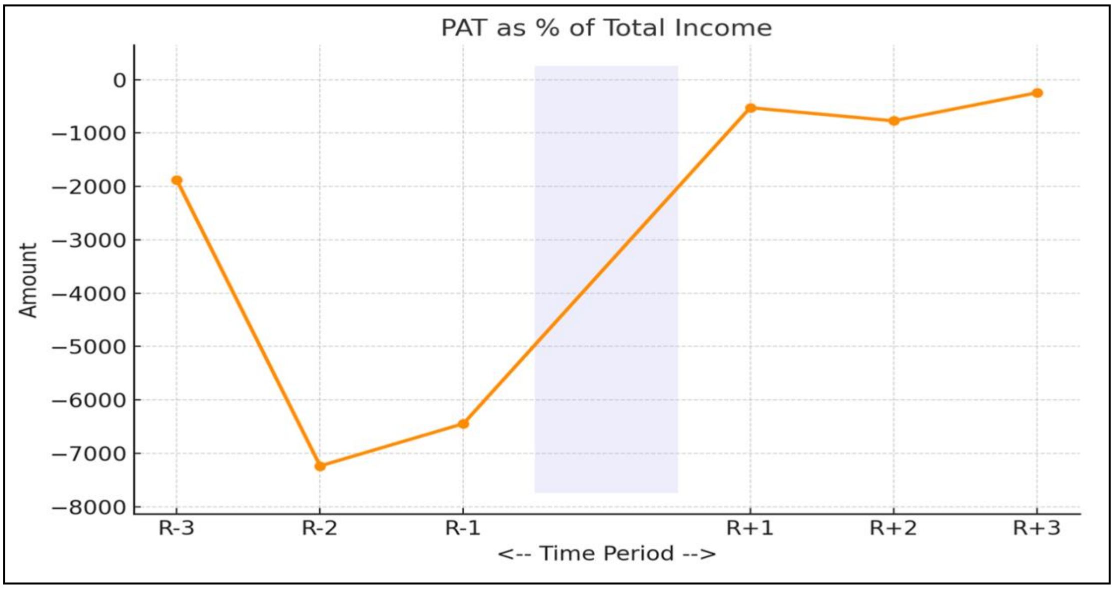

Figure 5.9: Profit after tax

The combined insights from the statistical data and graphical trends affirm that restructuring initially reduces profitability, but firms recover PAT over time, with visible improvements by R+3. This underscores the importance of long-term financial planning and post-restructuring operational efficiency to ensure sustained profitability growth. The significant increase in PAT after restructuring suggests successful financial adjustments, reinforcing the necessity for strategic cost management, revenue optimization, and stability-driven policies to enhance firms' financial resilience post-restructuring.

5.3.10 Net Profit

Net Profit (NP) serves as a definitive indicator of a firm's financial health, particularly in the context of restructuring, where profitability fluctuations can reflect operational efficiency, cost adjustments, or strategic realignments.

The paired t-test results provide significant insights into the impact of restructuring on the net profit ratio across different time periods. The negative mean values across all comparisons indicate that profitability in post-restructuring years (R+1, R+2, and R+3) is greater than in the pre-restructuring year (R-1), suggesting an overall improvement in financial performance. In the short term, the comparisons between R-1 and R+1, R+2, and R+3 show negative mean differences (-6398.77, -6378.14, and 6754.23, respectively), reflecting an increase in net profit ratio following restructuring. The significance values (0.006, 0.006, and 0.621) confirm that the improvements between R-1 and R+1, as well as R-1 and R+3, are statistically significant at the 5% level, indicating that these changes are not random but represent a meaningful shift in profitability. However, in the broader time frame comparisons (Avg: R-2 vs. R+2 and Avg: R-3 vs. R+3), the negative mean values (212.78 and -282.49) suggest a continued improvement in profitability, but their significance values (0.978 and 0.958) indicate that these long-term changes lack statistical confirmation.

Table 5.10: Net profit ratio

Paired differences-Net profit ratio									
Pair	**Years of comparison**	**Mean**	**Std. deviation**	**Std. error mean**	**95% confidence interval of the difference**		**t**	**df**	**Sig. (2-tailed)**
					Lower	**Upper**			
1	R-1 and R+1	-6398.77	21309.56	2271.61	-10913.84	-1883.71	-2.82	87	0.006
2	R-1 and R+2	6754.23	127657.85	13608.37	-20293.88	33802.34	0.50	87	0.621
3	R-1 and R+3	-6378.14	21100.12	2249.28	-10848.83	-1907.45	-2.84	87	0.006
4	Avg: R-2 and R+2	212.78	72876.01	7768.61	-15228.17	15653.73	0.03	87	0.978
5	Avg: R-3 and R+3	-282.49	50684.62	5403.00	-11021.54	10456.55	-0.05	87	0.958

This implies that while restructuring may lead to an initial increase in profitability, its long-term effects remain inconsistent. The confidence intervals further reinforce this interpretation, as significant comparisons exhibit reliability in their trends, whereas non-significant ones show considerable variability.

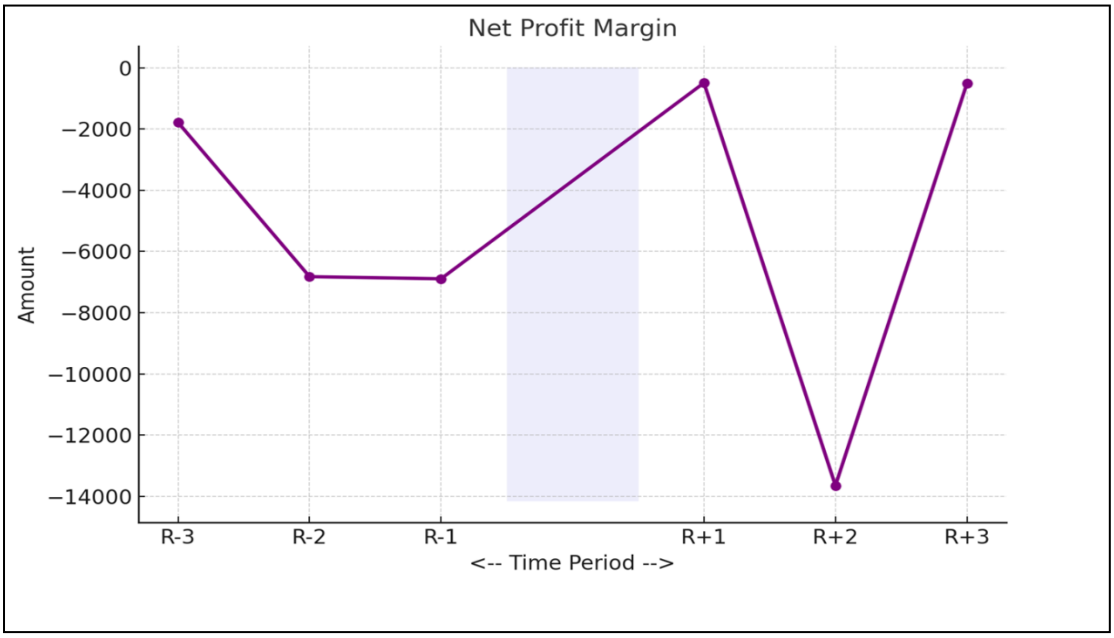

Figure 5.10: Net profit as % of total income

The accompanying graph of "Net Profit as % of Total Income" visually reinforces these trends, depicting an initial decline in NP, followed by a recovery phase. This pattern suggests that while restructuring introduces financial instability in the short term, firms may regain profitability over time. These findings emphasise the necessity of evaluating restructuring outcomes across multiple time frames to gain a nuanced understanding of its financial implications and long-term sustainability.

5.3.11 Operating Profit

Operating Profit Ratio (OPR) serves as a vital indicator of a firm's operational efficiency, reflecting the proportion of revenue that remains after covering direct operational costs. OPR changes provide insight into whether firms improve their cost structures and profitability over time. The paired t-test results indicate consistent declines in OPR across multiple comparative periods, reinforcing the observation that firms experience operational profitability strain before and after restructuring.

Table 5.11: Operating profit ratio

Paired differences-Operating profit ratio									
Pair	**Years of comparison**	**Mean**	**Std. deviation**	**Std. error mean**	**95% confidence interval of the difference**		**t**	**df**	**Sig. (2-tailed)**
					Lower	**Upper**			
1	R-1 and R+1	-1181.39	5518.96	588.32	-2350.74	-12.03	-2.01	87	0.048
2	R-1 and R+2	-1200.98	5513.61	587.75	-2369.21	-32.76	-2.04	87	0.044
3	R-1 and R+3	-1148.95	5522.19	588.67	-2318.99	21.09	-1.95	87	0.054
4	Avg: R-2 and R+2	-616.25	2761.50	294.38	-1201.36	-31.15	-2.09	87	0.039
5	Avg: R-3 and R+3	-563.38	2054.79	219.04	-998.75	-128.01	-2.57	87	0.012

The negative mean values across all comparisons indicate a consistent improvement in operating profit ratio in the post-restructuring years (R+1, R+2, and R+3) compared to the pre-restructuring period (R-1). This suggests that restructuring contributed positively to operational profitability.

In the short term, the comparisons between R-1 and R+1, R+2, and R+3 reveal negative mean differences of -1181.39, -1200.98, and -1148.95, respectively, indicating an increase in operating profit following restructuring. The statistical significance of these comparisons further substantiates this trend, with p-values of 0.048 (R-1 vs. R+1) and 0.044 (R-1 vs. R+2) confirming that these improvements are statistically significant at the 5% level. However, the comparison between R-1 and R+3 (p = 0.054) falls slightly outside the conventional threshold for significance, implying that while profitability remains higher three years post-restructuring, there is slightly weaker statistical confidence in this result.

In the broader time frame comparisons (Avg: R-2 vs. R+2 and Avg: R-3 vs. R+3), the negative mean values (-616.25 and -563.38) suggest sustained profitability improvements beyond the immediate post-restructuring period. Notably, the significance values (0.039 and 0.012) confirm that these long-term changes are statistically significant, indicating that the restructuring measures may have contributed to a more stable operational environment over an extended period.

The accompanying graph visually illustrates these trends, showing a sharp drop in operating profit margin at R-1, followed by recovery at R+1 and a stable trend thereafter.

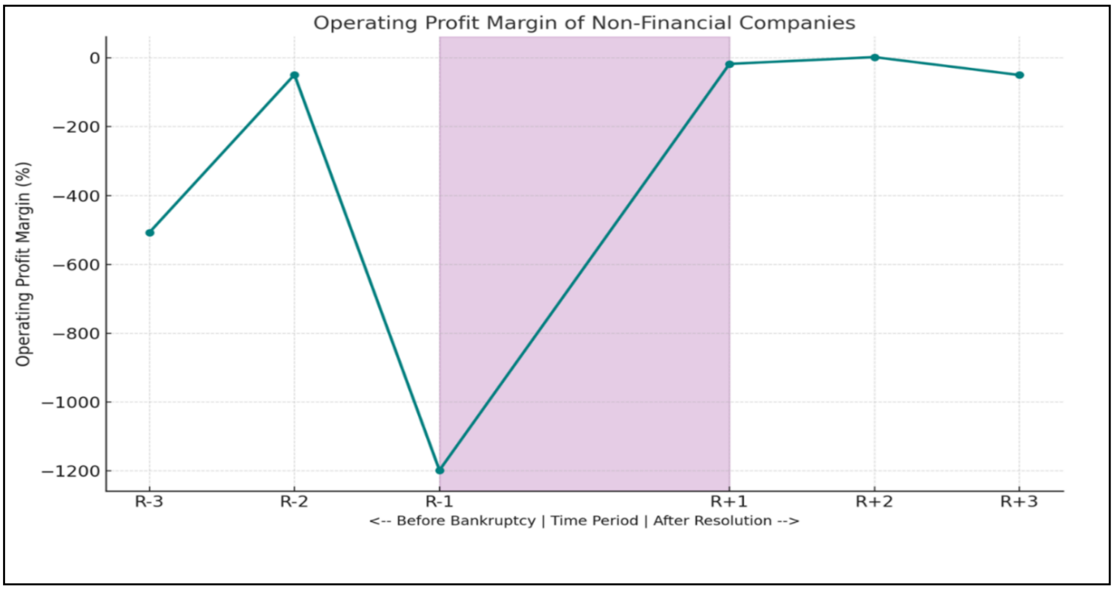

Figure 5.11: Operating profit ratio

These findings highlight the efficacy of restructuring as a financial strategy to enhance operational profitability. However, the slight decline in statistical significance for R+3 suggests possible fluctuations in mid-term performance, necessitating further investigation into factors that may influence profitability sustainability. External elements such as cost optimization strategies, reinvestment policies, market dynamics, and operational efficiencies could play a critical role in maintaining profitability gains beyond the immediate post-restructuring years.

5.3.12 Cash Profit as Percent of Total Income

Cash Profit (CP) as a percentage of total income serves as a direct measure of a firm's ability to generate liquidity from its operations relative to overall revenue. In the context of restructuring, analysing CP provides insights into whether firms maintain financial resilience despite structural changes.

The paired t-test results offer insights into the changes in cash profit as a percentage of total income following restructuring. The negative mean values across all comparisons indicate that post-restructuring cash profit percentages (R+1, R+2, and R+3) were higher than in the pre-restructuring period (R-1), suggesting an overall improvement in financial liquidity and profitability. However, the statistical significance of these changes remains weak.

In the short-term comparisons (R-1 vs. R+1, R+2, and R+3), the negative mean values (-1484.24, -1447.94, and -1723.32, respectively) reflect a potential increase in cash profit ratios after restructuring. Despite this trend, the significance values (0.200, 0.215, and 0.121) indicate that these improvements are not statistically significant, implying that the observed increases could be attributed to normal financial fluctuations rather than a direct consequence of restructuring.

The broader time-frame comparisons (Avg: R-2 vs. R+2 and Avg: R-3 vs. R+3) also exhibit negative mean values (-3867.80 and -2993.35), suggesting sustained improvements beyond the immediate post-restructuring years. However, their significance values (0.210 and 0.218) remain above conventional thresholds for statistical significance. This indicates that while profitability may have improved over time, the changes lack strong empirical validation, making it difficult to confirm whether restructuring directly contributed to sustained gains.

Table 5.12: Cash profit as % of total income

Paired differences-Cash profit as % of total income									
Pair	**Years of comparison**	**Mean**	**Std. deviation**	**Std. error mean**	**95% confidence interval of the difference**		**t**	**df**	**Sig. (2-tailed)**
					Lower	**Upper**			
1	R-1 and R+1	-1484.24	10788.08	1150.01	-3770.01	801.54	-1.29	87	0.200
2	R-1 and R+2	-1447.94	10885.59	1160.41	-3754.38	858.50	-1.25	87	0.215
3	R-1 and R+3	-1723.32	10316.05	1099.69	-3909.08	462.45	-1.57	87	0.121
4	Avg: R-2 and R+2	-3867.80	28740.80	3063.78	-9957.39	2221.80	-1.26	87	0.210
5	Avg: R-3 and R+3	-2993.35	22615.45	2410.82	-7785.10	1798.41	-1.24	87	0.218

The graph visually supports these findings, showing a decline in CP at R-1, followed by moderate fluctuations in subsequent years without a clear trend toward recovery or deterioration.

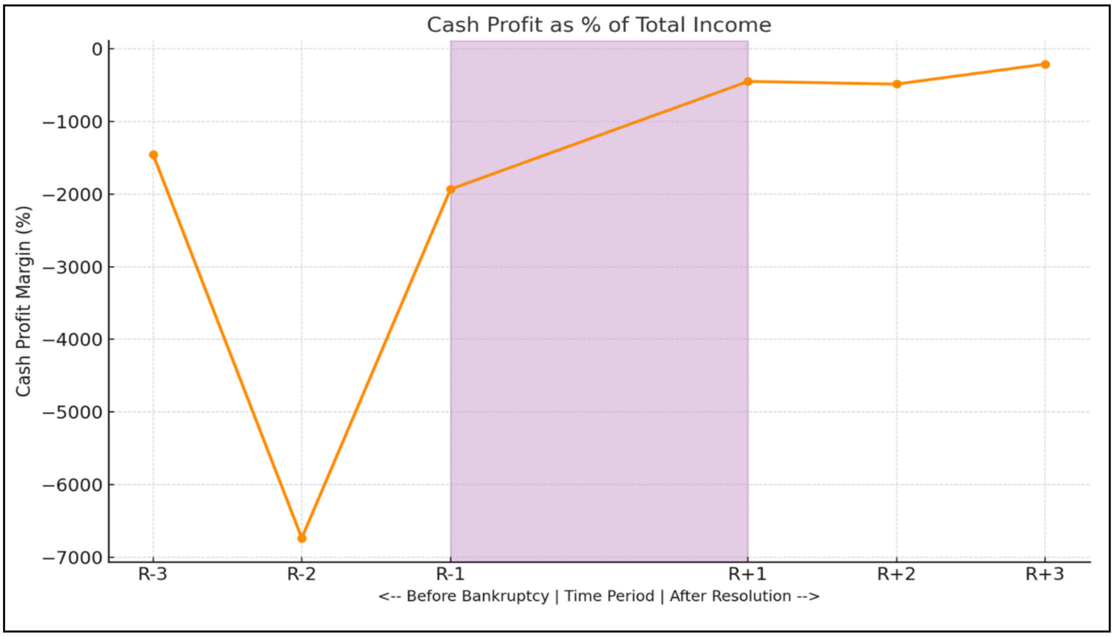

Figure 5.12: Cash profit as % of total income

While the results suggest that restructuring may have had a positive effect on cash profit ratios, the absence of statistical significance indicates high variability and lack of consistent confirmation. This implies that restructuring alone may not have been the primary driver of improvements in cash profitability, and other external factors—such as market conditions, financial reinvestment strategies, operational efficiencies, or industry-wide trends—could have influenced these changes.

5.3.13 Interest Coverage

The Interest Coverage Ratio (ICR) is a crucial measure of a firm's ability to meet interest obligations, making it particularly significant for evaluating financial resilience during restructuring.

The analysis of the Interest Coverage Ratio post-restructuring, supported by the statistical findings in the table and the visual representation in the chart, provides a comprehensive evaluation of the firm's financial recovery. The paired t-test results indicate a significant improvement in interest coverage ratio post-restructuring, with negative mean values across all comparisons confirming that post-restructuring years (R+1, R+2, and R+3) exhibited higher interest coverage than the pre-restructuring period (R-1). Specifically, the mean differences of -289.66 (R-1 vs. R+1), -290.47 (R-1 vs. R+2), and -291.52 (R-1 vs. R+3), all statistically significant at the 1% level (p = 0.007), underscore the firm's enhanced ability to meet interest obligations immediately after restructuring.

