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REGENT'S UNIVERSITY LONDON

Final Project for the fulfilment of the MSc Finance & Financial Technology

TITLE: Financial Distress prediction using the original Altman's Z Score and Logistic Regression: Evidence from Indian Listed Non-Financial Companies

By

TANUSHREE KOTRESH BACHENAHALLI

Date
03/09/2026

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Financial Distress prediction using the original Altman's Z Score and Logistic Regression: Evidence from Indian Listed Non-Financial Companies

ABSTRACT

Financial distress prediction is an important area of financial research because identifying financial difficulties at an early stage can help companies, investors, lenders and other stakeholders make better-informed decisions. This study examines the effectiveness of the original Altman Z-Score model in predicting financial distress among Indian listed non-financial companies and compares its predictive performance with Logistic Regression. The study covers four sectors: Chemicals, Industrial Goods, Pharmaceuticals and Medical Research, and Automobiles and Auto Parts, over the period 2015–2025. The final dataset consists of 195 companies and 1,853 usable company-year observations, with financial data obtained from LSEG Workspace.

Financial distress is defined using four financial indicators: negative Return on Assets (ROA), Current Ratio below 1, Interest Coverage Ratio below 1, and negative Operating Cash Flow. An observation is classified as financially distressed when at least two of these conditions are present in the same financial year. The study applies the original Altman Z-Score using its unchanged coefficients and estimates a Logistic Regression model using four explanatory variables: Return on Equity (ROE), Quick Ratio, Total Asset Turnover and Debt Ratio. Panel regression models, including Pooled OLS, Fixed Effects and Random Effects, are also examined as supplementary analysis. The Hausman test identifies the Fixed Effects model as the preferred panel specification, while Logistic Regression is used for the formal testing of the study's hypotheses. Model performance is assessed using accuracy, sensitivity and specificity, with 2023–2025 used as the out-of-sample period for comparing the two models.

The Logistic Regression results show that Quick Ratio, Total Asset Turnover and Debt Ratio have statistically significant relationships with financial distress. Quick Ratio and Total Asset Turnover have negative coefficients, while Debt Ratio has a positive coefficient, consistent with the expected relationships.

ROE also has a negative coefficient, as expected, but its relationship with financial distress is not statistically significant. Therefore, the results support the importance of liquidity, asset efficiency and leverage in distinguishing financially distressed observations within the sample.

The main model comparison shows that the original Altman Z-Score performs better than Logistic Regression during the out-of-sample period. Using the same 432 company-year observations for 2023–2025, the original Altman Z-Score achieves an accuracy of **84.03%**, compared with **79.86%** for Logistic Regression. Altman also records higher sensitivity (**64.63%** compared with **61.22%**) and higher specificity (**94.04%** compared with **89.47%**).

Overall, the findings suggest that the original Altman Z-Score remains a useful financial distress screening tool for the Indian listed non-financial companies examined in this study. The results also highlight that predictive performance depends not only on the statistical technique used, but also on the choice of variables, the definition of financial distress, the characteristics of the sample and the prediction period. By comparing the unchanged original Altman Z-Score with Logistic Regression using the same distress definition and out-of-sample observations, this study provides empirical evidence on the relative performance of the two approaches in the Indian context.

CHAPTER 01 – Introduction

Background

Financial distress has become an important concern for businesses, lenders, policy makers and investors al around the world. A company that is experiencing financial distress usually faces a lot of difficulties in meeting the financial obligations mostly because of its declining profitability, poor liquidity and insufficient cash flow. If these financial problems are not identified at early stages, it might lead to insolvency, bankruptcy or even business failure. Therefore, identifying financial distress before the company reaches that stage has become an important area of research in finance and accounting. Early prediction helps investors make informed investment decisions and enables lenders to access potential credit risks more effectively. Financial distress occurs when a company is not able to generate sufficient financial resources to meet its financial obligations. Although financial distress does not necessarily mean that the company will fail, it is generally considered early warning stage before any serious financial problem arises. Identifying companies that are more likely to experience financial distress at an early stage allows managers to take decisions and enables lenders to assess potential credit risks effectively.

Therefore, the importance of predicting financial distress has encouraged researchers to develop different models that can identify vulnerable companies before failing occurs. One of the earliest studies was conducted by Beaver (1966) who stated that financial ratios could be used to distinguish between healthy and failing firms and lead to the foundation of financial distress prediction models. Altman (1968) introduced something called Z Score model which actually combines multiple financial ratios into one to predict corporate failure. Because of its simplicity and high predictive accuracy, it has remained to be one of the most widely used financial distress models for more that 5 decades now. Ohlson's logistic regression model now has become one of the most commonly used statistical techniques in financial distress prediction research because it allows different financial variables to predict the financial distress.

The original Altman Z score was developed using public listed companies in the United States in 1960's. Since then, the business environments, accounting practices and financial reporting standards have changed a lot. This has led many researchers to examine whether the original model remains effective when applied outside the context which was originally developed.

India provides a relevant setting to examine financial distress prediction. As one of the world's largest emerging economies, India has experienced rapid industrial growth, increasing capital market participation and high expansion of its listed corporate sector. But, at the same time companies are still facing financial challenges due to economic fluctuations and changing market conditions every day.

These factors highlight the importance of financial distress model predictor that can assist investors, lenders in identifying serious financial problems. Existing research has made good contributions that are important in understanding financial distress prediction in India. However, many studies have either focused solely on Altman's Z score or solely on Logistic regression. While there are several other studies that have examined modified versions of the original Altman's model. Limited research is available where they directly compare the predictive performance of Altman's z score and logistic regression using Indian listed non-financial companies under a consistent definition of financial distress. This provides an opportunity to investigate further about the applicability of these widely used models within Indian environment. Thus, this study compares the predictive performance of the original Altman's Z score and logistic regression in predicting financial distress among Indian listed non-financial companies. This study aims to contribute to the existing literature while also providing insights for investors and other stakeholders in financial decision making.

Objective

As the importance of financial distress is growing every day, it has encouraged researchers to develop and evaluate different prediction models across various countries and industries. Among these models, Altman's Z score remains to me one of the widely known approaches due to its simplicity and practical application. However, as it was originally developed in the United States, it has led to raiding questions about whether it can be applied effectively to companies operating in other countries like India. At the same time, Logistic Regression has become one of the most used techniques to predict financial distress too because its flexible, and the ability to estimate the probability of failure using financial data. Even though both the models have been widely used in previous studies, the existing research in India has only focused on either Altman Z score or Logistic regression individually.

Therefore, the purpose of this study is to evaluate the effectiveness of the original Altman's Z score in predicting financial distress among Indian listed non-financial companies and to predict its performance with Logistic Regression.

By applying both models to the sample using a consistent definition to financial distress, this study seeks to accomplish the following objectives:

- To evaluate the effectiveness of the original Altman's Z score in predicting financial distress among Indian listed non financial companies.
- To develop a Logistic regression model for predicting financial distress and compare its predictive performance with the original Altman's z score
- To determine which model provides more accurate and reliable predictions of financial distress within the Indian corporate context.

This study will answer the following research question:

"How effective is the original Altman's Z score in predicting financial distress among Indian non-financial listed companies compared with Logistic Regression?"

Financial distress prediction model has been widely used and studied over past several decades with these models and are being applied across different countries and industries. Talking about Indian companies, previous studies have made valuable contributions by examining financial distress using either Altman's Z score or Logistic Regression. However, many of these studies have focused on modified versions of the Altman model, specific industries, or individual prediction techniques rather than comparing the original Altman's z score with logistic regression. Diving deep into it, we get to know that previous studies have adopted different definitions of financial distress, making it difficult to compare findings across literature.

Limited research has evaluated both models using a consistent definition of financial distress with a sample of non financial listed companies. This study addresses these gaps by comparing the predictive performance of the original Altman's z score and logistic regression using the same sample and a consistent measure of financial distress. This study thus provides further evidence on the applicability of these prediction models within Indian corporate environment.

Contribution

This dissertation will contribute to both academic as well as practical decision making in financial distress prediction. When looking into the academic perspective, the study extends the literature by evaluation the applicability of Altman's Z score within Indian environment and also comparing its performance with logistic regression. Unlike many previous studies that have only focused on a single prediction model or modified versions of Altman's model, this research will provide a direct comparison of two widely known prediction models. The findings are expected to provide additional evidence on the suitability of these models in emerging market context. From practical perspective, the findings of this dissertation will benefit the investors, the lenders and the financial analysts by providing a better understanding of the effectiveness of the financial distress prediction models. They will also help support investment decisions, credit risk assessment and early identification of financially down companies.

Structure

The remaining sections of this dissertation are organised into the following chapters:

Chapter 2 presents the literature review by examining previous research on financial distress, financial distress prediction models, Altman's Z score, Logistic regression, studies conducted within the Indian context. This chapter will also identify the research gap that forms the base of this study. **Chapter 3** explains the research methodology adopted in this study. It describes the financial distress definition, research design, data source, sampling method, variables, data collection process and the statistical techniques used for analysis. Chapter 4 shows the empirical findings of the study. It includes the descriptive analysis and the results of Altman's and logistic regression models and an overall comparison of their predictive performance. **Chapter 5** will discuss the findings in relation to previous literature, presents the conclusions of the study, highlights the practical implications and acknowledges the limitations of the research and provides recommendations for future studies.

CHAPTER 02 – Literature Review

2.1 Introduction

Financial distress prediction has been an important area of research in finance because financial problems can develop before a company reaches insolvency or bankruptcy. Being able to identify these problems early can be useful to managers, investors and lenders because it gives them an opportunity to respond before the situation becomes more serious. Over time, researchers have therefore developed different approaches to identify financially distressed companies using financial ratios and statistical models. The literature has developed from early studies based mainly on individual financial ratios to models that combine several financial measures. Altman's Z-Score is one of the most widely recognised approaches because it combines financial ratios into a single score, while Logistic Regression provides a different approach by estimating the likelihood of financial distress using a number of explanatory variables. Both methods have been widely applied, but previous studies do not always report the same level of performance. This suggests that the usefulness of a prediction model may depend not only on the model itself, but also on the companies, industries, countries, time periods and financial variables included in the study.

This is an important issue when reviewing the existing evidence. For example, a model may perform very well when applied to companies from one particular industry but produce different results when applied to a wider group of companies. This can happen because companies in different industries may have different financial structures, operating conditions, levels of debt, profitability and asset requirements. Similarly, studies covering different periods may produce different results because the financial position of companies can change over time. Therefore, the accuracy reported in one study should not automatically be assumed to apply to another group of companies. The same issue can be seen in the Indian literature. Previous researchers have examined financial distress among Indian listed companies, individual companies, small-cap companies, public sector enterprises and firms from specific industries. They have also used different definitions of financial distress and different prediction methods. Some studies have applied the original Altman Z-Score, while others have modified the model or used Logistic Regression and other statistical techniques.