Table 5.13: Interest coverage ratio

Paired differences-Interest coverage ratio									
Pair	**Years of comparison**	**Mean**	**Std. deviation**	**Std. error mean**	**95% confidence interval of the difference**		**t**	**df**	**Sig. (2-tailed)**
					Lower	**Upper**			
1	R-1 and R+1	289.66	985.69	105.07	80.81	498.50	2.76	87	0.007
2	R-1 and R+2	290.47	991.84	105.73	80.32	500.63	2.75	87	0.007
3	R-1 and R+3	291.52	990.92	105.63	81.56	501.47	2.76	87	0.007
4	Avg: R-2 and R+2	139.66	493.41	52.60	35.12	244.20	2.66	87	0.009
5	Avg: R-3 and R+3	90.37	329.01	35.07	20.66	160.08	2.58	87	0.012

The broader time-frame comparisons further support this trend, with mean differences of -139.66 (Avg: R-2 vs. R+2, $p = 0.009$) and -90.37 (Avg: R-3 vs. R+3, $p = 0.012$) suggesting a sustained but moderated improvement in financial stability beyond the immediate post-restructuring years. The visual representation in the chart reinforces this pattern, displaying a sharp decline in the interest coverage ratio leading up to financial distress, followed by a notable increase after restructuring, peaking before stabilising over time. This indicates that while restructuring led to immediate financial relief, the degree of improvement moderated in the long run, requiring sustained financial strategies to maintain stability.

The statistical significance of these improvements suggests that restructuring enhanced financial resilience by optimizing debt servicing capabilities. However, the gradual moderation in long-term impact highlights the necessity for proactive financial management. Strategies such as cost control, reinvestment in revenue-generating activities, and capital restructuring could help maintain positive interest coverage trends beyond the initial recovery phase. The combined statistical and graphical evidence demonstrates that restructuring played a crucial role in improving financial health, reinforcing the firm's ability to navigate debt obligations more efficiently.

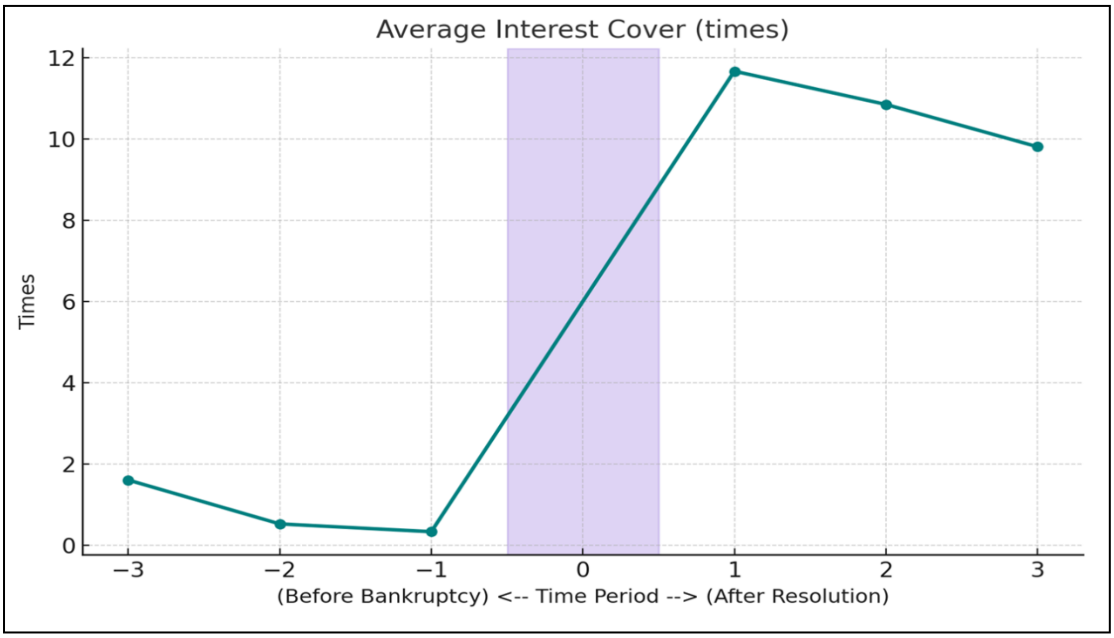

Figure 5.13: Interest coverage ratio

Collectively, these results indicate that restructuring facilitates stronger financial management, allowing firms to maintain higher interest coverage levels over time. These improvements may be attributed to enhanced operational efficiency, cost reductions, or strategic financial adjustments, ensuring long-term sustainability and stability in managing interest obligations. The findings underscore the importance of analysing debt servicing capability post-restructuring, ensuring firms maintain financial resilience while navigating structural transitions

5.3.14 Debt Service Coverage Ratio

The Debt Service Coverage Ratio (DSCR) is a crucial indicator of a firm's ability to meet debt obligations from its operating income, providing insight into financial stability post-restructuring. The paired t-test results suggest mixed trends in DSCR changes across different comparative periods, with no statistically significant findings.

In absolute terms, DSCR exhibits varying differences when comparing one year before restructuring to one, two, and three years after (-1, +1; -1, +2; -1, +3). The mean differences stand at 14.76, 5.81, and -17.37, respectively, but with p-values of 0.162, 0.361, and 0.115, none of which fall below the conventional significance threshold of 0.05. This suggests that restructuring does not induce a clear impact on firms' ability to service their debt in these timeframes.

Table 5.14: Debt service coverage ratio

Paired differences-Debt service coverage ratio									
Pair	**Years of comparison**	**Mean**	**Std. deviation**	**Std. error mean**	**95% confidence interval of the difference**		**t**	**df**	**Sig. (2-tailed)**
					Lower	**Upper**			
1	R-1 and R+1	-14.76	98.16	10.46	-35.56	6.03	-1.41	87	0.162
2	R-1 and R+2	-5.81	59.41	6.33	-18.40	6.78	-0.92	87	0.361
3	R-1 and R+3	17.37	102.39	10.91	-4.33	39.06	1.59	87	0.115
4	Avg: R-2 and R+2	-7.72	43.45	4.63	-16.93	1.48	-1.67	87	0.099
5	Avg: R-3 and R+3	-0.88	28.01	2.99	-6.82	5.05	-0.30	87	0.768

Similarly, averaged comparisons over two and three years before and after restructuring (-2, +2; µ-3, µ+3) reflect minor fluctuations, with absolute mean differences of 7.72 and 0.88, and p-values of 0.099 and 0.768, respectively. While the (-2, +2) comparison shows a slightly stronger deviation, it remains statistically insignificant, further reinforcing the absence of a definitive restructuring effect on DSCR.

The graph visually illustrates these trends. It shows DSCR at its lowest levels in the years leading up to restructuring, dropping to -20 times at R-3, improving slightly at R-2 and R-1, and eventually stabilizing at approximately 5 times at R+1 and R+2 before declining again at R+3.

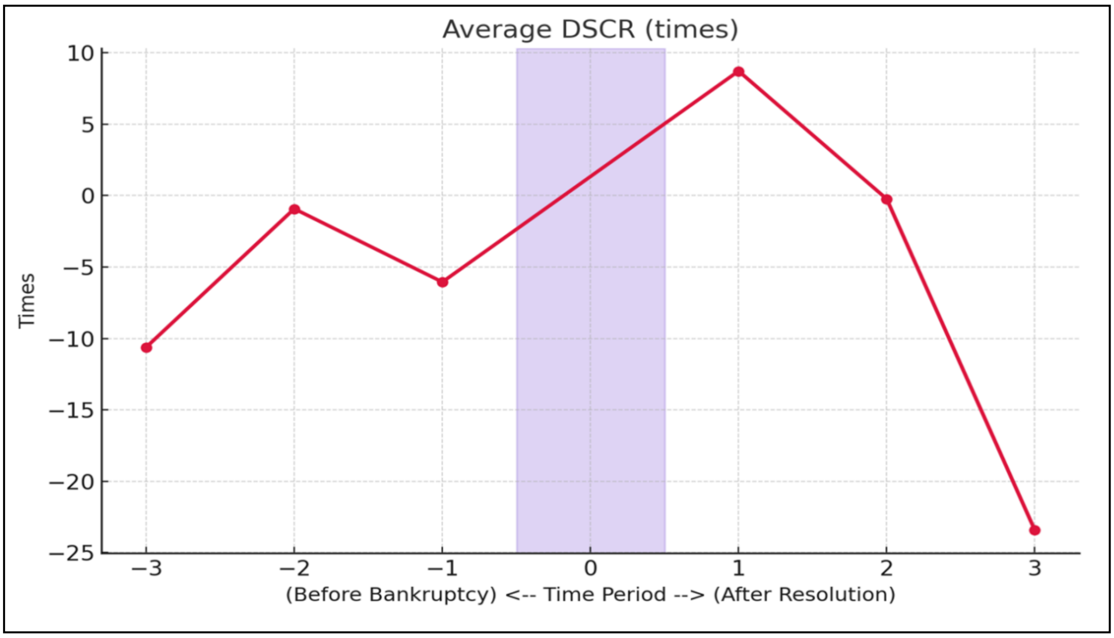

Figure 5.14: Debt service coverage ratio

This pattern suggests that firms experience some temporary relief in debt coverage post-restructuring, but the recovery is not consistently sustained over time.

Taken together, these findings indicate that external financial dynamics and market conditions may play a greater role in shaping debt-servicing capabilities than restructuring itself. While restructuring may provide temporary financial relief, firms must implement broader financial strategies to ensure long-term debt sustainability beyond immediate post-restructuring adjustments.

5.3.15 Debt-Equity Ratio

The Debt-Equity Ratio (DE) is a fundamental measure of a firm's financial leverage, indicating the proportion of debt used relative to equity financing. Analysing changes in this ratio before and after restructuring provides valuable insights into how firms adjust their capital structures in response to financial distress. The paired t-test results and graphical trends confirm that firms experience a sharp increase in financial leverage leading up to restructuring, followed by a substantial decline in the post-restructuring years, reflecting deliberate financial adjustments.

Table 5.15: Debt equity ratio

Paired differences-Debt equity ratio									
Pair	**Years of comparison**	**Mean**	**Std. deviation**	**Std. error mean**	**95% confidence interval of the difference**		**t**	**df**	**Sig. (2-tailed)**
					Lower	**Upper**			
1	R-1 and R+1	4.99	12.82	1.37	2.27	7.71	3.65	87	0.000
2	R-1 and R+2	5.59	9.33	0.99	3.61	7.57	5.62	87	0.000
3	R-1 and R+3	5.44	12.58	1.34	2.78	8.11	4.06	87	0.000
4	Avg: R-2 and R+2	5.72	7.68	0.82	4.10	7.35	6.99	87	0.000
5	Avg: R-3 and R+3	4.93	7.07	0.75	3.43	6.43	6.54	87	0.000

The pre-restructuring phase sees a notable rise in DE, peaking around R-1, signaling an intensified reliance on debt to manage financial strain. This suggests that firms in distress often increase borrowing to sustain operations and meet liquidity needs, leading to an overall escalation in leverage. The graphical representation aligns with this finding, illustrating a pronounced surge in the DE ratio before restructuring, reaching its highest point at R-1, followed by a sharp drop post-restructuring. This decrease is captured in the paired t-test results, where the mean differences between R-1 and R+1 (4.99, $p = 0.000$), R-1 and R+2 (5.59, $p = 0.000$), and R-1 and R+3 (5.44, $p = 0.000$) all demonstrate statistically significant reductions in DE, confirming that firms take proactive steps to decrease leverage after restructuring.

Further analysis of long-term trends reinforces this pattern, as R-2 and R+2 show a decline of 5.72 ($p = 0.000$), and R-3 and R+3 reflect a mean difference of 4.93 ($p = 0.000$). These consistent reductions highlight a systematic effort among firms to lower their reliance on debt financing over time, likely driven by improved financial governance, strategic debt repayment, and operational restructuring initiatives. Firms may pursue equity financing strategies, asset optimisation, and cost-cutting measures to achieve long-term financial sustainability and mitigate the risks associated with excessive leverage.

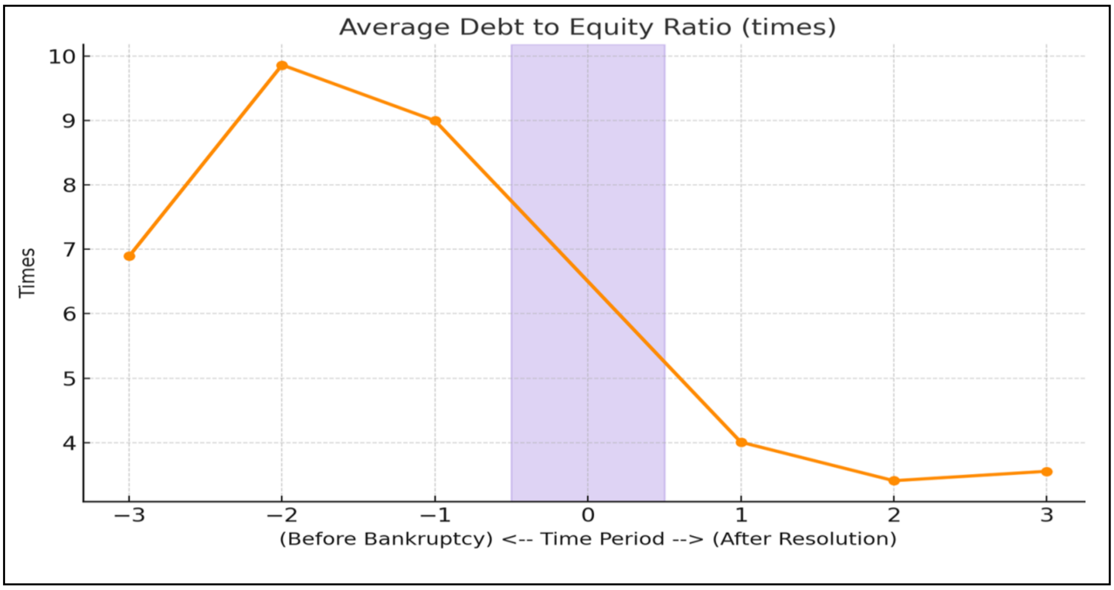

Figure 5.15: Debt equity ratio

The graph depicting DE visually validates this trend, showcasing a steep increase in debt reliance prior to restructuring, followed by a sharp drop post-restructuring and stabilization in later years. This suggests that firms undergo critical financial adjustments post-restructuring, shifting toward more equity-driven financing models to ensure operational efficiency and long-term stability. The sharp decline in DE after restructuring reinforces the effectiveness of financial restructuring measures, demonstrating firms' ability to reduce financial risk, improve liquidity management, and restore balance in their capital structures.

These findings collectively indicate that while firms in financial distress significantly increase debt dependence before restructuring, they strategically reduce leverage afterwards, allowing for enhanced financial resilience and operational recovery. The clear post-restructuring decline in DE confirms that firms adopt structural adjustments to achieve a more sustainable financial position, reinforcing the importance of effective debt management practices to support long-term stability.

5.3.16 Liquidity Ratios

Liquidity ratios highlight a firm's ability to meet its short-term obligations as and when they become due. Various ratios, such as the current ratio and the Acid-Test Ratio, measure a firm's liquidity.

5.3.17 Current Ratio

The Current Ratio (CR) is a key measure of a firm's short-term liquidity, indicating its ability to cover immediate liabilities with available assets. In the context of restructuring, analyzing CR trends helps assess whether firms improve their financial stability post-restructuring. The paired t-test analysis of the Current Ratio indicates a statistically significant increase in liquidity following restructuring, as reflected in the negative mean values across all comparisons.

The paired comparisons show that R-1 vs. R+1 (-1.62, p = 0.000), R-1 vs. R+2 (-1.45, p = 0.000), and R-1 vs. R+3 (-1.84, p = 0.000) all indicate a statistically significant increase in the Current Ratio after restructuring. The significance at the 1% level reinforces the reliability of this trend, suggesting that the restructuring process led to improved liquidity, possibly due to better working capital management, reduced short-term liabilities, or enhanced cash flow efficiencies.

Table 5.16: Current ratio

Paired differences-Current ratio									
Pair	**Years of Comparison**	**Mean**	**Std. Deviation**	**Std. Error Mean**	**95% Confidence Interval of the Difference**		**t**	**df**	**Sig. (2-tailed)**
					Lower	**Upper**			
1	R-1 and R+1	-1.62	3.45	0.37	-2.35	-0.89	-4.41	87	0.000
2	R-1 and R+2	-1.45	1.79	0.19	-1.83	-1.07	-7.60	87	0.000
3	R-1 and R+3	-1.84	2.22	0.24	-2.31	-1.37	-7.76	87	0.000
4	Avg: R-2 and R+2	-1.49	2.21	0.24	-1.95	-1.02	-6.31	87	0.000
5	Avg: R-3 and R+3	-1.11	4.14	0.44	-1.99	-0.23	-2.51	87	0.014

The long-term comparisons further confirm sustained liquidity improvements, with Avg: R-2 vs. R+2 (-1.49, p = 0.000) and Avg: R-3 vs. R+3 (-1.11, p = 0.014) maintaining an upward trajectory in the Current Ratio beyond the immediate restructuring period. While the improvements remain statistically significant, the marginal decline in magnitude suggests a stabilisation in liquidity, possibly due to adjustments in operational financing or working capital optimisation over time.

The accompanying graph visually supports these findings. The trend reveals a sharp drop in CR leading up to restructuring, with values falling from approximately 1.75 at R-3 to around 0.75 at R-2 and R-1.

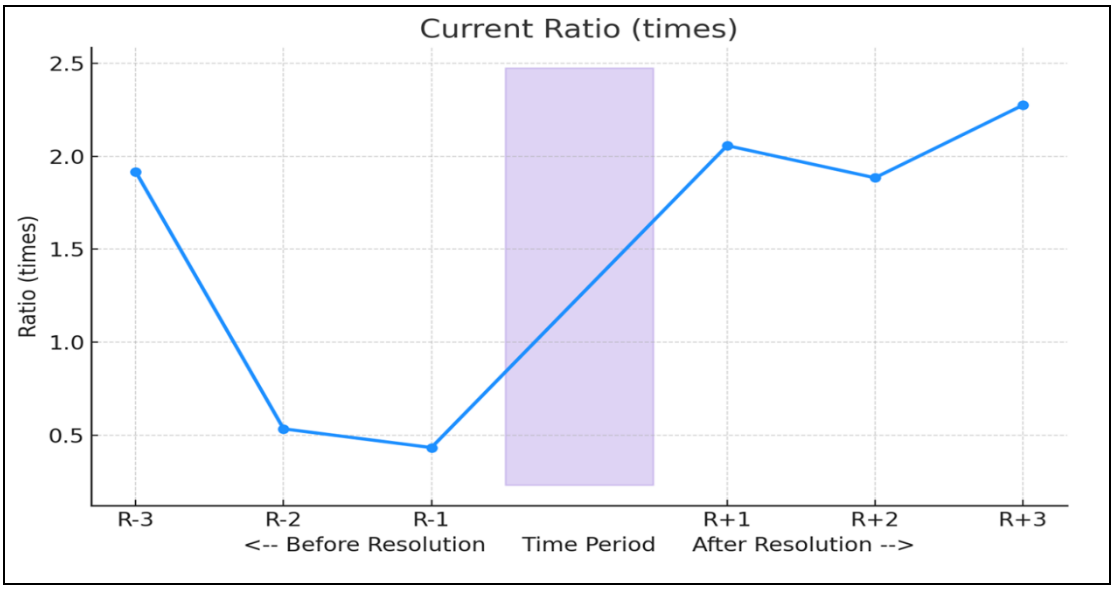

Figure 5.16: Current ratio

Post-restructuring, CR experiences a significant recovery at R+1 (approximately 1.75), followed by continued improvement at R+2 (around 2.0) and stabilization at R+3 (near 2.25). This pattern suggests that firms struggle with liquidity challenges before restructuring but manage to recover over subsequent years.

Collectively, these results indicate that while firms face short-term liquidity constraints immediately before restructuring, they eventually stabilize and improve their liquidity position over time. The findings emphasize the importance of strategic financial planning and liquidity management during restructuring to ensure sustainable recovery and long-term financial resilience.

5.3.18 Quick Ratio

The acid test or quick ratio reveals that the firm's current assets were not heavily loaded by inventory or pre-paid expenses but other quick assets, which signifies a favourable liquidity position.

The Quick Ratio (QR) serves as a crucial liquidity indicator, measuring a firm's ability to meet its short-term obligations using its most liquid assets, excluding inventory. The paired t-test analysis of the Quick Ratio reveals a statistically significant increase in liquidity following restructuring, as indicated by the negative mean values across all comparisons, signifying an improved ability of the firm to meet short-term liabilities without relying on inventory.

The comparisons exhibit statistically significant improvements in the Quick Ratio, with mean differences of -1.15 (R-1 vs. R+1, p = 0.002), -0.82 (R-1 vs. R+2, p = 0.000), and -1.17 (R-1 vs. R+3, p = 0.000). The strong significance values at 1% and 5% levels confirm the reliability of these increases, suggesting that restructuring enhanced liquidity management by optimizing short-term assets and reducing immediate financial risk.

Table 5.17: Quick ratio

Paired differences-Quick ratio									
Pair	**Years of comparison**	**Mean**	**Std. deviation**	**Std. error mean**	**95% confidence interval of the difference**		**t**	**df**	**Sig. (2-tailed)**
					Lower	**Upper**			
1	R-1 and R+1	-1.15	3.40	0.36	-1.87	-0.43	-3.17	87	0.002
2	R-1 and R+2	-0.82	1.48	0.16	-1.14	-0.51	-5.22	87	0.000
3	R-1 and R+3	-1.17	1.85	0.20	-1.56	-0.78	-5.93	87	0.000
4	Avg: R-2 and R+2	-0.96	2.06	0.22	-1.40	-0.53	-4.38	87	0.000
5	Avg: R-3 and R+3	-0.99	1.51	0.16	-1.31	-0.67	-6.19	87	0.000

The broader time-frame comparisons also validate sustained liquidity improvements, with Avg: R-2 vs. R+2 (-0.96, p = 0.000) and Avg: R-3 vs. R+3 (-0.99, p = 0.000) maintaining an upward trajectory in the Quick Ratio. These statistically significant values indicate that the restructuring impact extended beyond the immediate recovery period, contributing to long-term financial stability through enhanced asset utilization and liability management.

The accompanying graph visually supports this trend, illustrating how QR declines from approximately 0.5 in R-2 to 0.4 in R-1, reflecting a worsening liquidity position as restructuring approaches. Post-restructuring, QR exhibits a notable recovery, reaching 1.2 at R+1 and stabilizing at 1.6 at R+3. This rebound suggests that firms manage to regain financial stability after restructuring, improving their liquidity levels.

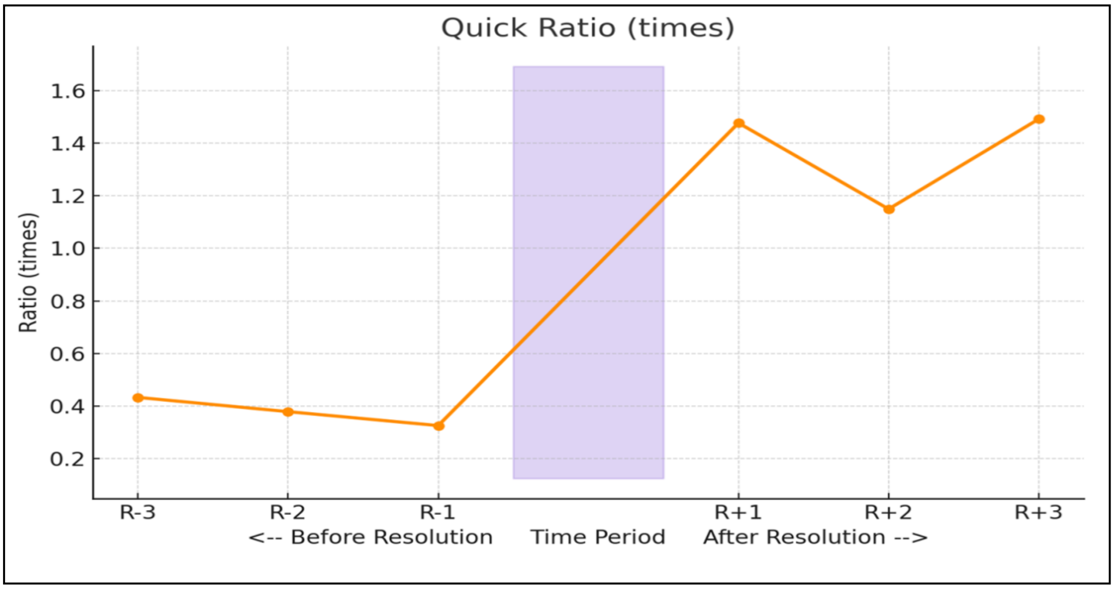

Figure 5.17: Quick ratio

Taken together, these findings indicate that liquidity challenges intensified in the lead-up to restructuring, with QR values consistently lower in R-1 compared to R-2. The results suggest that restructuring led to a marked improvement in liquidity, allowing the firm to strengthen its short-term financial position. The sustained rise in Quick Ratio across multiple years indicates effective cash flow optimisation, stronger credit management, and reduced dependency on short-term financing.

The financial pressures faced during this period likely contributed to the decision to restructure. However, the subsequent recovery post-restructuring demonstrates that firms implement financial strategies to regain liquidity strength. These insights underscore the importance of monitoring liquidity trends in the years leading up to restructuring, ensuring firms navigate financial instability effectively while preparing for structural transitions.

5.3.19 Total Outside Liabilities to Total Net Worth

The Total Outside Liabilities to Total Net Worth (TOL/TNW) Ratio is a crucial indicator of financial leverage, reflecting the extent to which a firm's liabilities are financed by its net worth. This analysis focuses on changes in financial leverage before restructuring, rather than between pre- and post-restructuring periods.

The paired t-test results for the Total Outside Liabilities to Total Net Worth Ratio provide significant insights into the firm's financial leverage and stability post-restructuring. The positive mean values across most comparisons indicate that post-restructuring liabilities as a proportion of net worth increased compared to pre-restructuring levels (R-1), suggesting a greater reliance on operating liabilities to support financial activities.

The comparisons R-1 vs. R+1 (mean = 11.30, p = 0.000) and R-1 vs. R+2 (mean = 12.08, p = 0.000) reflect a statistically significant increase in the liability-to-net worth ratio, indicating that restructuring led to heightened financial obligations relative to equity. However, the comparison of R-1 vs. R+3 (mean = 6.34, p = 0.162) lacks statistical significance, suggesting a moderation in liabilities beyond the immediate restructuring period.

Table 5.18: Total outside liabilities to total net worth ratio

Paired Differences-Total Outside Liabilities to Total Net Worth Ratio									
Pair	**Years of comparison**	**Mean**	**Std. deviation**	**Std. error mean**	**95% confidence interval of the difference**		**t**	**df**	**Sig. (2-tailed)**
					Lower	**Upper**			
1	R-1 and R+1	11.30	22.04	2.35	6.63	15.97	4.81	87	0.000
2	R-1 and R+2	12.08	18.37	1.96	8.18	15.97	6.17	87	0.000
3	R-1 and R+3	6.34	42.19	4.50	-2.60	15.28	1.41	87	0.162
4	Avg: R-2 and R+2	10.09	12.29	1.31	7.49	12.70	7.71	87	0.000
5	Avg: R-3 and R+3	6.75	16.62	1.77	3.23	10.27	3.81	87	0.000

The broader comparisons exhibit a continued increase in the ratio, with Avg: R-2 vs. R+2 (mean = 10.09, p = 0.000) and Avg: R-3 vs. R+3 (mean = 6.75, p = 0.000) confirming the sustained growth in financial leverage. The significant p-values suggest that restructuring had a prolonged impact on the firm's reliance on operating liabilities, though the decline in mean values over time indicates gradual stabilisation in financial leverage.

The graph depicting the ratio visually supports this pattern. It shows that leverage was relatively stable at R-3, increasing at R-2, and peaking at R-1 before stabilising post-restructuring. This trend suggests that firms enter restructuring after a period of financial strain, accumulating liabilities relative to their net worth, which may be a factor driving the decision to restructure.

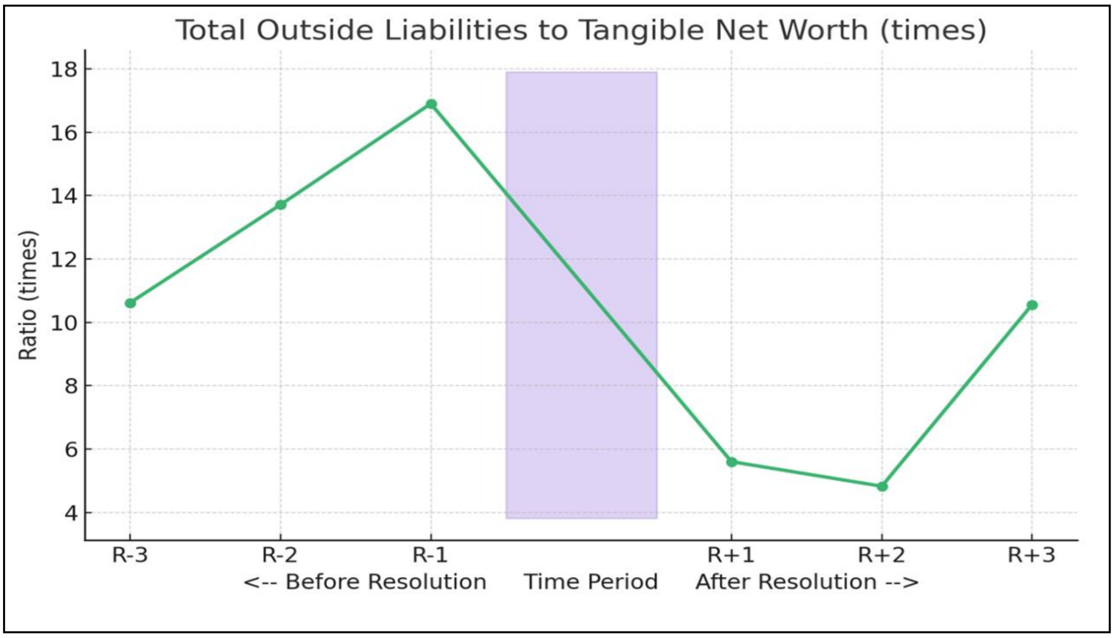

Figure 5.18: Total outside liabilities to total net worth

Averaged comparisons over broader periods reinforce the pre-restructuring leverage increase, with statistically significant differences at 10.09 and 6.75 (p = 0.000 for both). This indicates that firms, leading up to restructuring, experience increased reliance on liabilities, possibly due to financial distress, operational adjustments, or investment in restructuring-related activities.

Restructuring initially increased financial risk by raising operating liabilities relative to net worth. The short-term spike suggests that the firm depended more on debt financing post-restructuring, possibly to sustain operations or fund recovery efforts. While this trend persisted in the long run, the decline in mean values beyond three years suggests that financial adjustments may have led to a reduction in liability burdens, indicating potential operational efficiencies or capital restructuring strategies to restore stability.

The analysis of various financial ratios provides a structured approach to assessing the impact of restructuring on key financial indicators of firms. By examining the variations in these ratios, it is possible to determine how restructuring influences financial performance, liquidity, profitability, leverage, and operational efficiency. Additionally, evaluating the statistical significance of these changes allows for a more precise interpretation of whether the observed effects are substantial or merely reflective of normal financial fluctuations. This comprehensive assessment aids in understanding the broader financial implications of restructuring and identifying areas that may require further strategic intervention to ensure long-term stability and growth. The above analysis has been summarised in Table 5.19.

Table 5.19: Summary of results

Type of Ratio	Ratio	Short-Term Impact	Long-Term Impact	Null Hypothesis
Liquidity	Current Ratio (CR)	Significant improvement	Sustained improvement	**Reject**
	Quick Ratio (QR)	Significant improvement	Sustained improvement	**Reject**
Efficiency	Net Fixed Asset Utilisation Ratio	Increase	No consistent effect	**Accept**
	Finished Goods Turnover Ratio	Decline	Statistically significant decline	**Reject**
	Debtors Turnover Ratio	Improvement	Sustained improvement	**Reject**
	Creditors Turnover Ratio	Improvement	No statistical confirmation	**Accept**

Type of Ratio	Ratio	Short-Term Impact	Long-Term Impact	Null Hypothesis
Profitability	Return on Total Assets (ROTA)	Decline	Persistent decline	**Accept**
	Return on Capital Employed (ROCE)	Increase	Statistically significant gain	**Reject**
	Return on Equity (ROE)	Significant improvement	Sustained growth	**Reject**
	Profit Before Tax (PBT) Ratio	Significant increase	No statistical confirmation	**Accept**
	Profit After Tax (PAT) Ratio	Significant increase	No statistical confirmation	**Accept**
	Net Profit Ratio	Significant increase	Improvement lacks confirmation	**Accept**
	Operating Profit Ratio	Significant increase	Sustained growth	**Reject**
	Cash Profit Ratio	Increase observed	No statistical confirmation	**Accept**
Coverage	Interest Coverage Ratio	Significant decline	Decline persists	**Reject***
	Debt Service Coverage Ratio (DSCR)	Mixed trend	Inconsistent	**Accept**
Leverage	Debt-Equity Ratio	Significant decline	Sustained reduction	**Reject**
	Total Operating Liabilities to Net Worth (TOL/TNW)	Significant increase	Stabilised over time	**Reject**

5.4 Conclusion

Restructuring has had a significant influence on various financial metrics, affecting liquidity, profitability, leverage, and operational efficiency. The effects differ across short-term and long-term horizons, demonstrating both immediate improvements and sustained financial adjustments. While some financial indicators show strong initial recovery, others reveal persistent financial strain or fluctuations over time, indicating the necessity for strategic financial management beyond the restructuring phase.

5.4.1 Liquidity Ratios

Liquidity ratios measure a firm’s ability to meet short-term financial obligations, and restructuring substantially improved liquidity management both immediately and over time. The Current Ratio and Quick Ratio experienced statistically significant increases post-restructuring, suggesting that firms successfully optimised their working capital and cash flow efficiency. This short-term improvement indicates stronger financial flexibility, allowing firms to navigate immediate operational challenges more effectively. Over the long term, these liquidity benefits remained consistent, reinforcing that restructuring contributed to sustained financial resilience. However, the stabilisation of improvements over extended periods suggests that firms needed to strategically balance liquidity needs with operational efficiency to maintain long-term stability.

5.4.2 Efficiency Ratios

Efficiency ratios evaluate how effectively a firm manages its assets and turnover rates post-restructuring. The Net Fixed Assets Utilisation Ratio showed a significant increase in the short term, reflecting better asset productivity and improved operational efficiency. This suggests that firms leveraged existing infrastructure more effectively post-restructuring to maximise output and financial returns. However, in the long run, asset utilization benefits became inconsistent, implying that firms either adjusted their investment strategies or faced market fluctuations that impacted asset deployment. Turnover ratios, including Debtors Turnover Ratio and Creditors Turnover Ratio, displayed efficiency gains in receivables and supplier payments, ensuring that firms could optimise collections and payment cycles post-restructuring. The Debtors Turnover Ratio sustained its improvements in the long term, reinforcing strong financial discipline and credit risk management. However, the Finished Goods Turnover Ratio exhibited a significant decline over time, suggesting potential difficulties in inventory and production cycle management, requiring adjustments in stock control and supply chain efficiency.

5.4.3 Profitability Ratios

Profitability ratios assess the firm’s ability to generate earnings and improve financial performance post-restructuring. The Return on Equity (ROE), Operating Profit Ratio, and Net Profit Ratio showed immediate financial recovery, confirming the restructuring’s positive impact on operational efficiency and profitability. The statistically significant short-term improvements highlight better cost control, revenue optimisation, and strengthened profit margins. However, while ROE maintained its long-term growth, other profitability indicators, including ROCE, PAT, and PBT ratios, exhibited fluctuations over extended periods, suggesting that profitability required continued efficiency measures and financial discipline. The Operating Profit Ratio demonstrated sustained long-term profitability, reinforcing restructuring's contribution to financial stability, though the variability in Net Profit and PAT ratios indicates challenges in maintaining profitability amid external market influences.