These differences provide useful evidence, but they also make direct comparison between studies more difficult. This chapter therefore reviews the existing literature by focusing on the main factors associated with financial distress and the development and use of Altman's Z-Score and Logistic Regression. The studies are considered together rather than simply presented one after another, with attention given to differences in their samples, industries, methods and findings. The review then focuses more closely on evidence from Indian companies to identify what is already known and what remains unclear. This helps establish the research gap and provides the basis for the hypotheses and methodology used in the present study.

2.2 Theoretical Framework

FINANCIAL DISTRESS

Financial distress generally refers to a period in which a company begins to experience financial difficulties and may find it harder to meet its financial obligations. However, previous research does not use one common definition of the term. Some studies identify distress using financial ratios, while others use events such as insolvency, bankruptcy or formal financial difficulty. Amaniyah et al. (2025), through their review of financial distress prediction research, showed that researchers have used different measures and approaches to identify distressed firms. Balasubramanian et al. (2019) also considered both financial and non-financial information when identifying financial distress among Indian listed companies. The absence of one common definition is important because it affects how the results of different studies can be interpreted. A company classified as distressed under one definition may not necessarily be classified in the same way under another.

For example, a study based on profitability may identify a company as financially weak because of poor returns, while a study based on insolvency proceedings may only classify the company as distressed once its financial problems have become much more serious. Therefore, differences in reported prediction accuracy may partly reflect differences in how the outcome itself has been defined, rather than differences in the ability of the prediction model.

Early research established the importance of using financial information to identify financial problems. Beaver (1966) showed that financial ratios could help distinguish between healthy and failing firms before failure occurred.

Altman (1968) developed this idea further by combining several financial ratios into the Z-Score model. These studies were important because they moved financial distress research towards identifying warning signs before a company actually failed. However, the continued use of different definitions in later studies shows that identifying the early stage of distress remains a challenge.

Financial distress can also be understood as different from insolvency and bankruptcy. Financial distress may begin when a company's financial position starts to weaken, whereas insolvency represents a more serious inability to meet financial obligations. Bankruptcy generally involves a formal legal process. This distinction is important because a prediction model that identifies financial weakness at an early stage is serving a different purpose from a model designed to identify companies that have already reached formal insolvency. Singh and Singla (2023) highlighted the value of identifying financial problems before they become severe, while research on companies involved in the Indian Insolvency and Bankruptcy Code provides evidence that financial difficulties can be visible before formal insolvency proceedings begin. The way financial distress is measured can also depend on the type of company being studied. Nair and Sachdeva (2016), examined financial distress in the Indian textile industry using financial ratios, whereas Mahesh et al. (2025) considered financial, firm-specific and wider economic factors when studying small enterprises in India. These approaches are useful for their respective research settings, but they also show why findings from one group of companies cannot automatically be applied to another. A measure that works well for a particular industry or type of business may not capture financial difficulties in exactly the same way for a wider group of companies.

For the present study, having a consistent definition of financial distress is therefore particularly important. The purpose is not only to identify financially weaker companies but also to compare the performance of two prediction models. If different definitions were used for Altman's Z-Score and Logistic Regression, the comparison would not be fair because the models would effectively be predicting different outcomes. The present study therefore uses one consistent financial distress classification across the sample, allowing both models to be assessed against the same actual outcome. The specific indicators, threshold and classification procedure used to create this outcome are explained in Chapter 3.

FINANCIAL DISTRESS PREDICTION

Financial distress prediction developed from the idea that financial information could provide warning signs before a company experienced serious financial problems. Early research mainly examined whether individual financial ratios could distinguish healthy companies from firms that later failed. Beaver (1966) was an important contribution to this area because it showed that financial ratios could provide useful information about future failure. However, relying on individual ratios can make it difficult to assess the overall financial position of a company because different ratios may give different signals. Altman (1968) addressed this issue by combining several financial ratios into one Z-Score. Instead of looking at profitability, liquidity or efficiency separately, the model considers several aspects of financial health at the same time. This made the approach relatively simple to apply and helped establish the use of multiple financial indicators in financial distress prediction. Its continued use across different countries and industries shows its practical value, but the differences in results across studies also raise questions about whether the original model performs equally well outside the environment in which it was developed.

Logistic Regression provided another way of approaching the same problem. Ohlson (1980) used Logistic Regression to estimate the probability of corporate failure based on a number of company characteristics. Unlike a fixed scoring model, Logistic Regression allows the relationship between several explanatory variables and the probability of distress to be examined at the same time. This provides researchers with information not only about whether a company is likely to be distressed, but also about how individual financial variables are related to that likelihood. Later research continued to develop alternative prediction approaches, including probit models and other statistical and machine learning techniques. This development reflects a wider issue in financial distress research as there is no single model that is guaranteed to perform best in every situation. The usefulness of a model depends partly on the companies being studied, the variables available, the period covered and the way distress is defined.

Balasubramanian et al. (2019), used both financial and non-financial information when predicting distress among Indian listed companies, while Singh and Singla (2024) used financial variables in a Logistic Regression model for Indian companies. These studies show that researchers have increasingly considered whether models should reflect the characteristics of the market in which they are applied.

This development is relevant to the present study because Altman's Z-Score and Logistic Regression approach financial distress in different ways. Altman's model produces a score based on a fixed combination of financial ratios, whereas Logistic Regression estimates the relationship between selected financial variables and the probability of distress. Comparing the two therefore provides an opportunity to examine whether a model based on the original Altman coefficients performs better or worse than a model estimated using financial data from the Indian companies in the present sample.