5.4.4 Leverage Ratios

Leverage ratios provide insights into financial risk and debt management post-restructuring. The Debt-Equity Ratio experienced a significant decline, reinforcing successful deleveraging and capital structure optimisation in the short term. This suggests that firms actively reduced their reliance on debt financing, shifting toward a more sustainable balance between equity and liabilities. Over the long term, this trend persisted, further confirming lower financial risk exposure post-restructuring. The Total Outside Liabilities to Net Worth Ratio increased significantly, reflecting greater financial obligations post-restructuring, though gradual stabilisation suggests that firms adopted financial strategies to manage liabilities more effectively.

5.4.5 Coverage Ratios

Despite improvements in leverage structure, the Interest Coverage Ratio showed a significant decline, highlighting financial strain in servicing debt obligations after restructuring. Firms may have incurred additional interest costs, increasing financial pressure despite initial operational efficiencies. Similarly, the Debt Service Coverage Ratio (DSCR) initially improved but later exhibited volatility, demonstrating challenges in sustaining long-term debt repayment capacity.

The restructuring process produced mixed financial results, with clear distinctions between short-term financial recovery and long-term sustainability challenges. Liquidity ratios experienced strong post-restructuring gains, ensuring enhanced financial flexibility, while operational efficiency demonstrated both improvements and inconsistencies, necessitating ongoing strategic adjustments. Profitability metrics reinforced immediate fiscal recovery, but some long-term fluctuations indicate that firms needed to implement efficiency measures to sustain financial growth.

While deleveraging efforts successfully reduced financial risk, other leverage-related metrics, including Interest Coverage Ratio and DSCR, revealed persistent financial strain, suggesting increased pressure to manage debt servicing obligations over extended periods.

To mitigate financial uncertainty and sustain restructuring benefits, firms must adopt targeted financial interventions, including debt restructuring, cost optimisation, liquidity management, and reinvestment strategies. A balanced financial strategy post-restructuring can help maintain stability, ensuring that short-term gains transition into long-term financial resilience.

5.5 Case Study on Performance Analysis of Ellora Paper Mills Post-restructuring

The case of Ellora Paper Mills Ltd. largely mirrors the broader patterns identified across restructured firms in Chapter 5. Like the average firm-level analysis, Ellora showed post-restructuring gains in profitability (ROA, PAT) and liquidity (CR), validating the trends identified in Table 5.18. However, its Z-score trajectory deteriorated sharply after an initial rebound, indicating a relapse into financial stress. This aligns with the finding that post-restructuring liquidity improvements do not always translate to long-term solvency, especially if operational improvements lag. Furthermore, Ellora's continued decline in the Altman Z-score contrasts with the average firm recovery profile in Chapter 6, where a select group achieved operational efficiency gains. As such, Ellora exemplifies a restructured firm that experienced financial reprieve but not operational recovery—a nuance that reinforces the need to jointly track profitability and productivity metrics to assess true turnaround success.

5.5.1 Ellora Paper Mills Limited: An Overview

Ellora Paper Mills Limited is a Public Company incorporated on 14 November 1974 in Calcutta. It is classified as a Non-Government company. "The company was originally promoted by Satyanarayan Kedia and Sitaram Kedia of Ajanta Paper & General Products Pvt. Ltd. The company manufactures writing paper, printing paper, kraft paper, and packing paper—Vishwanath Kedia of Nitin Castings Ltd., and Bajranglal Dalmia of M/s. Prahladrai Dalmia & Sons joined as co-promoters in 1976. M/s. Prahladrai Dalmia & Sons became the present promoters of the Company in 1977 when Kedias of Nitin Castings Ltd took up the share of Kedias of Ajanta Paper & General Products. The company had a working capacity of 13,200 tonnes per annum. In 1988, the Company came under the provisions of the Sick Industrial Companies (Sp. Provisions) Act, 1985, and as per the requirement, a reference to the Board for Industrial and Financial Reconstruction was made. In 1993, the performance of the Company was severely impacted by the prolonged strike by the workers. The Company introduced a four crore modernisation plan spanning over a period of two years to reduce costs and improve quality in 1997. In 2007 and 2008, the company paid a dividend of 12% and 10%, respectively. Ellora Paper Mills Ltd. shifted its Registered office from Kolkata to Ahmedabad in 2016. On 19.07.2017, Ellora Paper Mills got a notice from NCLT (Mumbai Bench) to begin the Insolvency Resolution process." (Quarterly newsletter for July-September 2017, IBBI)

The Ellora Paper Mills Limited had been in bankruptcy for several years. This study attempts to reflect that not all companies in the public sector are performing financially well. It examines the firm's operating performance after inducing financial restructuring.

The current study focuses on assessing the operating efficiency of Ellora Paper Mills Ltd. after undertaking financial restructuring. The study period spans from 2007-08 to 2022-2023 i.e. 15 years.

The data was collected for 15 years, from 2007-08 to 2002-23. The ratios required to measure financial restructuring and operating performance have been extracted from CMIE-Prowess.

5.5.2 Research Methodology

The study has been conducted by analysing the impact of financial restructuring on the firm's operating performance.

The study uses Altman's z-score model to predict the firm's risk of bankruptcy. A simple linear regression model (equation 1) indicated the company's operating performance. The prediction was made based on the effect of the financial restructuring on the firm's economic performance.

5.5.3 Linear Regression Model

$$Y = \beta_0 + \beta_1 x_1 + e \qquad (1)$$

Where;

x_1 = Financial Restructuring; e = error term; β_0 = intercept, β_1 = coefficient of x_1

The financial restructuring of the firm has been measured through two ratios: total debt to total assets (TDTA) and debt-equity ratio (DER).

Financial Performance (Y) has been assessed in terms of Profitability (Return on Assets, i.e.ROA), Liquidity (Current Ratio, i.e. CR), Efficiency (Working capital to total Assets, i.e. WCTA) and Turnover (Sales to Total Assets, i.e. SALETR).

5.5.4 Altman's z-score Model

The study first tries to assess the financial performance of the firm, Ellora Paper Mills Ltd., using the method provided by Edward Altman in 1968. The technique, known as Altman's z-score model, states that specific ratios have predictive power to predict a firm's bankruptcy and financial distress. Altman suggested five ratios in his model. The ratios used in Altman's model are shown in Table 5.20.

Equation (2) defines Altman's z-score formula.

$$\text{Z-score} = 0.012X1 + 0.014X2 + 0.033X3 + 0.006X4 + 0.999X5 \qquad (2)$$

Table 5.20: Altman's z-score model

	Formula	Indicator	Description
X1	Working capital/total assets	Liquidity	The company's Working Capital is out of the total amount invested as Total Assets.
X2	Retained earnings/total assets	Profitability	The firm's ability to generate retained earnings out of the company's total assets. This parameter helps measure how much invested in the firm is being reploughed in the business.
X3	Earnings before interest and taxes/total assets	Earning Capacity	The company's ability to generate profits from the company's assets before interest payments and taxes.
X4	The market value of equity/book value of total debt	Market Performance	The value of the owner's fund in the business as compared to the outsider's fund.
X5	Sales/total assets	Efficiency	The measure of the ability of assets to generate revenue/sales.

Source: Altman et al., 2017

Based on the z-score obtained by a particular firm, Altman's model helped to identify if a specific firm is heading towards bankruptcy. The guidelines for reading Altman's z-score are provided in Table 5.21.

Table 5.21: Altman's z-score guidelines

Situation	Z-Score	Zone	Remarks
I	Below 1.8	Red Zone	There is a high probability that the business will face financial distress shortly, and the company may need desperate measures to survive in the market.
II	Between 1.8 to 2.99	Yellow Zone	The firm falls in the grey area, which means there is less probability that the firm will face financial distress shortly.
III	3.0 and above	Green Zone	The business is financially sound, and there is very little probability that the firm will face financial distress in future.

Source: Sharma & Patra, 2021

Z-scores were calculated for 15 years for Ellora Paper Mills Ltd. The results obtained are shown in Table 5.22.

Table 5.22: Altman's z-Score calculation of Ellora Paper Mills Ltd.

Year	Z Score	ZONE
2007-08	1.23	Distress
2008-09	1.75	Distress
2009-10	1.19	Distress
2010-11	0.86	Distress
2011-12	0.89	Distress
2012-13	1.22	Distress
2013-14	1.17	Distress
2014-15	1.66	Distress
2015-16	1.54	Distress
2016-17	1.50	Distress
2017-18	1.53	Distress
2018-19	2.11	Safe
2019-20	1.99	Safe
2020-21	0.23	Distress
2021-22	0.31	Distress
2022-23	**0.33**	Distress

Source: Author's calculation

Table 5.22 exhibits the value of the Altman z-score model of The Ellora Paper Mills Ltd from 2007-08 to 2022-23. The firm went through a period of financial distress until it went for restructuring in 2017-18. A further look at Table 4 shows that the financial health of Ellora Paper Mills Ltd. was in a distress zone after undergoing restructuring, except for two years following restructuring in 2018-19. For the rest of the period, the score has been below 1.80, indicating poor financial health. This shows that the firm was heading towards financial distress, which signalled bankruptcy soon. On 19th July 2017, the company was put under the Insolvency Resolution process. On 26.06.2018, the company's resolution plan was approved, and the firm underwent financial restructuring, thereby bringing about a change in the capital structure of the firm. After undergoing restructuring, the firm saw an improved performance for two years, but the z-score of the firm after that signalled a state of distress. Therefore, the company was required to improve its liquidity, profitability and efficiency to improve its economic performance.

5.5.5 Testing of Hypothesis

A simple linear regression model assessed the firm's financial performance as expressed in equation (1). The prediction was made by evaluating the impact of financial restructuring on the firm's financial performance.

Financial restructuring of the firm has been measured through the two ratios, i.e. Total debt to total assets (TDTA) and Debt-Equity ratio (DER)

Financial performance has been assessed in terms of Profitability (Return on Assets, i.e. ROA), Liquidity (Current Ratio, i.e. CR), Efficiency (Working capital to total Assets, i.e. WCTA) and Turnover (Sales to Total Assets, i.e. SALETR).

5.5.6 Performance Assessment

A thorough analysis of results in terms of studying the impact of financial restructuring on the firm's operating performance was conducted to understand the relationship between the two. The firm's operating performance can be measured in terms of positive profitability, liquidity, turnover and efficiency improvement. The summarised results are shown in Table 5.23.

Table 5.23: Model summary

Model	R	R^2	Adjusted R^2	Std. error
Profitability	0.769	0.591	0.523	6.62834
Liquidity	0.290	0.084	-0.068	0.31520
Turnover	0.600	0.360	0.253	0.46989
Efficiency	0.309	0.095	-0.055	0.21072

Source: Author's calculation

Table 5.23 indicates that the model coefficient of determination (adjusted R^2) was 0.591, 0.084, 0.360 and 0.095 for profitability, liquidity, turnover and efficiency, respectively.

The firm's operating performance variance is explained by its profitability and turnover. It means that a firm should focus on improving its sales and profits to see a change in its operating performance.

The summarised results of the study concerning the acceptance/rejection of the hypothesis are depicted in Table 5.24. The hypothesis statement regarding no impact of financial restructuring on liquidity, profitability, turnover and efficiency of the firm stands rejected as the findings suggest that financial restructuring does improve the liquidity (p value=0.001), profitability (p value=0.049) and turnover (p value=0.001) of Ellora Paper Mills Ltd. However, there is no significant effect on the firm's operating efficiency (p value=0.447).

Table 5.24: Summary of results at 5% level of significance

S. No.	Hypothesis Statement	p-value	Results	Accepted/Rejected
H01	Financial restructuring does not improve the profitability of Ellora Paper Mills Ltd.	0.049	$p<0.05$	**Rejected**
H02	Financial restructuring does not improve the liquidity of Ellora Paper Mills Ltd.	0.001	$p<0.05$	**Rejected**
H03	Financial restructuring does not improve the turnover position of Ellora Paper Mills Ltd.	0.001	$p<0.05$	**Rejected**
H04	Financial restructuring does not improve the operating efficiency position of Ellora Paper Mills Ltd.	0.447	$p>0.05$	**Accepted**

5.5.7 Conclusion

The study involves assessing the impact of financial restructuring on the firm's operating performance, The Ellora Paper Mills Ltd.

It highlights that financial Restructuring positively affected the enterprise's liquidity, profitability and turnover. The firm's restructuring changes its debt-equity structure, writing off unpaid liabilities and rearranging the capital structure components to achieve better operating performance. Sick companies can improve their performance by restructuring and releasing the funds invested for better use. This would lead to a better utilisation of the limited financial resources available in the economy. It provides insight to policymakers regarding allocating funds to various industries and firms. The financial institutions can use the Altman z-score model to assess the firms in distress and then decide on the release of funds. Also, the management can determine the operating efficiency and the utilisation of funds for proper management.

CHAPTER 6

MEASURING OPERATIONAL EFFICIENCY OF RESTRUCTURED COMPANIES: A DEA-MI APPROACH

An efficient company demonstrates good financial health, which is vital for the various stakeholders. The shareholders, creditors and management analyse it for their decision-making and for the Government to assess its financial and economic policies (Stanková & Hampel, 2023). One primary reason for a company's failure is its poor management, and its efficiency is a significant indicator of the quality of management. Financial ratios provide a useful, albeit limited, picture of corporate health. Chapter 6 deepens the analysis by examining operational efficiency using DEA and the Malmquist Productivity Index—unpacking whether firms translate restructured balance sheets into leaner, more productive operations.

This chapter examines the application of Data Envelopment Analysis (DEA), in **Section 6.1**, a non-parametric linear programming method used to evaluate the relative efficiency of firms undergoing financial restructuring. DEA enables the assessment of multiple inputs and outputs, facilitating a comprehensive benchmarking of corporate performance within the financial system. **Section 6.2** introduces the Malmquist Productivity Index (MPI), which quantifies efficiency changes over time, distinguishing between technical and technological advancements in post-restructuring firms. **Section 6.3** presents an empirical analysis, identifying firms that demonstrate above-average efficiency and those exhibiting operational inefficiencies. Finally, **Section 6.4** synthesises key findings, discussing the broader implications of efficiency trends for corporate recovery and financial decision-making.

6.1 Data Envelopment Analysis (DEA)

DEA, a linear programming model, assesses the relative efficiency of a company (decision-making unit) with multiple inputs and outputs, employing a non-parametric approach. It is a valuable tool for evaluating and benchmarking the efficiency of firms in various sectors, thereby contributing to better decision-making and resource allocation. Researchers can identify firms that operate at the production frontier (fully efficient) and those that are less efficient.

Assessing a firm's efficiency over a particular period or for one year is a static concept; one assesses the firm's efficiency in a particular period concerning the peer firms. It is imperative to assess how efficiency changes over time as the changes in the business environment are dynamic, and so is the firm's performance.

When DEA efficiency is a factor in dynamic models, assessing it across multiple periods is crucial. Traditional Data Envelopment Analysis (DEA) models, being static in nature, are designed to evaluate efficiency within a single time period. However, significant interest is in extending these models to track efficiency changes over time. If a Decision-Making Unit (DMU) can be studied and analysed at various times, the efficiency changes can provide valuable insights for predicting future financial distress.

The efficient frontier method, utilising the Malmquist productivity index is employed, based on Data Envelopment Analysis (DEA). It assesses the company's efficiency over some time. This index alters two distinct and comprehensive elements: variations in the firm's technical efficiency as time progresses and technological shifts over time.

The Malmquist DEA model is especially effective for handling panel data. The Malmquist Index (MI), originally designed to compare two economies in terms of their production technology, was incorporated into DEA by Färe, Grosskopf, Lindgren, and Roos (1992). Later on Färe, Grosskopf, Norris, and Zhang (1994), developed a DEA-based Malmquist productivity index. The disintegrated elements of the MI can identify how much of an efficiency change (increase or decrease) from period t to t + 1 is due to individual effort versus industry innovation. Efficiency change refers to the extent to which a DMU's performance improves or deteriorates over time, whereas technological change captures the shift in the efficiency frontier between two periods.

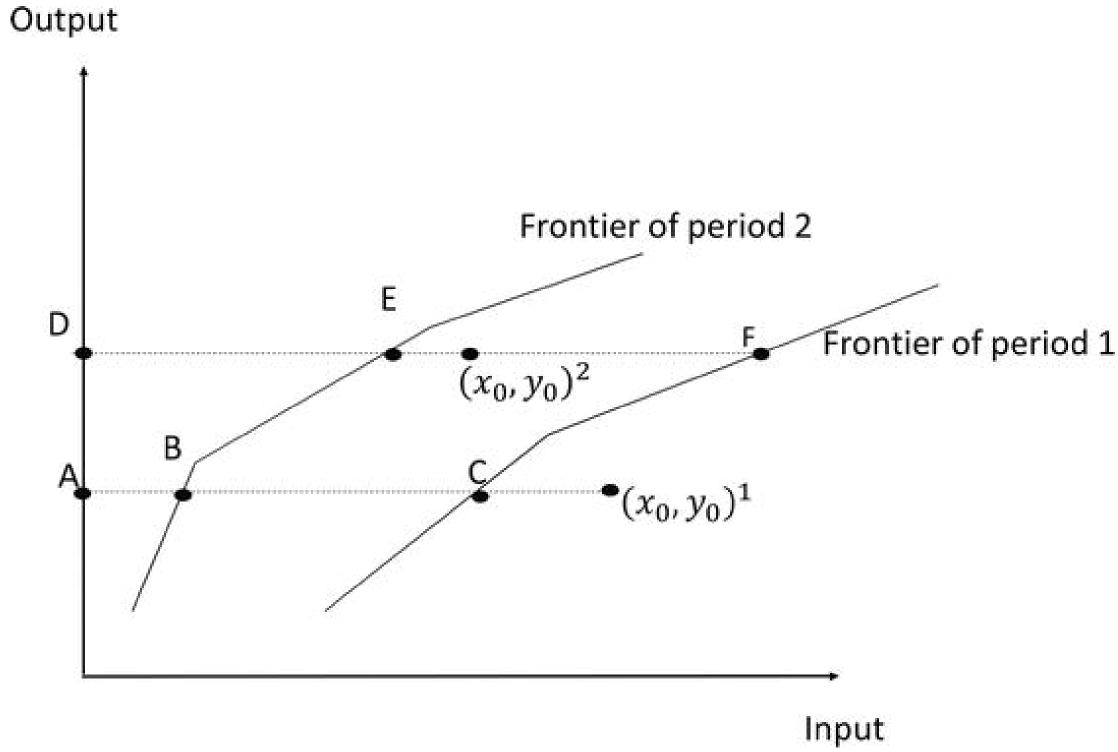

Figure 6.1: Malmquist Frontier for subsequent periods; Source: Sanchez, 2018

Since the introduction of the Malmquist Index (MI), numerous studies have investigated productivity changes across various sectors, including Italian manufacturing firms (Costa, 2012), Spanish government tax offices (Fuentes & Lillo-Banuls, 2015), Taiwanese banks (Shyu & Chiang, 2012), and Korean universities (Sohn & Kim, 2012). These studies primarily examined efficiency changes over time to derive managerial insights and strategic recommendations, without addressing the issue of distress prediction.