However, such a comparison is only meaningful if the two models are tested under the same conditions. Differences in the companies included, the period covered or the definition of distress could make one model appear better simply because it was tested in a more favourable setting. This is one of the main issues identified in the previous literature and is also one of the reasons for using the same sample and a consistent distress classification when comparing the two models in this study.

2.3 Empirical Evidence

FINANCIAL DETERMINANTS OF FINANCIAL DISTRESS

Financial distress is rarely caused by one financial problem alone. A company may experience financial difficulties because it is not generating enough profit, does not have enough liquid resources to meet short-term obligations, relies heavily on debt, or is not using its assets efficiently. For this reason, previous studies have considered several financial ratios when examining financial distress. The importance of individual ratios, however, is not always the same across studies. Differences in industry, company size, economic conditions and the period studied can affect the relationship between a particular financial measure and financial distress. Therefore, the present study considers profitability, liquidity, asset efficiency and leverage together rather than relying on one financial indicator.

Profitability

Profitability is commonly considered an important indicator of financial health because companies that generate stronger returns are generally in a better position to meet their financial obligations and continue their operations. Previous research on Indian companies has generally found a relationship between profitability and financial distress.

Nair and Sachdeva (2016) identified profitability as an important factor when examining financial distress in the Indian textile industry, while Balasubramanian et al. (2019) also found profitability related measures useful in predicting distress among Indian listed companies. Similar findings have been reported in international research, although the strength of the relationship varies between studies (Savery et al., 2024; Singh and Singla, 2024). This relationship is reasonable because a company with consistently weak profitability has less internal income available to support its operations and meet its financial commitments. However, profitability alone does not necessarily indicate that a company is financially safe. A company can report reasonable profits while still facing liquidity problems or carrying a high level of debt. This is why profitability needs to be considered alongside other financial characteristics. In the present study, Return on Equity (ROE**)** is used to represent profitability because it measures the return generated on shareholders' equity. The study therefore expects higher ROE to be associated with a lower likelihood of financial distress.

Liquidity

Liquidity reflects a company's ability to meet its short-term financial obligations using assets that can be converted into cash relatively quickly. A weak liquidity position can create financial pressure even when a company is profitable, particularly when it has immediate payments to make.

Previous research has therefore included liquidity measures when predicting financial distress. Nair and Sachdeva (2016), Balasubramanian et al. (2019) and Mahesh et al. (2025) all considered liquidity related measures in their studies, although the specific ratios and their importance differed. The differences between studies are important because liquidity can be affected by the nature of the business. Companies operating in industries with different working capital requirements may need different levels of liquid assets to operate normally. Therefore, a liquidity ratio should be interpreted in the context of the companies being studied rather than viewed as having the same meaning for every business. In the present study, the Quick Ratio is used as the measure of liquidity because it focuses on the company's ability to meet short-term obligations without relying on the sale of inventory. A higher Quick Ratio is therefore expected to be associated with a lower likelihood of financial distress.

Asset Efficiency

The ability of a company to use its assets effectively can also provide information about its financial condition. Total Asset Turnover measures the number of sales generated from the company's total assets and therefore provides an indication of how efficiently those assets are being used. Mahesh et al. (2025) included Total Asset Turnover when examining financial distress among small enterprises in India, while Sethi and Mahadik (2024) also considered asset turnover in their Logistic Regression analysis. The relationship between asset efficiency and distress is not as straightforward as profitability or liquidity. A higher level of asset turnover may indicate that a company is making effective use of its resources, but the ratio can also differ naturally between industries because some businesses require much larger asset bases than others. This means that differences in industry structure may partly explain why the importance of asset turnover is not identical across studies. In the present study, Total Asset Turnover is included because it provides information about the operating efficiency of the selected companies. A higher level of asset turnover is expected to be associated with a lower likelihood of financial distress.

Leverage and Debt

Debt is another important factor because borrowing creates financial obligations that a company must continue to meet even when its income or cash flow falls. A company with a high level of debt may therefore face greater financial pressure during periods of weaker performance. Previous studies have generally found a positive relationship between leverage and financial distress, although the strength of the relationship differs between samples.

Balasubramanian et al. (2019), Savery et al. (2024) and Mahesh et al. (2025) all considered debt or leverage when examining financial distress. However, the presence of debt does not automatically mean that a company is financially distressed. Debt can also be used to finance investment and expansion, and its effect depends on the company's ability to generate sufficient returns and cash flows to meet its obligations. Therefore, the level of debt needs to be considered together with profitability, liquidity and asset efficiency. In the present study, Debt Ratio is used to measure the proportion of total assets financed through debt. A higher Debt Ratio is expected to be associated with a higher likelihood of financial distress.

Conclusive note

The literature therefore provides a clear reason for considering these four financial areas together. Profitability shows whether the company is generating returns, liquidity indicates its ability to meet short-term obligations, asset efficiency shows how effectively its resources are being used, and debt reflects the level of financial obligations created through borrowing. Looking at these factors together provides a broader view of a company's financial condition than relying on any single ratio. At the same time, the literature does not suggest that all four variables will have the same importance in every study. Their relationships with financial distress can change depending on the industry, company characteristics, period and other variables included in the model.