Data Envelopment Analysis (DEA) is a nonparametric method incorporating two main models: Constant Return to Scale (CRS) and Variable Return to Scale (VRS). The output-oriented DEA model concentrates on identifying and assessing changes in output, achieving enhanced efficiency by proportionally increasing outputs while maintaining constant input quantities.

The two distinct DEA models based on the assumptions of returns to scale are Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS). The CRS assumption is only valid for DMUs operating at an optimal scale. When DMUs operate at a different optimal level, the measurement of technical efficiency becomes intertwined with scale efficiency.

DEA is used (a) to locate the DMUs responsible for these technical inefficiencies, and (b) to identify the sources and amounts of inefficiency in each of its inputs and outputs (Banker et al., 1984).

Coelli et al. (2005) suggested that the difference between the technical efficiency ratios derived from DEA-CRS and DEA-VRS for the same firm serves as a reliable indicator of the firm's scale efficiency. To assess this, both the DEA-CRS and the DEA-VRS models should be applied to the same dataset. If a firm shows a difference in efficiency ratios between these two DEA models, it signals that the firm is operating at a suboptimal scale.

The gap between CRS technical inefficiency and VRS technical inefficiency can determine scale inefficiency. This method facilitates an investigation into the factors that influence the levels of efficiency or inefficiency.

Consider a set of DMUs indexed by i=1,2,3…..,m. Let x_{ij} denote the amount of input j used by DMU i and y_{ik} denote the amount of output k produced by DMU i.

For VRS DEA, the efficiency score E_i for each DMU i can be derived by using the following linear programming problem.

Maximise: E_i

Subject to:

$$\sum_{j=1}^{n} \lambda_i \, x_{ij} < E_i x_i k \text{ (for all k inputs)} \tag{1}$$

$$\sum_{k=1}^{s} \mu_k y_{ik} \geq \; y_{ij} \;\text{ (for all j outputs)} \tag{2}$$

$\sum \lambda_j = 1$

E_i, λ_j , $\mu_k \geq 0$ (non − negativity constraints)

For CRS DEA, the efficiency score E_i for each DMU i can be derived using the following linear programming problem:

Maximise: E_i

Subject to:

$$\sum_{j=1}^{n} \lambda_j \; x_{ij} \leq \; E_i x_{ik} \text{ (for all k inputs)} \tag{3}$$

$$\sum_{k=1}^{s} \mu_k y_{ik} \geq y_{ij} \text{ (for all j outputs)} \quad (4)$$

E_i , λ_j , $\mu_k \geq 0$ (non − negativity constraints)

This study employs both Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS) models within the DEA framework to provide a comprehensive assessment of the operational efficiency of restructured firms. The CRS model assumes that all firms operate at an optimal scale, which may not hold true for companies emerging from financial distress. In contrast, the VRS model relaxes this assumption and allows for increasing or decreasing returns to scale, making it more suitable for capturing managerial efficiency when scale inefficiencies are present.

By calculating efficiency scores under both CRS and VRS assumptions, the study is able to decompose overall technical efficiency into two distinct components: pure technical efficiency (from the VRS model) and scale efficiency (derived as the ratio of CRS to VRS scores). This decomposition is critical for understanding whether inefficiencies arise from suboptimal resource utilisation (managerial inefficiency) or from operating at a non-optimal scale (scale inefficiency). Given that restructured firms often face transitional constraints, underutilised capacity, or downsizing, this dual-model approach provides a more nuanced and diagnostically useful evaluation of post-revival performance.

This methodology aligns with the recommendations of Coelli et al. (2005) and Banker et al. (1984), who advocate using both models to distinguish between technical and scale-related inefficiencies. The resulting insights are particularly valuable for policymakers and managers seeking to identify whether performance improvements should focus on operational practices or strategic resizing.

Our study consists of Sales as output, raw material expense, Salaries and wages, and investment in property, plant, and equipment as input.

To identify the inefficiency arising from scale and the one occurring due to technical inefficiency, we calculate scale efficiency as:

$$\text{Scale Efficiency} = \text{CRS Efficiency}/\text{VRS Efficiency}$$

6.2 Malmquist Productivity Index (MPI)

While traditional Data Envelopment Analysis (DEA) models are designed for a single period, scholars and professionals are significantly interested in tracking efficiency changes over time. In particular, observing a Decision-Making Unit (DMU) at various time points can provide valuable insights into its efficiency evolution, which can be instrumental in forecasting potential financial difficulties.

Productivity change is driven by efficiency and technical changes in firms. We have employed the adjacent-period version of the Malmquist Productivity Index, as proposed by Fare et al. (1989), to measure firms' productivity. The Malmquist Productivity Index is defined by Fare et al. (1989) using the Shepherd Distance function for period t and t+1 in terms of the following equation:

$$\text{MI} = \sqrt{\frac{\boldsymbol{D^t}\,(\boldsymbol{x^{t+1}},\boldsymbol{y^{t+1}})}{\boldsymbol{D^t}(\boldsymbol{x^t},\boldsymbol{y^t})} * \frac{\boldsymbol{D^{t+1}}(\boldsymbol{x^{t+1}},\boldsymbol{y^{t+1}})}{\boldsymbol{D^{t+1}}(\boldsymbol{x^t},\boldsymbol{y^t})}} \tag{5}$$

Where $D^t(x^t, y^t) = \min(\theta_j^k;\,(x_j^k, \theta^{-1}y_j^k) \in S^{kt})$

The distance function represents the maximum proportion by which a firm's output in period t can be expanded while keeping the input constant. Similarly, $D_{t+1}(x_t,y_t)$ reflects the proportional expansion of the same firm's output relative to the technology set in period t+1.

The ratio of the distance function

$$\left[\frac{D^t\left(x^{t+1},y^{t+1}\right)}{D^t(x^t,y^t)}\right] \tag{6}$$

measures the change in the productivity of a DMU, taking the base period as the benchmark for comparison.

The Malmquist Index (MI) is calculated as the geometric mean of two distance function ratios. An MI greater than 1 indicates productivity growth, while an MI less than 1 signifies a decline in productivity. The Malmquist Index is chosen for its ability to be decomposed into two distinct and exhaustive components: technical change (TC) and efficiency change (EC) (Fare et al., 1989).

i.e. $$\text{MI} = \text{E x T} \tag{7}$$

Malmquist Index = Technical Efficiency Change x Technological Change
(catching up effect) (innovation effect)

Where

$$EC=\left[\frac{D^{t+1}\,(x^{t+1},y^{t+1})}{D^{t}(x^{t},y^{t})}\right] \text{ and } TC=\left[\frac{D^{t}(x^{t+1},y^{t+1})}{D^{t+1}(x^{t+1},y^{t+1})} * \frac{D^{t}(x^{t},y^{t})}{D^{t+1}(x^{t},y^{t})}\right] \quad (8)$$

TC represents Technical Change, and a value greater than one indicates progress in technology practice, whereas a value less than one signals a technical regress. It signifies adopting best practices and measures the DMU's innovation effect.

EC represents a firm's efficiency change and is known as the catching-up effect. It is characterised by the relative shift of a firm towards or away from the production possibility frontier and is hence also known as the frontier shift.

A firm's output level increases due to an increase in its efficiency level or technological advancement. The improvement in the efficiency level is either due to pure technical efficiency or due to the efficiency of the scale.

Using the Fare et al. approach, we can thus have four efficiency indices for each DMU and a measure of technological progress over time. These indices are-

1. Pure Technical Efficiency Change (concurrent to VRS technology) {PT}
2. Scale Efficiency Change {S}
3. Technical efficiency change (relative to CRS technology) {E}
4. Technological progress change {T}
5. Total factor productivity (Malmquist index) {MI}

Fare et al. defined Technical efficiency change as follows:

Technical efficiency change = Pure Technical efficiency change x Scale efficiency

$$E = PT \times S \quad (9)$$

After incorporating the impact of Technological advancement into the above equation, we get the Total Factor Productivity (known as the Malmquist Index) as follows:

Total factor productivity = Technical efficiency Change x Technological Progress change

$$MI = E \times T \quad (10)$$

i.e. $$MI = PT \times S \times T \qquad (11)$$

The calculation of various efficiency scores and the decomposition of Malmquist index into Technical efficiency and technological change can be summarised as shown in Figure 6.2.

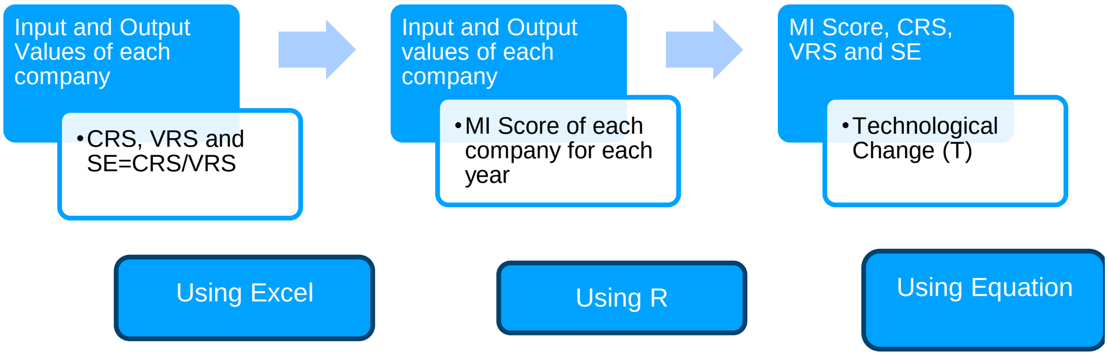

Figure 6.2: Flowchart for calculation; Source: The Authors

The step-by-step process is as shown in Figure 6.2. The blue box signifies the input required to obtain the output that has been shown in the white boxes. The Software or mechanism used has been indicated below each step. The flowchart reflects the mechanism adopted to calculate the MI score and categorise the change in the efficiency scores of the companies into pure technological change and changes due to operational efficiency and scale efficiency. Using the input and output values of each firm, the Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS) are calculated with the help of Excel Solver. Also, MI score of each company is calculated, through R software, using the same input and output values. The results obtained are then used to disintegrate the MI score into Technological change, Pure technical efficiency change and Scale efficiency changes using the equations mentioned above.

Productivity experiences an increase when $M > 1$ and decreases when $M < 1$. The increase or decrease of technical efficiency is determined by whether E is more or less than one, respectively. Similarly, T is more or less than one, indicating technological advancements or setbacks. One can identify the main contributors to productivity changes by comparing E and T. If E exceeds T, efficiency improvements are the primary driver of productivity gains. On the other hand, if E is less than T, technological advancements are the primary source of productivity gains. Furthermore, if PT is more significant than S, the primary factor in efficiency change is an enhancement in pure technical efficiency. However, if PT is less than S, the main factor in efficiency change is a scale improvement.

6.3 Analysis of Results

Based on the calculation of Efficiency scores obtained for the various firms over three years post-restructuring through NCLT, the average MI score has been 0.69 for all the decision-making units in the sample. Based upon this, there have been 20 DMUs with above-average performance compared to 20 DMUs whose performance has been below average, as given in Table 6.1.

Table 6.1: Malmquist index of companies

Companies Above Average	Malmquist Index	Companies Below Average	Malmquist Index
Tata Steel B S L Ltd. [Merged]	1	Amalgam Steel & Power Ltd.	0.6544
Ellora Paper Mills Ltd.	1	M I C Electronics Ltd.	0.6296
Ultratech Nathdwara Cement Ltd.	1	Uttam Strips Ltd.	0.588366667
S P S Steels Rolling Mills Ltd.	1	Raj Oil Mills Ltd.	0.568233333
Tehri Iron & Steel Casting Ltd.	1	Other electronics	0.563233333
Olive Lifesciences Pvt. Ltd.	1	Danalakshmi Paper Mills Pvt. Ltd.	0.553666667
Patanjali Foods Ltd.	1	Icomm Tele Ltd.	0.551833333
Logic Eastern India Pvt. Ltd.	1	Calyx Chemicals & Pharmaceuticals Ltd.	0.5351
Tantia Constructions Ltd.	1	G B Global Ltd.	0.5349
Bhushan Power & Steel Ltd.	0.9981	Orchid Pharma Ltd.	0.484766667
Paragon Steels Pvt. Ltd.	0.9	Sun Paper Mill Ltd.	0.4766
Swadisht Oils Pvt. Ltd.	0.8591	Trinity Auto Components Ltd.	0.473033333
Bansal Steel & Power Ltd.	0.8048	Allied Strips Ltd.	0.4723
Ved Cellulose Ltd.	0.7939	Shirdi Industries Ltd.	0.467266667
Deccan Chronicle Holdings Ltd.	0.772266667	Bafna Pharmaceuticals Ltd.	0.431566667
Shaifali Rolls Ltd.	0.758133333	Star Agro Marine Exports Pvt. Ltd.	0.417333333
Alok Industries Ltd.	0.751833333	Cosmic Ferro Alloys Ltd.	0.409733333
Sree Metaliks Ltd.	0.751533333	F M Hammerle Textiles Ltd.	0.297866667
Era T & D Ltd.	0.730466667	New Phaltan Sugar Works Ltd.	0.286733333
Sunstar Overseas Ltd.	0.700766667	Maiyas Beverages & Foods Pvt. Ltd.	0.269533333

Source: The Authors

Subsequently, the Malmquist index and Efficiency scores were calculated for various firms, and a quadrant analysis was done to find out the relative impact of technical efficiency and Technological change on the efficiency of the firms. A firm's total factor productivity or the Malmquist Index is influenced by either the change in its technical efficiency or technological change, which brings along progress or regress in efficiency. Figure 6.3 shows the technological change and change in efficiency of the firms.

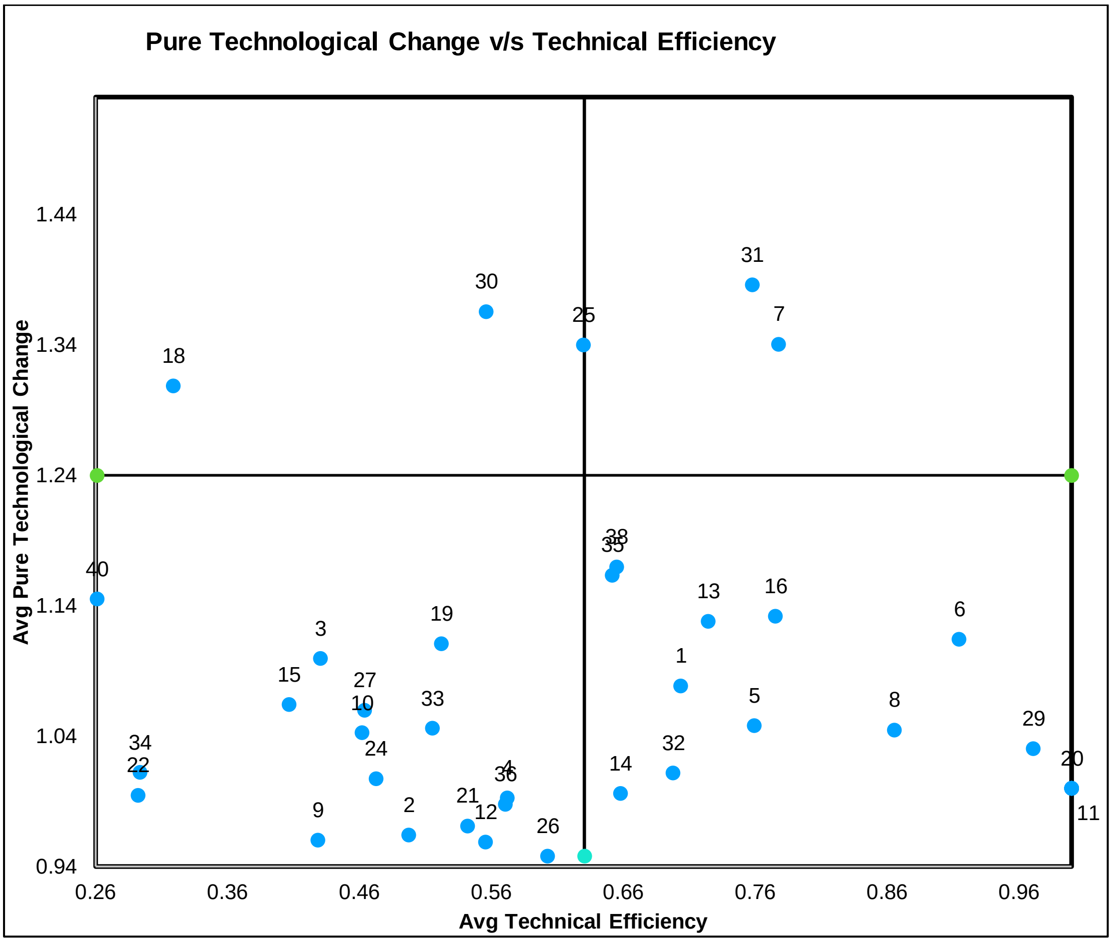

Figure 6.3: Pure technological change v/s Technical efficiency change; Source: The Authors

The x-axis shows the DMU's average Technical Efficiency change (E) three years after the restructuring. The y-axis represents the average Pure Technological Change (T) three years after the restructuring.

The dots represent the 40 DMUs. In Figure 6.3, the first quadrant represents a significant technological change, while a low technical efficiency change is present. We can see only two firms, i.e. Star Agro Marine (Firm No. 18) and MIC Electronics Ltd.

(Firm no. 30), in the quadrant, signifying that in these two firms, the level of technological progress was high as compared to the Technical efficiency change in determining the total factor productivity of the firm; reflecting a higher impact of technological change as compared to the change in the efficiency of the firm.

Most DMUs lie in the second quadrant, reflecting low technical efficiency and technological change. This implies that post-restructuring, these firms made much technological progress and experienced low technical efficiency.