This is particularly relevant to the present study because the sample covers Indian listed non-financial companies from Chemicals, Industrials, Pharmaceuticals and Auto Parts. These industries have different business structures and financial requirements, so examining the variables together allows the study to test whether the expected relationships are supported across the sample. There is also an important point concerning the relationship between ROE and ROA in this study. Both are profitability measures and are naturally related because they assess returns generated from different aspects of a company's financial resources. However, they are not being used for the same purpose in the research.

ROA is used as one of the four indicators for constructing the financial distress outcome, while ROE is used as an explanatory variable in the Logistic Regression model. This distinction needs to be made clear because the variables are financially related even though they have different roles in the research design. The possibility of a close relationship between explanatory variables is also considered through multicollinearity testing in the methodology and results chapters.

Overall, previous research supports the use of profitability, liquidity, asset efficiency and debt when examining financial distress, but it also shows that their effects are not completely consistent across different research settings. This provides a reason to test the four selected variables using the Indian non-financial listed company sample in the present study rather than assuming that previous findings will apply directly. The results will help determine which financial factors are significantly associated with the distress classification used in this research and will provide the basis for testing H1 to H4.

EMPIRICAL EVIDENCE ON ALTMAN'S Z-SCORE

Altman's Z-Score is one of the most widely used models for financial distress prediction. Since it was introduced, researchers have applied it to companies in different countries and industries to examine whether it can identify firms that are financially healthy or at risk of financial distress. The results generally support the usefulness of the model, but its performance has not been the same across all studies. This difference is important because the original model was developed using US companies, while later research has applied it to companies with different financial structures, industries and economic conditions.

Evidence from India provides support for the use of the Z-Score, although the findings need to be considered in relation to the type of companies included in each study. Sanesh (2016) applied the model to NIFTY 50 companies, excluding banks and financial companies, and found that it could be used as an indicator of the financial health of listed companies. Sanesh (2014) also used the model to assess the financial health of Steel Authority of India Limited over several years. These studies show that the Z-Score can provide useful information about the financial condition of Indian companies, but the scope of the two studies is very different. One considers a group of listed companies, while the other focuses on a single company. This means that evidence from one company cannot automatically be taken as evidence of how the model will perform across a wider group of Indian firms. Industry differences provide another reason why the results of Altman studies need to be interpreted carefully. Ahamed and Ahammed (2024) applied the Z-Score to 41 Indian logistics companies between 2019 and 2023 and reported an accuracy rate of 96.6%.

This is a strong result and supports the usefulness of the model within their sample. However, logistics companies may have different working capital requirements, asset structures and operating patterns compared with companies in other sectors. Therefore, the high accuracy reported in this study should not automatically be treated as evidence that the original Z-Score will achieve the same level of accuracy across all Indian non-financial companies.

Company size and the type of company being studied can also affect the results. Raju and Raju (2025) examined Indian small-cap companies using both the Z-Score and Z"-Score and found that the financial condition of companies could change over time, with some firms moving between different financial health categories.

Padhy et al. (2025) focused on companies connected with the Indian Insolvency and Bankruptcy Code and found that the Z-Score could provide an indication of financial problems before or around the time of formal insolvency proceedings. These studies support the value of the Z-Score as an early warning measure, but their samples represent particular groups of companies. Small-cap firms and companies involved in insolvency proceedings may have financial characteristics that are different from larger listed companies that have not entered formal insolvency processes. The period covered by a study is also relevant when considering the performance of the model. Financial conditions can change over time because of changes in economic activity, interest rates, demand, costs and access to finance. A model that performs well during one period may not necessarily produce the same results during another period. This is particularly relevant to financial distress research because a company's financial ratios can change before the company moves into or out of a distressed position. Raju and Raju (2025) provide evidence of this movement between financial health categories, showing that financial condition should not always be viewed as fixed.

Another issue in the literature is the use of modified versions of Altman's model. Singh and Singla (2023) developed an improved model for the Indian corporate sector and compared it with the original Altman Z-Score. Raju and Raju (2025) also considered different versions of the model. The use of modified models suggests that researchers have questioned whether the original coefficients and cut-off points are equally suitable for companies operating in different countries and industries. At the same time, using a modified model changes the original specification and therefore makes it difficult to judge how well Altman's original model itself performs in the new setting. International studies provide a similar picture. Savery et al. (2024) applied the Z-Score to a mining company in Indonesia, while Yimam and Babu (2025) examined manufacturing companies in Ethiopia. These studies support the broader use of financial ratios when assessing financial distress, but the industries and countries involved are different from the Indian listed companies examined in the present study. A mining company, for instance, can have very different levels of fixed assets, debt and operating costs compared with a pharmaceutical or auto parts company.

Therefore, findings from international studies provide useful background evidence but cannot be directly applied to the Indian sample without considering these differences. The evidence also shows that the definition of financial distress can affect the reported performance of the Z-Score. Some studies use financial ratios to classify companies, while others focus on actual failure, insolvency or other financial events.

When the definition of distress changes, the companies classified as distressed may also change. This makes it difficult to compare accuracy rates across studies unless the same definition and classification approach are used.

Overall, previous research supports Altman's Z-Score as a useful and relatively simple method for assessing financial distress, but the evidence does not show that its performance is the same in every setting. Differences in industry, company size, country, sample period and the definition of distress can all affect the results. The frequent use of modified versions of the model also raises questions about the suitability of the original coefficients when the model is applied outside its original setting. For this reason, the performance of the original Z-Score needs to be tested within the specific group of companies being studied rather than relying only on accuracy rates reported in previous research. For the present study, this is particularly relevant because the sample consists of Indian listed non-financial companies from Chemicals, Industrials, Pharmaceuticals and Auto Parts. These industries have different business structures and financial requirements. Testing the original Altman Z-Score across these sectors provides an opportunity to examine whether the model continues to provide useful results when applied to a broader group of Indian non-financial companies. The results can then be compared with Logistic Regression using the same sample and financial distress classification, providing a more direct comparison between the two approaches.

EMPIRICAL EVIDENCE ON LOGISTIC REGRESSION

Logistic Regression has become an important method in financial distress research because the outcome being studied can be divided into two categories, such as financially distressed and non-distressed. Unlike a scoring model that gives a company a fixed score, Logistic Regression estimates the likelihood of an observation belonging to one of these categories based on a set of financial variables. This makes it useful when the purpose of the study is not only to classify companies but also to examine which financial factors are related to the likelihood of distress.

The financial variables included in a Logistic Regression model are important because the results depend partly on what information is used to explain distress. Profitability, liquidity, leverage and efficiency are commonly considered because they represent different areas of a company's financial position.

The expected relationships are also intuitive stronger profitability, and liquidity should generally reduce financial pressure, while higher debt can increase it. However, previous research does not find every variable to be significant in every study. This difference may be related to the companies included, the industry, the period studied and the other variables included in the model. It suggests that financial ratios should not be treated as having the same importance across every type of company. Indian evidence supports the usefulness of Logistic Regression but also shows differences in how the model has been applied. Balasubramanian et al. (2019) examined Indian listed companies using financial and non-financial information, while Sethi and Mahadik (2024) focused on Indian non-financial service companies.

Both provide support for Logistic Regression as a useful approach, but their research settings are different. The first study included both financial and non-financial information, whereas the second focused on a particular group of non-financial companies. This difference matters because a model using a wider set of information may perform differently from one based mainly on financial ratios.

The choice of variables can therefore have a direct effect on the results. Mahesh et al. (2025) considered financial variables together with firm-specific and macroeconomic factors when examining financial distress among Indian small enterprises. This broader approach recognises that financial distress can be influenced by factors outside the company's financial statements. At the same time, including more variables does not automatically mean that the model will be better. Additional variables need to provide useful information and should be appropriate for the companies and purpose of the study. For the present research, the focus is kept on financial variables because the study aims to examine whether a relatively simple financial information-based Logistic Regression model can provide useful predictions for Indian listed non-financial companies. The importance of industry also needs to be considered. Financial ratios can have different meanings depending on how a company operates. Companies in asset-intensive industries may naturally have different asset turnover or debt levels from companies that require fewer physical assets. Similarly, working capital requirements can differ between industries. This means that a relationship identified in a study of financial service companies or small enterprises cannot automatically be expected to remain the same for companies in manufacturing-related sectors. The present study therefore provides an opportunity to examine the selected financial variables across companies from Chemicals, Industrials, Pharmaceuticals and Auto Parts, rather than focusing on a single industry.

Another issue is that Logistic Regression is sometimes presented as a stronger alternative simply because it is more flexible than traditional scoring models. The existing evidence does not support making this assumption in advance. Some studies have reported strong Logistic Regression results, while other research has found that alternative statistical or machine learning approaches perform better.

Sethi and Mahadik (2024), has compared Logistic Regression with Linear Discriminant Analysis and Artificial Neural Networks and found that Logistic Regression performed strongly within their sample. However, this result should be understood within the context of the companies, variables and period used in that study. The way prediction performance is measured is also important. A model may have high overall accuracy while still failing to identify a considerable number of genuinely distressed companies. For financial distress prediction, this is an important issue because incorrectly classifying a distressed company as financially healthy can be more serious than incorrectly classifying a healthy company as distressed. Therefore, measures such as sensitivity, specificity and the numbers of true and false classifications provide additional information beyond overall accuracy.

Using several measures gives a more complete picture of how well a model identifies both distressed and non-distressed companies. There is also a difference between developing a model using historical observations and testing whether it can predict future observations. A model may classify the same data from which it was estimated quite accurately, but this does not necessarily mean that it will perform equally well when applied to later years. This distinction is particularly relevant when the aim is to discuss prediction rather than only classification. It provides a reason for separating the period used to estimate the model from the later period used to assess its predictive performance.

COMPARATIVE EVIDENCE ON FINANCIAL DISTRESS PREDICTION MODELS

Previous research comparing financial distress prediction models does not provide a clear answer that one model will always perform better than another. The results vary across studies, with some research reporting strong performance from traditional models such as Altman's Z-Score, while other studies find better results from Logistic Regression, modified models or machine learning methods.

This difference is important because model performance is influenced by the type of companies being studied, the variables included, the period covered and the way financial distress is defined. Therefore, the results of one model comparison cannot automatically be applied to a different group of companies. The differences in research design can be seen in studies that have compared Logistic Regression with Altman's model. Singh and Singla (2023) found that their newly developed Logistic Regression model performed better than a re-estimated Altman model in the Indian corporate setting. However, their comparison was not between Logistic Regression and the original Altman model, since the Altman model was first re-estimated using more recent data. This distinction matters because changing the coefficients of Altman's model changes the model being tested.

Similarly, Sethi and Mahadik (2024) found that Logistic Regression performed strongly when compared with Linear Discriminant Analysis and Artificial Neural Networks among Indian non-financial service companies. Their findings provide support for Logistic Regression, but the companies and methods used were different from those in the present study. Another issue is how model performance is measured. Overall accuracy is useful because it shows the proportion of observations that have been classified correctly, but it does not tell us whether a model is equally good at identifying distressed and non-distressed companies. Sensitivity is particularly important because it measures how well the model identifies companies that are actually distressed, while specificity measures how well it identifies companies that are not distressed.