Few firms, reflected in quadrant 3, experienced low technological progress and high technical efficiency. Their productivity growth is mainly due to efficiency changes rather than technological progress.

Out of all the 40 DMUs included in the study, only two firms, Ellora Paper Mills Ltd. (Firm No. 7) and Bhushan Power and Steel Ltd. (Firm No. 31), had high technological progress and technical efficiency post-restructuring. The average MI of the two firms is also high (1 and 0.9981, respectively), signifying a positive effect on factor productivity.

The firms' technical efficiency results from either pure technical efficiency or a change in scale. Figure 6.4 reflects the firm's technical efficiency change vis-a-vis pure technical efficiency and changes in the scale of operations.

On the x-axis is the average change in pure technical efficiency over three years post-restructuring; on the y-axis is the change in the scale of operations during the same period.

A look at Figure 6.4 reveals that the change in technical efficiency and the scale of operations could have been higher for most firms. Only two firms, i.e. Dhanalakshmi Paper Mills Pvt. Ltd. (Firm No. 19) and Era T&D Ltd. (Firm No. 38), have improved their scale of operations. However, on the other hand, the technical efficiency has been low, reflecting a below-average MI Score of 0.55. This implies that even a substantial positive change in the firm's scale of operations was insufficient to improve its productivity score. This means that the firm needed to be higher in terms of pure technical efficiency.

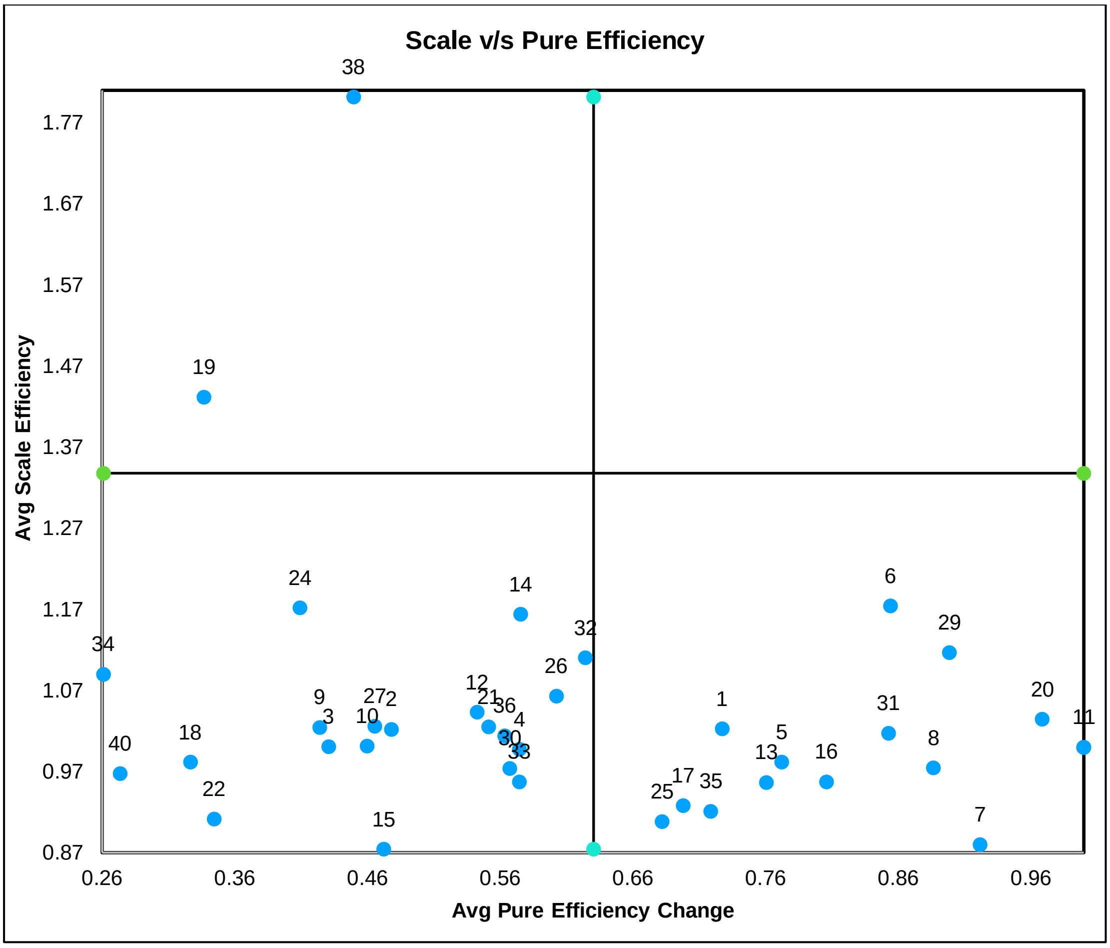

Figure 6.4: Scale efficiency v/s Pure technical efficiency; Source: The Authors

Out of the 40 firms, only 14 lie in quadrant 3, reflecting low efficiency in scale operations but a positive technical efficiency improvement. At the same time, no firm could achieve high efficiency in terms of technical and scale operations. This could be because the firms cannot improve their technical efficiency by increasing their scale of operations and achieving technical efficiency simultaneously. This could also be because firms need time to improve their scale of operations and technical efficiency. The capital-intensive nature of manufacturing organisations leads to a delay in achieving the optimum scale of operations. Also, the restructuring process leads to a delay in achieving the optimum or desired levels of efficiency.

6.4 Conclusion

Evaluating performance is vital for businesses across all industries. It is not just about assessing their effectiveness and accomplishments but also about comparing themselves to their competitors. This benchmarking process allows them to understand where they stand in the market.

The firms facing financial distress look for ways to overcome it. Inefficiency on the financial front leads to inefficiency in the working and operations of the firm. Financial restructuring of firms is a change in the debt-equity component of the firm and is one of the measures that help firms overcome financial distress. The impact of economic restructuring on the firm's operational efficiency can identify the success of the process. This paper applies the Malmquist Productivity Index to evaluate the firms' productivity, using multiple inputs and producing multiple outputs over time.

The total factor productivity growth of the firms restructured through NCLT has been measured over three years post-restructuring of the firm. Over time, the efficiency changes have been studied concerning technological change and changes in technical efficiency. Technical efficiency, also known as the catching-up effect, represents progress towards the production frontier. On the other hand, technological change, referred to as frontier shift, signifies innovation and investment. In light of the above findings, several valuable managerial insights and implications have been explored within the manufacturing sector.

The overall productivity of all the firms under study has shown a downward trend in Total Factor Productivity, as shown in 6.2. This can be attributed to the firm's technical efficiency, which has shown a similar downward trend three years after restructuring. The technical efficiency change was 0.7361 in the first year post-restructuring and was further reduced to 0.6305 in the second year and to 0.5703 in the third year. The technical efficiency change can be decomposed into pure technical efficiency and change in the scale efficiency of the firm. While the pure technical efficiency has improved over the years, the scale efficiency has spiralled down. This reflects that, as the firm comes out of the resolution process, there is an improvement in the utilisation of the scales of production. After that, the firms do not look for upgrades in the scale of the business, which, on the whole, leads to a marked decrease in the factor productivity of the firm, scaling down from 1.3224 to 0.8829 in three years.

Table 6.2: Average values of various components post restructuring

Year(s) after restructuring	Total factor productivity (MI)	Technical efficiency change (E)	Technological change (T)	Pure technical efficiency (PT)	Scale efficiency (S)
One year	0.7206	0.7361	0.9751	0.5923	1.3224
Two years	0.6945	0.6305	1.1167	0.6982	0.909
Three years	0.6465	0.5703	1.1749	0.6487	0.8829

Source: The Authors

The companies included in this study are those that experienced financial distress and underwent restructuring through the National Company Law Tribunal (NCLT). Despite changes to their capital structure, restructured firms require time to return to their normal operational routines. The delayed positive returns from restructurings may indicate the initially high costs incurred, where these costs are temporarily offset by the organisation's ability to adjust to the required scale of change. However, these benefits are quickly outpaced due to the episodic nature of restructuring. The observed negative returns in most cases suggest that the indirect costs, such as disruptions to established routines and complementarities, may indeed exceed the advantages gained from organisational adjustments. The return lag could be attributed to the organization's inability to sustain and return to regular operations during this transitional period. Additionally, while technological innovation created new production opportunities, many firms were unable to capitalise on these advancements fully.

This implies that firms need to work on achieving the optimum scale of production, which is a significant component in assessing the firm's overall factor productivity.

The technological change has been positive and has shown an upward trend, moving from 0.9751 to 1.1167 and 1.1749 over three years, reflecting the technological advancements embraced by the decision-making units.

There are efficiency indices, including total factor productivity as well as technical and technological change indices. However, their use has been somewhat limited, as has the broader application of DEA models combined with the Malmquist index. DEA and Malmquist analysis show that despite technological upgrades, most firms fail to improve operational scale or efficiency, implying that structural reforms must go beyond financial tinkering to include process redesign and capacity utilisation. It thus helps to ascertain whether improvements in efficiency are necessary through technological advancements or adjustments to the firm's scale parameters. Additionally, policymakers can gain a clearer perspective on whether restructuring was a more effective decision than liquidation in the context of firm recovery.

CHAPTER 7

FINANCIAL DISTRESS PREDICTION USING MACHINE LEARNING TOOLS

With a full picture of which firms recover best and how they do so operationally, Chapter 7 tackles prevention. We build on the ratio- and efficiency-based evidence to train and test logistic regression, neural networks and random forests on financial and firm-specific data—moving the discussion from ex post diagnosis to ex ante distress prediction. Future bankruptcy could result in substantial losses, necessitating proactive measures to mitigate and preempt such losses. Misclassification of potential and future bankruptcy could lead to allocating scarce financial resources to inefficient firms, further leading to the erosion of public finance. Consequently, there is a need to enhance the accuracy of bankruptcy prediction.

Section 7.1 highlights the various techniques that can be adopted to ensure stakeholders derive certain benefits. **Section 7.2** discusses data handling and pre-processing methodologies essential for ensuring the reliability of machine learning models. **Section 7.3** outlines key performance evaluation metrics, including the confusion matrix, ROC curves, and the Gini coefficient, which assess classification accuracy. **Section 7.4** presents an empirical analysis of predictive models, comparing their effectiveness in identifying early indicators of financial distress. Finally, **Section 7.5** synthesises the findings, highlighting the practical implications of adopting machine learning-based approaches for corporate financial risk assessment.

7.1 Statistical V/s Machine Learning Techniques

The literature review shows that machine learning has been used to predict bankruptcy and credit risk management since the 1990s. Statistical tools, which relied more on assumptions of normality and linearity of data, gave way to machine learning techniques, which were data-driven, robust, and distribution-free (Gupta, 2022).

They are non-parametric, and despite requiring more computational power, they have become the primary bankruptcy prediction method, outperforming statistical models

(Clement, n.d.). Machine learning models are good at classifying almost any variable selection method and are more robust to multicollinearity (Liang et al., 2015)

Since both statistical and Machine learning techniques have their own merits and limitations, the study employs one statistical technique and two machine learning techniques to identify the accuracy and performance of each method.

The study applies random forest, artificial neural network, and logistic regression models, which are used to predict the firm's outcome (in terms of bankruptcy or restructuring)[2] With a certain level of accuracy.

The following techniques were used for data analysis:

1. **Random Forest (Machine Learning Model):** This model is a supervised algorithm that creates a random forest. Many decision trees are combined to make a random forest. It is used in regression and classification problems. This structure is easier to understand, and its interpretation is straightforward. It has certain advantages: the tree structure is visualised, and there is no need for extensive data preparation for analysis (Aker & Karavardar, 2023). Also, the diversity is created by incorporating the benefit of double randomisation, where each tree is estimated based on a synthetic sample drawn randomly from an estimation sample (Klaus-Peter Hellwig, 2021)
2. **Artificial Neural Network (Machine Learning Model):** This model adopts the human brain system and can generalise knowledge for predicting future events. This model is used widely for optimisation support and prediction with a backpropagation algorithm (Alamsyah et al., 2021).
3. **Logistic Regression (Statistical Technique):** This model emerged as the most suitable for handling situations wherein the dependent variable is classified or categorical. It helps in determining cause-effect relationships with certain explanatory variables. The prediction in this model is made using equations. This model is focused on finding an equation that would minimise the difference between the dependent variable's actual value and the independent variable's

[2] Bankruptcy and Liquidation have been used interchangeably. Restructuring and reorganisation have been used interchangeably as reorganisation is financial restructuring.

predicted value (Özdamar, 2002). Cross-validation and stratified sampling techniques were adapted to conduct the modelling as specified by Japkowicz & Shah (2011).

7.2 Data Handling

7.2.1 Data Pre-processing

Machine learning models follow the Garbage in, Garbage out (GIGO) principle (Arora & Saurabh, 2022). Therefore, the data must be preprocessed before the modelling stage for accurate results. Preprocessing required dealing with an imbalanced dataset, as the liquidated firms were dominant in number, and spreading the sample to enable random selection of instances. SMOTE, spread subsample, and randomise filter were used to deal with this.

Ten sets were randomly created using 10-fold cross-validation, with 100 iterations performed to get the best results. Cross-validation is a technique for evaluating model performance on unseen data.

7.2.2 Optimisation Parameters for Model

The study is based on machine learning models that must be tuned for optimum results. Optimising the hyperparameters to achieve the best possible model architecture is often necessary to implement machine learning algorithms successfully (Beniwal et al., 2023). The hyperparameter optimisation for the machine learning models is as follows-

1. **Random Forest:** The default batch size was 100, the number of iterations remained the same, and the seed's initial value remained 1.
2. **Neural Network:** The neural network's learning rate was 0.3, and the batch size was 100. The hidden layers were set to half the sum of attributes and class.

7.3 Performance Evaluation Metrics

The study applied the performance evaluation metrics to evaluate the model's predictive and classification ability: the Confusion Matrix and its indicators, ROC (Receiver Operating Characteristics), and the Gini coefficient.

7.3.1 Prediction Performance (Confusion Matrix) and its Indicators

A confusion matrix gives valuable information about the classifier's performance by comparing actual and predicted classes (Balasubramanian et al., 2019).

A sample confusion matrix is provided in Table 7.1.

7.3.2 Sample Confusion Matrix

Table 7.1: Sample confusion matrix

Predicted			
Actual		**Positive**	**Negative**
	Positive	TP	FN
	Negative	FP	TN

The reorganised cases have been referred to as positive, and bankrupt cases have been referred to as unfavourable.

Classification accuracy rates calculated from the confusion Matrix as follows-

1. **Accuracy Ratio (AR):** It is the proportion of cases that have been correctly classified (positive or negative)

   Accuracy Ratio = (Npp+Nnn)/Total Sample

   Where, Npp (Nnn) is the number of positive (negative) cases classified as positive (negative)

2. **Sensitivity:** It is the proportion of negative cases correctly classified as harmful.

   Sensitivity = Nnn/(Nnn+Nnp)

   Where Nnn (Nnp) is the number of negative (negative) cases classified as negative (positive)

3. **Specificity:** It is the proportion of positive cases correctly classified as positive and is measured as follows-

   Specificity = Npp/(Npp+Npn)

Where, Npp(Npn) is the number of positive (positive) cases classified as positive (negative)

4. **Precision:** It is the proportion of correctly classified negative cases out of all those classified as harmful. It is measured as

   Precision = Nnn/(Nnn+Npn)

   Where, Nnn(Npn) id number of negative (positive) cases classified as negative (negative)

5. **Type I and Type II Errors:** Type I error is the proportion of negative cases classified as positive. In contrast, type II error is the proportion of Positive cases classified as unfavourable.

   Type I error = 1-Sensitivity

   Type II error = 1-Specificity

6. **Gini Coefficient:** The Gini coefficient is an essential tool for assessing the consistency in the results of a machine learning model. It is also the widely used index for validating credit scoring models. (Gupta, 2022)

   It is calculated as G = 2(AUROC) – 1

Classification rates calculated from the confusion Matrix provide information about assessing a classification model's accuracy and appropriateness. Out of all the parameters discussed above, the most important one from a decision-maker's perspective is the type I error. The reason is that the cost of classifying a negative case as positive far exceeds that of a positive case as unfavourable. For example, the losses to a bank from lending to a bankrupt firm (Type I error) are expected to be much higher than the losses from refusing to lend to a typical going concern, which are the foregone interest payments (Type II error) (Almaskati et al., 2021). It is worth mentioning, however, that the costs to society and the economy from Type II errors might be significant when suitable opportunities are systematically declined due to this error (Almaskati et al., 2021). Thus, error cost should be an essential criterion for model evaluation (Adnan Aziz & Dar, 2006).

7.3.3 Classification Power (Receiver Operating Characteristic (ROC) Curve) and Gini Coefficient

Apart from the confusion matrix and its accuracy rates for prediction ability, the ROC curve or Area under the curve (AUC) and the Gini coefficient are used as classification ability indicators.

The analysis uses the sensitivity (the percentage of default positive outcomes that have been correctly classified) v/s 1- specificity (the percentage of default adverse outcomes that have been correctly classified) to make the curve. The false positive rate is plotted on the horizontal axis, with the actual positive rate on the vertical axis. With this, we get the area under the ROC curve (AUROC) based on a particular model. The area ranges from 0.5 (for a worthless model) to 1 (for a perfect classifier). The larger the area under the curve, the better the model's classification ability.

The Gini Coefficient highlights the difference between a base classifier (taken as the default 0.5 for each class) and the classifier model in question.

7.4 Analysis of Results

The results indicate the output of a Machine Learning or statistical technique in the form of Accuracy Rate, Precision, Type I error and AUC. The output was generated by first including only financial variables and later incorporating firm-specific characteristics with the economic variables.

The analysis was spread over five years before the date of Liquidation/restructuring. Also, the study was carried out each year by including financial variables only and later on by including financial variables and firm-specific characteristics. It was observed that the accuracy rate was higher when firm-specific characteristics were included along with the economic variables to predict the financial distress outcome of the firm. Also, the accuracy declines as we move further away from the date of liquidation/ restructuring. However, accuracy cannot be considered as the criterion for measuring the prediction accuracy of a model. According to (Hsieh, 1993). The cost linked with Type I error is higher for the stakeholders than the cost related to Type II error, so the best model is the one with the lowest Type I error.

The results of the various models one year before bankruptcy/restructuring are given in Table 7.2. As we compare Panels A and B, we observe that the accuracy rate, precision, area under the curve (AUC), and Gini coefficient provide a better classification and prediction measure when the firm-specific characteristics are included with the financial variables. Out of the three models employed in the study, the Random Forest is the best bet in the distress prediction models as it has the lowest Type-I error. As per Anandarajan et al., (2001), "The objective of learning classifications from sample data is to classify and predict successfully on new data. A classifier's error rate is the most commonly used measure of success or failure. The error rate is statistically defined as the error rate of the classifier on an asymptotically large number of new cases that converge in the limit to the actual population distribution." For the analysis results, one year before the actual event of bankruptcy/restructuring, as shown in Table 7.2. It can be seen that the type-I error is lower in the analysis done when considering only financial variables. One reason for that could be that, as the firm approaches bankruptcy or restructuring, the financial position of the firm, as exhibited in the financial statements, has already deteriorated to a great extent. An analysis of attributes using the attribute selector indicates that size, Return on Total Assets, and Interest Cover are the significant attributes impacting the firm's failure. Thus, as the firm nears failure, the ability to pay the financial creditors becomes a major deciding factor in terms of the fate of the firm.

Table 7.2: One year before bankruptcy/restructuring

Model	**Accuracy rate**	**Precision**	**Type I error (1-sensitivity)**	**AUC**	**Gini coefficient**
Panel A: Only financial variables					
Random forest	**.613**	.586	**.087**	**.631**	**0.262**
Neural network	.557	.559	.233	.565	0.13
Logistic	.543	.543	.146	.518	0.036
Panel B: Financial variables and firm-specific characteristics					
Random forest	**.735**	.711	**.160**	**.784**	**0.568**
Neural network	.727	.736	.244	.740	0.48
Logistic	.718	.708	.204	.764	0.528

As we move further away from the date of liquidation and restructuring, it can be seen (Table 7.3) that the accuracy rate of the model declines. Also, the probability of a Type I error increases. This highlights that distress prediction is more accurate one year before liquidation/restructuring. Also, the attributes impacting the final decision concerning the firm's fate are size, and Gross fixed asset utilisation ratio. The size of the firm plays a significant role, and this follows the results as defined by Malakauskas & Lakštutienė, (2021) and Arora & Saurabh (2022).

Table 7.3: Two years before bankruptcy/restructuring

Model	Accuracy rate	Precision	Type I error (1-sensitivity)	AUC	Gini coefficient
Panel A: Only financial variables					
Random forest	**.577**	.568	**.164**	**.617**	**0.234**
Neural network	.557	.581	.414	.604	0.208
Logistic	.522	.531	.166	.546	.092
Panel B: Financial variables and firm-specific characteristics					
Random forest	**.736**	.715	**.166**	**.789**	**0.578**
Neural network	.723	.729	.241	.745	0.490
Logistic	.723	.711	.196	.754	0.508

Gupta (1994) opine that a firm is in financial trouble if its Earnings before interest, tax, depreciation, and amortisation (EBITDA) are less than its expenses. Therefore, the current study examines three years before the firm is adjudicated to be liquidated or restructured and calculates the accuracy rate and other prediction and classification indicators.

As we look at the results of Table 7.4, we see better prediction accuracy and a lower type-I error. This signifies that the prediction based on financial variables and firm-specific characteristics was more accurate three years before the firm was declared bankrupt or eligible for restructuring.

Table 7.4: Three year before bankruptcy/restructuring

Model	Accuracy rate	Precision	Type I error (1-sensitivity)	AUC	Gini coefficient
Panel A: Only financial variables					
Random forest	**.607**	.590	**.153**	**.665**	0.33
Neural network	.591	**.627**	.437	.653	**0.306**
Logistic	.546	.554	.270	.567	0.134
Panel B: Financial variables and firm-specific characteristics					
Random forest	**.729**	**.709**	**.174**	**.782**	**0.564**
Neural network	.701	.707	.259	.739	0.478
Logistic	.707	.698	.215	.745	0.490

Thus, it can be analysed that to predict a firm's financial distress, it is imperative to look into its performance as soon as it starts showing warning signals regarding low income and inability to pay operational creditors. Three years before the judgement of the distressed firms as bankrupt or restructured, the significant attributes/variables that are important are size and Profit after tax as a percentage of total income.

Early detection of a firm's movement towards failure in the early stages benefits business stakeholders. (Ashraf et al., 2019) In all the years of analysis, random forest emerged as a clear winner in predicting early distress and had the lowest Type I error, indicating its superiority over the traditional Logit model. This can be due to the fundamental difference between traditional statistical and Machine Learning models in handling data and making predictions. Statistical models, such as linear and logistic regression, are based on predefined assumptions about data distribution and variable relationships. These models are typically parametric, assuming a specific functional form (e.g., linearity) to define the relationship between input variables and the outcome. Statistical models are often effective with smaller datasets and perform well when the relationships among variables are well-understood. However, their predictive accuracy can be limited if data distribution assumptions are unmet. Here, the dataset comprises 1146 firms, which is a large dataset in terms of statistical models. On the other hand, Machine-learning models focus on flexible learning from complex, high-dimensional data, resulting in enhanced predictive capabilities. ANN follows Random Forest, indicating the superiority of machine learning models over conventional prediction models. The study's results are similar to those reported by Gupta (2022), Balasubramanian et al. (2019), and Sehgal et al. (2021).

7.5 Conclusion

The analysis indicates that predicting a firm's financial distress necessitates early detection through evaluating performance indicators, particularly when warning signs such as declining income and an inability to meet obligations to operational creditors become apparent. This would enable the firm to move towards sustainable measures in terms of innovation and creativity so as to deal with the ever-growing and dynamic business environment (Sinha et al., 2009; Gupta & Jain, 2017). The predictive accuracy of distress models improves considerably when firm-specific characteristics, including age, industry, and size, are incorporated alongside financial variables. Among the models assessed, Random Forest demonstrated the highest predictive efficacy, followed by neural networks and logistic regression, underscoring the superior performance of machine learning algorithms compared to traditional statistical models in forecasting financial distress. Firm size emerged as a particularly influential determinant, with smaller firms exhibiting a greater vulnerability to liquidation, consistent with prior findings by (2021) and Sehgal et al. Furthermore, the analysis revealed a decline in predictive accuracy as the forecasting horizon extended, aligning with observations by Charalambakis & Garrett(2019) and Sehgal et al. (2021). Key financial variables influencing distress prediction were profit after tax as a percentage of total income, return on assets and interest coverage. Notably, the cost associated with Type I errors exceeded that of Type II errors, emphasising the importance of models with minimised Type I errors. Finally, while statistical models offer interpretability through predefined relationships, machine learning models leverage flexibility in learning from complex, high-dimensional data, enhancing predictive capabilities.

Machine learning models, particularly Random Forest, outperform traditional approaches in predicting distress 1–3 years in advance, especially when augmented with firm-specific characteristics. This arms decision-makers with proactive insights that complement retrospective analysis.

CHAPTER 8

DISCUSSION, CONCLUSIONS AND IMPLICATIONS

Having demonstrated how macro signals, post-restructuring metrics, efficiency trajectories and predictive algorithms each illuminate different facets of corporate distress and recovery, Chapter 8 pulls all strands together. It discusses what our integrated findings mean for managers, creditors, investors, regulators and researchers—pointing the way toward more proactive, data-driven approaches to alleviating financial distress. This chapter presents a comprehensive analysis of the findings, synthesising the key insights from the study to understand the implications of financial distress and restructuring.

Section 8.1 discusses the factors contributing to corporate bankruptcy and examines post-restructuring financial performance, including liquidity, solvency, and revenue-generation capabilities. The discussion also examines efficiency measures and recovery trends across various industries, providing a deeper insight into corporate restructuring outcomes. **Section 8.2** outlines the study's broader implications for various stakeholders, including management, creditors, investors, regulators, employees, and researchers, highlighting the practical applications of financial distress prediction and recovery strategies. Finally, **Section 8.3** provides directions for future research, addressing extended period analysis, the inclusion of additional variables, advancements in machine learning techniques, the impact of macroeconomic conditions, operational efficiency post-restructuring, policy implications, and stakeholder outcomes. By integrating these perspectives, this chapter contributes to the academic discourse on insolvency, restructuring, and corporate recovery, offering industry practitioners and policymakers actionable insights.

8.1 Discussion

While each analytical strand—macroeconomic causality (Chapter 4), financial performance (Chapter 5), operational efficiency (Chapter 6), and predictive modelling (Chapter 7)—has been treated independently, their interconnections offer additional insight. The limited predictive power of macroeconomic indicators (~12.7%) in explaining distress (Chapter 4) contrasts sharply with the substantial role of firm-level financials in driving post-restructuring improvement (Chapter 5). This suggests that while macro forces may trigger systemic stress, recovery is more tightly governed by managerial agility and capital structure decisions. Moreover, DEA-based findings (Chapter 6) highlight that firms failing to improve post-revival scale efficiency often exhibit inconsistent performance in ML prediction models—especially in the Random Forest and ANN outputs (Chapter 7). Machine learning algorithms, in other words, don't just "learn" patterns from ratios; their success is amplified when those ratios reflect sustained efficiency improvements. This layered interaction suggests predictive models will be strongest when financial diagnostics and post-revival operational benchmarks are considered together, not in isolation.

To understand the reasons for the firm's bankruptcy, leading to decreased financial performance, it is imperative to understand the factors leading to such a situation. The financial performance indicators are not the reason but the result of the firm's distress. Although the firms operate through their production facilities and formulate their policies, their business outcomes are measured in terms of sales, profits, costs, and future business prospects, which are determined by the macroeconomic conditions prevalent in the domestic and world economies. A change in the macroeconomic policies leads to changes in the macroeconomic variables of the financial markets, such as interest rate, gross advances, non-performing assets, etc. Thus, the numbers on the firm's balance sheets and income statements are influenced by the macroeconomic conditions of the economy in which they are operating and the financial ecosystem around them. Thus, to understand the factors contributing to financial distress and its severity, it is required to study and investigate the aggregate-level factors contributing to corporate bankruptcy, which include factors associated with the banking sector and the factors relating to the Indian Economy. This has helped to analyse the cause-effect relationship of the variables interconnected in fiscal space (Halder et al., n.d.)

The assessment of the financial and operating performance of firms post-restructuring is important to assess the efficacy of the process and would thus underpin the relevance of the Tribunal. Financial restructuring plays a pivotal role in shaping corporate performance, particularly in liquidity management, turnover efficiency, leverage optimisation, and profitability restoration. Firms undergoing restructuring often face immediate liquidity constraints, as reflected in declining Current and Quick Ratios, indicating tight cash flows and working capital shortages. This initial decline underscores the financial strain associated with restructuring, necessitating strategic interventions to stabilise liquidity. Over time, firms employ improved governance mechanisms and optimise financial management practices, gradually restoring solvency. Similarly, turnover efficiency experiences temporary disruptions due to inefficiencies in receivable collections, creditor payments, and inventory turnover. Firms initially struggle with liquidity constraints, affecting their ability to manage trade credit and operational workflows effectively. However, post-restructuring, adjustments in supply chain management, production planning, and inventory control contribute to progressive stabilisation. Improved asset utilisation follows as firms realign business models and operational frameworks, reinforcing the need for integrating efficiency-enhancing measures alongside financial restructuring to sustain long-term recovery.

Leverage management remains a core component of restructuring, with firms actively reducing excessive dependency on debt financing. A notable decline in the Debt-to-Equity Ratio suggests a strategic transition toward equity-based financing, promoting financial stability and reducing insolvency risks. This deliberate approach to debt minimisation reflects firms' efforts to build more resilient financial frameworks while restoring investor confidence. Additionally, profitability indicators such as ROE, ROCE, and ROTA exhibit significant declines in the short term due to restructuring complexities. Firms face operational adjustments, revenue reallocation challenges, and financial stabilisation efforts, contributing to initial profitability strain. However, as cost optimisation measures, revenue enhancement strategies, and efficiency improvements take effect, firms demonstrate progressive recovery in earnings. This underscores the importance of structured financial governance, efficient debt management, and well-planned operational restructuring in facilitating long-term corporate sustainability.

The comprehensive impact of restructuring extends beyond financial realignment, demanding an integrated approach that balances liquidity stabilisation, leverage minimisation, and profitability restoration. Firms undergoing restructuring must adopt proactive financial governance mechanisms and strategic debt management approaches to mitigate short-term financial instability while fostering long-term resilience. Successful restructuring requires continuous operational optimisation, ensuring firms effectively navigate post-restructuring complexities while sustaining their market positioning. The study highlights restructuring as a transformative corporate process, necessitating adaptive financial strategies and efficiency-driven operational adjustments to secure durable financial stability. This research provides valuable insights into post-restructuring corporate performance, emphasising the necessity for a holistic recovery framework that aligns restructuring efforts with sustainable financial health, ensuring competitiveness in evolving market conditions. Ultimately, effective financial restructuring enables firms to fortify solvency, restore investor trust, and maintain operational efficiency, reinforcing their ability to thrive in dynamic economic landscapes.

The firms facing financial distress look for ways to overcome it. Inefficiency on the financial front leads to inefficiency in the working and operations of the firm. Financial restructuring of firms is a change in the debt-equity component of the firm and is one of the measures that help firms overcome financial distress. The impact of economic restructuring on the firm's operational efficiency can identify the success of the process. Over time, the efficiency changes have been studied concerning technological change and changes in technical efficiency. Technical efficiency, also known as the catching-up effect, represents progress towards the production frontier. On the other hand, technological change, referred to as frontier shift, signifies innovation and investment. In light of the above findings, several valuable managerial insights and implications have been explored within the study.

Efficiency analysis is a vital tool for assessing a company's performance. It indicates how the company optimally uses the limited available inputs to obtain the maximum output. Minimising the input utilised can also achieve the same output level.

However, their use has been somewhat limited, as has the broader application of DEA models combined with the Malmquist index. Most research on non-parametric efficiency measures has focused on the financial sector, particularly on banks, insurance companies, non-banking financial institutions, and financial cooperative societies. In contrast, applying these methods to non-financial firms remains relatively underexplored.

No recovery period in firms after the Tribunal's restructuring has been examined. Monitoring efficiency measures across various industries was particularly insightful, as it traced the recovery and pinpointed factors that aided in enhancing the efficiency measures.

The study offers valuable insights into the factors driving changes in firm efficiency, enabling management to explore the underlying causes of operational performance variations. This understanding can help determine whether efficiency improvements are necessary through technological advancements or adjustments to the firm's scale parameters. Additionally, policymakers can gain a clearer perspective on whether restructuring was a more effective decision than liquidation in the context of firm recovery.

An efficient company demonstrates good financial health, which is vital for the various stakeholders. The shareholders, creditors and management analyse it for their decision-making and for the Government to assess its financial and economic policies. (Stanková & Efficiency indices have been introduced, including total factor productivity and technical and technological change indices.

Financial distress leads to significant economic losses for all stakeholders, making it imperative to identify early distress signals. It encompasses several adverse consequences, including reduced market share and reputational standing, increased capital costs, a withdrawal of favourable trade credit terms from suppliers, and losses associated with asset sales conducted under distressed conditions (Li, 2024a). Additionally, financial distress often leads to the departure of valuable human capital and heightened exposure to aggressive strategies from competitors. The objective was therefore to determine the predictive and classification ability of the traditional logit model and the machine learning models. The traditional logit model was compared to two machine learning models: Random Forest and Artificial Neural Network. It was found that three years before the liquidation/restructuring of the firm, the Random Forest model had the highest predictive accuracy and lowest error rate. It is also observed that all the models had a predictive accuracy greater than 75%, thus confirming their robustness.

8.2 Implications

The implications of this research on various stakeholders are as follows-

1. Management and Shareholders

The research underscores the critical role of early detection in identifying financial distress, allowing management to implement corrective measures to mitigate potential failure proactively. Timely intervention facilitates financial stability and operational continuity, safeguarding firms from irreversible decline.

Furthermore, insights into performance improvement provide a deeper understanding of the key factors influencing changes in firm efficiency. By analysing these determinants, management can devise targeted strategies to enhance operational effectiveness and profitability, ensuring sustained business growth and resilience in competitive markets.

The findings also contribute to decision-making, offering a structured basis for evaluating financial restructuring and operational adjustments. A data-driven approach enables organisations to optimise their financial strategies, allocate resources efficiently, and navigate complex economic environments more precisely.

2. Creditors and Financial Institutions

The study emphasises the importance of credit risk management in safeguarding financial institutions against exposure to distressed firms. Implementing robust risk assessment frameworks enables lenders to mitigate the likelihood of default, ensuring a more resilient credit environment. Effective credit risk management strategies can enhance financial stability by improving lending decisions and minimising systemic vulnerabilities.

Additionally, integrating predictive models into credit evaluation processes offers a data-driven approach to assessing default probabilities. Financial institutions can leverage these models to anticipate potential insolvency risks and reduce the accumulation of non-performing assets (NPAs). By utilising advanced machine learning techniques, lenders can refine their credit assessment methodologies, ensuring a more precise and proactive approach to managing financial risk.

3. Investors

The research provides valuable insights for investment decision-making, enabling investors to identify firms with a heightened risk of financial distress. By leveraging these findings, investors can make more informed choices, strategically allocating resources to minimise exposure to financially unstable entities and optimise portfolio performance.

Moreover, the risk assessment capabilities of predictive models offer a data-driven approach to evaluating the financial health of prospective investment targets. These models enhance the accuracy of financial analysis, allowing investors to assess corporate viability with greater precision, thereby facilitating prudent investment strategies that align with long-term financial sustainability.

4. Regulators and Policymakers

The research offers critical insights into policy formulation, highlighting the macroeconomic and financial market factors contributing to corporate financial distress. Policymakers can develop targeted strategies to mitigate financial instability and enhance corporate resilience by identifying systemic risks and underlying economic inefficiencies. The findings serve as a valuable foundation for crafting regulatory frameworks supporting early intervention and effective risk management, fostering a more robust economic environment.

Additionally, the study provides meaningful contributions to the insolvency framework, offering empirical evidence that can inform improvements in the Insolvency and Bankruptcy Board of India (IBBI) and potential amendments to the Insolvency and Bankruptcy Code (IBC). Strengthening insolvency mechanisms ensures a more efficient resolution process, enhancing creditor confidence and facilitating corporate recovery. By refining insolvency regulations based on empirical insights, policymakers can enhance the effectiveness of financial restructuring, contributing to a more efficient and equitable business ecosystem.