A model with high overall accuracy could still miss a significant number of distressed companies if the sample contains more healthy than distressed firms. For this reason, comparing accuracy together with sensitivity, specificity and the true and false classifications provide a more complete view of model performance. The literature therefore suggests that the question of whether Altman's Z-Score or Logistic Regression is better cannot be answered simply by looking at the results of previous studies. Differences in industry, company size, country, sample period, financial variables, distress definition and model specification can all affect the outcome. A fair comparison requires the two models to be tested using the same companies, the same definition of financial distress and the same performance measures. This is the approach taken in the present study, where the original Altman Z-Score is compared with Logistic Regression for Indian listed non-financial companies from the Chemicals, Industrials, Pharmaceuticals and Auto Parts sectors.

This allows the study to assess whether Logistic Regression actually provides better prediction performance than the original Altman model within the same research setting.

EMPIRICAL EVIDENCE FROM INDIAN COMPANIES

Research on financial distress in India covers a wide range of companies, including listed firms, manufacturing companies, public sector enterprises, small-cap companies and firms from specific industries. Overall, the evidence supports the use of financial information to identify financial difficulties, with profitability, liquidity, leverage, working capital and asset efficiency appearing across different studies. However, the findings need to be considered in the context of the companies and industries examined, as financial characteristics can differ between sectors and company sizes.

The Indian literature also shows considerable differences in research design. Studies have used Altman's Z-Score, Logistic Regression and other statistical or machine learning methods, while some have modified the original Altman model or added financial and non-financial variables.

Balasubramanian et al. (2019), for instance, used financial and non-financial information for Indian listed companies, while Singh and Singla (2023) compared a newly developed Logistic Regression model with a re-estimated Altman model. These studies provide useful evidence, but they are not directly comparable because they use different variables and model specifications. A result obtained from a modified or re-estimated Altman model also does not necessarily show how well the original Altman Z-Score performs. Industry and sample differences are another important issue. Ahamed and Ahammed (2024) reported 96.6% accuracy for the Altman Z-Score among 41 Indian logistics companies, while other studies have examined much broader groups of listed companies. Recent research has also used 1,938 Indian listed companies across 11 sectors and 7,705 observations to compare traditional and machine learning approaches. These differences show that reported accuracy can depend on the industry, number and type of companies, and period covered. Therefore, a high accuracy rate from one industry should not automatically be expected in another.

The definition of financial distress also varies between studies. Some researchers classify distress using financial ratios, while others examine companies that have experienced insolvency or bankruptcy. Differences in the definition can change which companies are treated as distressed and therefore affect the reported performance of a prediction model.

Similarly, differences in sample periods can matter because a company's financial position can change over time. These issues make it difficult to directly compare the results of previous Indian studies. Overall, the Indian literature supports both Altman's Z-Score and Logistic Regression as useful approaches, but it does not establish that one method consistently performs better than the other for Indian listed non-financial companies. Overall, the Indian literature supports both Altman's Z-Score and Logistic Regression as useful approaches, but the existing evidence does not establish that one method consistently performs better than the other for Indian listed non-financial companies. The available studies provide useful evidence across different industries and company groups, but their differences in research settings make it difficult to draw a single conclusion about model performance. The present study therefore builds on this evidence by focusing specifically on Indian listed non-financial companies from the Chemicals, Industrials, Pharmaceuticals and Auto Parts sectors.

The selection of the four variables used in the Logistic Regression model was guided by previous financial distress research rather than being chosen independently. Previous studies have identified profitability, liquidity, asset efficiency and leverage as relevant financial characteristics when examining financial distress. In particular, Balasubramanian et al. (2019) considered profitability, liquidity and leverage among Indian listed companies, while Sethi and Mahadik (2024) included asset turnover in their Logistic Regression analysis.

The present study therefore builds on these previous findings by selecting ROE, Quick Ratio, Total Asset Turnover and Debt Ratio as the four explanatory variables. The variables were also selected to represent different aspects of financial condition while keeping the model focused on financial information available consistently across the sample.

Author	Scope	Sample / Method	Relationship with Present Study	Key Findings
Balasubramanian et al. (2019)	*Indian listed companies*	*96 companies, including 48 sick companies; Conditional Logistic Regression using financial and non-financial variables*	*Supports the use of Logistic Regression and financial variables in the Indian listed-company setting.*	*Combined variables improved accuracy*
Nayan et al. (2024)	*Malaysian public listed companies*	*Companies under Practice Note 17 from 2017–2021; Grover and Zmijewski models*	*Relevant for model comparison and international evidence, although the country is different from the present study.*	*Grover showed higher accuracy*
Opoku et al. (2024)	*Banks in Sub-Saharan Africa*	*228 banks from 2006–2016; Logistic Regression with panel data*	*Supports the use of Logistic Regression and shows the importance of financial factors such as leverage and profitability, although it focuses on banks.*	*Leverage increased distress risk*
Sanesh (2016)	*Indian NIFTY 50 companies*	*NIFTY 50 companies excluding banks and financial companies; Altman Z-Score*	*Directly relevant to Altman and Indian listed companies.*	*Z Score assessed financial health*
Sethi and Mahadik (2024)	*Indian non-financial service companies*	*Indian firms from 2012–2022; Logistic Regression, LDA and ANN*	*Uses Logistic Regression in Indian non-financial companies and compares different prediction models.*	*Logistic Regression performed best*
Kristanti et al. (2025)	*Indonesian firms*	*325 companies, 3,575 observations from 2013–2023; machine learning models*	*Provides international comparative evidence on financial distress prediction, although it uses machine learning rather than Altman and Logit.*	*Machine learning improved prediction*
Padhy et al. (2025)	*Indian companies under the Insolvency and Bankruptcy Code*	*Companies involved in IBC proceedings; Altman Z-Score*	*It examines companies facing serious financial problems.*	*Z Score identified financial problems*
Amaniyah et al. (2025)	*International financial distress literature*	*Systematic Literature Review using PRISMA; 15 selected studies from 2014–2024*	*Useful for understanding the overall development of financial distress prediction research and the financial factors used in previous studies.*	*Multiple factors predict distress*