5. Employees

Job security is a crucial consideration in corporate financial health, as early identification of financial distress allows firms to implement corrective measures that mitigate the risk of bankruptcy. By proactively addressing financial vulnerabilities, organisations can preserve workforce stability, ensuring continuity of employment and minimising disruptions for employees and stakeholders. Effective financial management strategies strengthen long-term sustainability, reinforcing the firm's capacity to withstand economic fluctuations and safeguard jobs.

Additionally, operational efficiency plays a vital role in post-restructuring stability. An improved efficiency framework following financial restructuring enhances productivity, optimises resource utilization, and fosters a more resilient work environment. Streamlining processes and refining organizational structures enable firms to achieve long-term performance gains, contributing to overall business sustainability and workforce security.

6. Academia and Researchers

The study offers significant opportunities for further research, particularly in applying machine learning models for financial distress prediction and the influence of macroeconomic factors on corporate performance. Expanding upon these areas can provide deeper insights into the evolving methodologies used in risk assessment, helping to refine predictive accuracy and enhance decision-making frameworks in financial analysis. Future studies could explore advanced algorithms, industry-specific adaptations, and the integration of external economic indicators to strengthen predictive capabilities.

Additionally, the research makes methodological contributions by systematically comparing traditional statistical models with machine learning techniques, offering a comprehensive evaluation of their strengths and limitations. This comparative analysis enhances the existing literature by showcasing machine learning approaches' superior predictive power and adaptability, reinforcing their applicability in corporate financial risk assessment and insolvency forecasting.

Overall, the research offers valuable insights and practical tools for various stakeholders to manage and mitigate the risks associated with financial distress, ultimately contributing to the stability and growth of the corporate sector.

8.3 Future Research Direction

The scope of future research based on the current study includes the following areas:

1. Extended Period Analysis

Future research could benefit from longitudinal studies that extend the analysis beyond the limited period examined in the present study. A more extensive time frame would enhance the robustness of the findings, offering more profound insights into the sustained impact of financial restructuring on firm performance. By assessing corporate trajectories over a longer horizon, researchers could better understand the evolving dynamics of financial distress, recovery patterns, and strategic adaptation in response to restructuring efforts.

Additionally, conducting a pre- and post-restructuring comparison over an extended period would provide a more comprehensive evaluation of restructuring effectiveness. A broader time frame could capture long-term financial stability, operational adjustments, and the sustainability of improvements following reorganisation. Such an approach would enable a nuanced assessment of whether restructuring measures lead to enduring positive outcomes or if firms face continued vulnerabilities post-recovery.

2. Inclusion of Additional Variables

Expanding financial distress models to incorporate non-financial factors such as management quality, corporate governance practices, and prevailing market conditions can significantly enhance predictive accuracy. While traditional models primarily focus on financial indicators, integrating qualitative variables provides a more holistic understanding of corporate viability. Strong governance frameworks and effective leadership can play a crucial role in mitigating financial risks, enabling firms to navigate crises more efficiently. Moreover, market dynamics, including competitive positioning and industry trends, influence a firm’s financial health, making their inclusion in predictive models essential for a more comprehensive assessment.

Additionally, sector-specific analysis presents an opportunity for more targeted research into financial distress determinants across industries. Different sectors exhibit unique financial structures, operational challenges, and market sensitivities, all of which contribute to varying distress and recovery patterns. By conducting industry-specific studies, researchers can identify sectoral vulnerabilities, tailor financial risk mitigation strategies, and develop predictive models that account for the distinct characteristics of each industry. This approach enhances the practical applicability of financial distress predictions, leading to more effective policy interventions and strategic corporate decision-making.

3. Advanced Machine Learning Techniques

Expanding the scope of algorithm comparison by evaluating the performance of advanced machine learning techniques, such as gradient boosting, support vector machines, and deep learning models, can enhance the accuracy and reliability of financial distress predictions. Each of these algorithms offers distinct advantages, with gradient boosting excelling in handling complex relationships within financial data, support vector machines providing robust classification capabilities, and deep learning models leveraging multi-layered architectures for high-dimensional analysis. By systematically comparing these methodologies, future research can identify the most effective algorithm for predicting corporate insolvency and financial vulnerability.

Additionally, the development of hybrid models that integrate traditional statistical methods with machine learning techniques presents an opportunity to refine predictive capabilities further. While statistical models offer interpretability and foundational economic reasoning, machine learning approaches provide adaptability and improved data processing power. Combining these methodologies could lead to more comprehensive risk assessment frameworks, balancing precision with explanatory power. Such hybrid models would be particularly beneficial in financial forecasting, allowing for more nuanced analysis of firm-specific characteristics alongside broader macroeconomic trends.

4. Modelling Limitations and Temporal Dynamics

While the study offers a comprehensive analysis of macroeconomic and firm-level determinants of financial distress, certain methodological limitations warrant further exploration. First, the use of recursive PLS-SEM in Objective 1, though appropriate for modelling latent constructs and causal pathways, does not fully capture the dynamic and time-sensitive nature of macroeconomic variables. Macroeconomic indicators such as GDP, inflation, and fiscal deficit evolve over time and may exert lagged or nonlinear effects on firm-level outcomes. The current model, based on quarterly panel data, provides a static snapshot of these relationships and may underestimate their cumulative or delayed impact.

Future research could address this limitation by employing dynamic panel data models such as Vector Autoregression (VAR), Autoregressive Distributed Lag (ARDL), or Time-Series SEM to better capture temporal dependencies and feedback loops. Additionally, incorporating interaction terms (e.g., GDP × firm size or inflation × industry type) could help uncover conditional effects that are masked in aggregate models. Exploring regime-switching models or structural breaks may also reveal how macroeconomic shocks differentially affect firms across time periods or sectors.

Moreover, while the current study focuses on firm-level financial ratios and macroeconomic aggregates, integrating qualitative variables such as governance quality, managerial turnover, or board composition could enrich the explanatory power of future models. These enhancements would allow for a more nuanced understanding of how external shocks and internal resilience mechanisms jointly shape corporate distress trajectories.

5. **Operational Efficiency Post-Restructuring**:

A detailed efficiency analysis using advanced methodologies such as the Malmquist Productivity Index (MPI) and Data Envelopment Analysis (DEA) can provide a more nuanced understanding of operational performance across industries. These techniques enable researchers and practitioners to evaluate firm-level efficiency, distinguishing between technical efficiency and technological progress. By applying these models to various sectors, firms can identify best practices, pinpoint inefficiencies, and formulate targeted strategies to enhance productivity. A sector-wide comparison of efficiency scores can offer valuable insights into industry-specific challenges and opportunities for performance optimisation.

Furthermore, the role of technological advancements in improving operational efficiency post-restructuring warrants deeper exploration. Innovation-driven transformations, including process automation, digitalisation, and AI-driven analytics, have significantly contributed to operational resilience and financial recovery. Examining how firms leverage technological advancements to streamline processes, reduce costs, and enhance overall productivity can provide actionable recommendations for organisations facing financial distress. A systematic evaluation of post-restructuring efficiency improvements can help establish frameworks for sustainable recovery, guiding firms in effectively integrating emerging technologies into their operational models.

6. Policy and Regulatory Implications

Future research could focus on IBC amendments, assessing their impact on distressed firms' recovery and financial performance. As regulatory changes shape the insolvency landscape, understanding their implications on corporate restructuring, creditor recoveries, and stakeholder outcomes is crucial. A detailed examination of recent amendments could provide insights into their effectiveness in streamlining resolution processes, enhancing transparency, and improving firm survival rates post-restructuring. Additionally, evaluating whether specific policy revisions have led to measurable improvements in firm sustainability would offer valuable recommendations for further refining the Insolvency and Bankruptcy Code (IBC).

Moreover, cross-country comparisons of insolvency and bankruptcy frameworks could yield valuable lessons for strengthening India's regulatory environment. By analysing international best practices, policymakers can identify strategies that enhance efficiency, promote creditor rights, and facilitate successful corporate restructuring. Comparative studies of diverse legal and economic systems would allow India to benchmark its insolvency mechanisms against global standards, fostering refinements that improve debtor-creditor dynamics, resolution timelines, and financial recovery outcomes.

7. Stakeholder Impact Analysis

Examining the impact of financial restructuring on employee outcomes offers a crucial perspective on the broader effects of corporate recovery efforts. Restructuring decisions significantly impact job security, productivity levels, and workplace morale, ultimately shaping the overall stability and engagement of the workforce. While effective financial restructuring may safeguard employment and create opportunities for operational optimisation, poorly managed recovery processes can lead to uncertainty, layoffs, and decreased employee motivation. Assessing these dynamics gives organisations insights into mitigating disruptions, fostering resilience, and ensuring that restructuring initiatives support long-term workforce sustainability.

Additionally, investor confidence is a key determinant of post-restructuring corporate success. Analysing how successful financial restructuring efforts impact market perceptions, shareholder trust, and investment behaviour offers valuable insights into broader financial recovery implications. When firms demonstrate effective financial repositioning, they often regain market credibility, attract investor interest, and enhance capital inflows. Conversely, unresolved financial instability or ineffective restructuring may deter investment and prolong corporate distress. Understanding these investor-driven responses enables firms to refine their restructuring strategies, communicate financial health transparently, and enhance market confidence.

By addressing these areas, future research can build on the current study's findings, providing a more comprehensive understanding of financial distress, restructuring, and recovery processes, ultimately contributing to the stability and growth of the corporate sector.

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ANNEXURES

ANNEXURE I

2017-18 [7 companies]	2018-19 [31 companies]	2019-20 [46 companies]	2020-21 [42 companies]
Burn Standard Co. Ltd.	A Power Himalayas Ltd.	A R G L Ltd.	Aircel Cellular Ltd.
Kohinoor C T N L Infrastructure Co. Pvt. Ltd.	Alok Industries Ltd.	Ambey Iron Pvt. Ltd.	Aircel Ltd.
Shirdi Industries Ltd.	Amalgam Steel & Power Ltd.	Angul Energy Ltd. [Merged]	Amar Remedies Ltd.
Sree Metaliks Ltd.	Arcelormittal Nippon Steel India Ltd.	Apex Drugs Ltd.	Asahi Industries Ltd.
Synergies-Dooray Automotive Ltd.	B J N Hotels Ltd.	Bheema Cements Ltd.	B P Food Products Pvt. Ltd.
Trinity Auto Components Ltd.	Bafna Pharmaceuticals Ltd.	Bhushan Power & Steel Ltd.	Badami Sugars Ltd. [Merged]
West Bengal Essential Commodities Supply Corpn. Ltd.	Bansal Steel & Power Ltd.	Calyx Chemicals & Pharmaceuticals Ltd.	Bansal Aradhya Steel Pvt. Ltd.
	Cosmic Ferro Alloys Ltd.	D D Steel & Power Ltd.	Benlon India Ltd.
	Danalakshmi Paper Mills Pvt. Ltd.	Deccan Chronicle Holdings Ltd.	Dhar Textile Mills Ltd.
	Ellora Paper Mills Ltd.	Dighi Port Ltd.	Digjam Ltd.
	G B Global Ltd.	Era T & D Ltd.	Dishnet Wireless Ltd.
	Jyoti Structures Ltd.	F M Hammerle Textiles Ltd.	Drake & Scull Water & Energy India Pvt. Ltd.
	Orissa Manganese & Minerals Ltd.	Flamingo Landbase Pvt. Ltd.	Ebixcash Mobility Software India Ltd.
	Paragon Steels Pvt. Ltd.	Golden Jubilee Hotels Pvt. Ltd.	Educomp Infrastructure & School Mgmt. Ltd.
	Quantum Ltd.	Govind Rubber Ltd.	Evonith Metallics Ltd.
	Rainbow Papers Ltd. [Merged]	Haryana Steel & Alloys Ltd.	G K C Projects Ltd.
	Raj Oil Mills Ltd.	I L C Inds. Ltd.	G V R Infra Projects Ltd.
	Rave Scans Pvt. Ltd.	Icomm Tele Ltd.	H C P Plastene Bulkpack Ltd.
	Rishi Ganga Enterprises Ltd.	Indus Fila Ltd.	Jal Power Corpn. Ltd.
	S M D Strategic Real Estate Ltd.	Jaihind Infra Tech Projects Pvt. Ltd.	Kharkia Steels Pvt. Ltd.

2017-18 [7 companies]	2018-19 [31 companies]	2019-20 [46 companies]	2020-21 [42 companies]
	Star Agro Marine Exports Pvt. Ltd.	Krishna Power Utilities Ltd.	Maharashtra Vidhyut Nigam Pvt. Ltd.
	Subburaj Spinning Mills Pvt. Ltd. [Merged]	Logic Eastern India Pvt. Ltd.	Micromax Energy Ltd.
	Sun Paper Mill Ltd.	M I C Electronics Ltd.	Multiwal Pulp & Board Mills Pvt. Ltd.
	Swadisht Oils Pvt. Ltd. [Merged]	Maharashtra Shetkari Sugar Ltd.	N I I L Infrastructures Pvt. Ltd.
	Taloja Steel Service Centre Ltd.	Maiyas Beverages & Foods Pvt. Ltd.	N S Papers Ltd. [Merged]
	Tata Steel B S L Ltd. [Merged]	Marsons Ltd.	Narayan Industries Global Ltd.
	Ultratech Nathdwara Cement Ltd. [Merged]	Maruti Koatsu Cylinders Ltd.	P V S Memorial Hospital Pvt. Ltd.
	Universal Power Transformer Pvt. Ltd.	Mohak Carpets Pvt. Ltd.	Prime Retail India Ltd.
	Vangal Amman Health Service Ltd.	Mynah Industries Ltd.	Prius Commercial Projects Pvt. Ltd.
	Ved Cellulose Ltd.	New Phaltan Sugar Works Ltd.	Reliance Infratel Ltd. [Merged]
	Venky Hi-Tech Ispat Ltd.	Noble Explochem Ltd.	S E L Manufacturing Co. Ltd.
		Olive Lifesciences Pvt. Ltd.	Sai Lilagar Power Generation Ltd.
		Orchid Pharma Ltd.	Sejal Glass Ltd.
		P Dot G Constructions Pvt. Ltd.	Shekhar Resorts Ltd.
		Patanjali Foods Ltd.	Shree Bhomika International Ltd.
		Rana Global Ltd.	Swastik Fruits Products Ltd.
		S P S Steels Rolling Mills Ltd.	Technovaa Plastic Inds. Pvt. Ltd.
		Scotts Garments Ltd.	Uniworld Sugars Pvt. Ltd. [Merged]
		Shaifali Rolls Ltd.	V I L Ltd.
		Sri Murugarajendra Oil Industry Pvt. Ltd.	V S Lignite Power Pvt. Ltd.
		Sunstar Overseas Ltd.	V S P Udyog Pvt. Ltd.
		Tehri Iron & Steel Casting Pvt. Ltd.	Vardhman Chemtech Ltd.
		Twamev Construction & Infrastructure Ltd.	
		Ushdev International Ltd.	
		Uttam Strips Ltd.	
		Zion Steel Ltd. [Merged]	

ANNEXURE II

2017-18 [3 companies]	2018-19 [14 companies]	2019-20 [23 companies]	2020-21 [0 companies]
Sree Metaliks Ltd.	Raj Oil Mills Ltd.	Star Agro Marine Exports Pvt. Ltd.	
Shirdi Industries Ltd.	Ved Cellulose Ltd.	Danalakshmi Paper Mills Pvt. Ltd.	
Trinity Auto Components Ltd.	Tata Steel B S L Ltd. [Merged]	S P S Steels Rolling Mills Ltd.	
	Ellora Paper Mills Ltd.	Calyx Chemicals & Pharmaceuticals Ltd.	
	Paragon Steels Pvt. Ltd.	Maiyas Beverages & Foods Pvt. Ltd.	
	Cosmic Ferro Alloys Ltd.	Tehri Iron & Steel Casting Ltd.	
	Sun Paper Mill Ltd.	Allied Strips Ltd.	
	Ultratech Nathdwara Cement Ltd.	Deccan Chronicle Holdings Ltd.	
	G B Global Ltd.	Uttam Strips Ltd.	
	Bansal Steel & Power Ltd.	Orchid Pharma Ltd.	
	Amalgam Steel & Power Ltd.	Olive Lifesciences Pvt. Ltd.	
	Bafna Pharmaceuticals Ltd.	Patanjali Foods Ltd.	
	Swadisht Oils Pvt. Ltd.	M I C Electronics Ltd.	
	Alok Industries Ltd.	Bhushan Power & Steel Ltd.	
		Sunstar Overseas Ltd.	
		Icomm Tele Ltd.	
		New Phaltan Sugar Works Ltd.	
		Shaifali Rolls Ltd.	
		A R G L Ltd.	
		Logic Eastern India Pvt. Ltd.	
		Era T & D Ltd.	
		Tantia Constructions Ltd.	
		F M Hammerle Textiles Ltd.	

LIST OF PUBLICATIONS

S.No.	Authors	Article/Title	Description	Journal/Conference
1.	Pallavi Sethi, Archana Singh, Vikas Gupta	Measuring Operational Efficiency of Restructured Companies: A DEA-MI Approach	Journal (ABDC indexed – ‘C’)	Journal of Business Thought (Accepted & Published) https://doi.org/10.18311/jbt/2024/44696
2.	Pallavi Sethi, Archana Singh, Vikas Gupta	Achieving Financial Sustainability Through Financial Restructuring: Evidence from the Ellora Paper Mills Ltd.	SAGE Journal	IMIB Journal of Innovation And Management (Accepted & Available Online) https://doi.org/10.1177/ijim.251314643
3.	Pallavi Sethi, Archana Singh, Vikas Gupta	Predicting Financial Distress Using Machine Learning Techniques	Journal (ESCI, SCOPUS, ABDC indexed- ’C’	Asia Pacific Financial Markets (Published) https://doi.org/10.1007/s10690-025-09525-7

LIST OF INTERNATIONAL CONFERENCES ATTENDED

S.No.	Authors	Article/Title	Description	Journal/Conference
1.	Pallavi Sethi, Archana Singh, Vikas Gupta	Changing Paradigms of Insolvency Law	International Conference	FISAT Business School, Angamaly, India on 29-30 July 2021 (Accepted & Presented)
2.	Pallavi Sethi, Archana Singh, Vikas Gupta	Achieving Financial Sustainability Through Financial Restructuring	International Conference	DSM, DTU on 19-20 January 2023 (Accepted & Presented)