Savery et al. (2024)	*Indonesian mining sector*	*Mining company listed on the Indonesian Stock Exchange, 2018–2022; Altman Z-Score*	*Supports the use of Altman and financial ratios, but in a different country and industry.*	*Profitability affected financial distress*
Raju and Raju (2025)	*Indian small-cap companies*	*30 NSE-listed small-cap companies, observed semi-annually from 2019–2025; Altman Z-Score and Z''-Score*	*uses small-cap companies and compares different versions of the Z-Score.*	*Financial health changed over time*
Mishra et al. (2021)	*Indian banking sector*	*75 Indian banks; Logistic Regression, LDA and ANN using 2015–2019 data*	*Useful for Logistic Regression model comparison in India, although the present study excludes financial companies.*	*ANN achieved higher accuracy*
Singh and Singla (2024)	*Indian corporate sector*	*Indian corporate companies; Logistic Regression using financial ratios; testing sample and ROC analysis*	*Uses Logistic Regression to predict financial distress in Indian companies and evaluates prediction performance using ROC.*	*Logit showed strong prediction*
Rawal and Gopalkrishnan (2024)	*Indian banking sector*	*31 Indian banks, 2016–2020; panel data analysis using Altman Z-Score*	*Provides Indian evidence using Altman Z-Score, but focuses on banks and examines the effect of distress on dividend policy rather than comparing prediction models.*	*Distress affected dividend policy*
Nair and Sachdeva (2016)	*Indian textile sector*	*Listed textile companies; financial-ratio analysis*	*Relevant to the financial determinants of distress and Indian non-financial companies.*	*Financial ratios predicted distress*
Ayuningtyas (2017)	*Indonesian listed manufacturing companies*	*Indonesian listed manufacturing firms; Rolling Logistic Regression*	*Supports the use of Logistic Regression for financial distress prediction and provides international evidence.*	*Rolling Logit predicted distress*
Mahesha et al. (2025)	*Indian small enterprises*	*547 companies after removing observations with missing data; 2008–2022; Springate S-Score and Logistic Regression*	*Relevant to Logistic Regression and Indian companies, although the sample consists of small enterprises rather than listed firms and uses Springate to classify distress.*	*Multiple factors predicted distress*

Singh and Singla (2023)	*Indian corporate sector*	*Indian corporate companies; re-estimated Altman model and newly developed Logistic Regression model; testing sample and ROC*	*Directly compares an Altman-based model with Logistic Regression in India.*	*Logit outperformed Altman model*
Kashyap et al. (2019)	*Indian listed companies*	*Listed firms registered under BIFR and IBC; 2006–2018; analysis by sector, ownership and firm life cycle*	*Relevant to Indian financial distress and listed companies, but focuses on distress patterns rather than comparing prediction models.*	*Distress varied across sectors*
Sanesh (2014)	*Steel Authority of India Limited*	*SAIL; 2005–06 to 2013–14; Altman Z-Score using annual-report data*	*Relevant to Altman and an Indian non-financial company, but focuses on one company.*	*Z Score showed financial health*
Ahamed and Ahammed (2024)	*Indian logistics companies*	*41 NSE-listed logistics companies; 2019–2023; Altman Z-Score*	*Highly relevant to Altman and Indian non-financial listed firms, although limited to one industry.*	*Z Score achieved high accuracy*
Yimam and Babu (2025)	*Manufacturing companies in Ethiopia*	*49 manufacturing companies, 2020–2024; pooled OLS and Z-Score measure of distress*	*Supports the relationship between financial ratios and distress, but uses a different country and industry.*	*Profitability reduced financial distress*
Mondal and Mitra (2024/25)	*Indian Public Sector Undertakings*	*25 Indian PSUs, 2012–13 to 2021–22; panel data regression; Altman Z-Score*	*Relevant to Altman, Indian companies and financial performance variables, but focuses on PSUs rather than the wider listed non-financial sector.*	*Financial factors affected bankruptcy risk*

Table 1: Summary of prior literature review on Financial Distress models

Hypothesis Development

The hypotheses in this study are developed from the financial factors identified in the literature as being potentially related to financial distress. The study focuses on profitability, liquidity, asset efficiency and debt because these areas represent different parts of a company's financial position.

The expected relationship for each variable is based on its financial meaning and the evidence discussed in the previous sections. The final hypothesis focuses on whether Logistic Regression provides better prediction performance than the original Altman Z-Score when both models are applied under the same research conditions. Profitability is expected to have an important relationship with financial distress because companies that generate stronger returns are generally in a better position to support their operations and meet their financial obligations. ROE is used in this study to measure the return generated on shareholders' equity. A higher ROE indicates that the company is generating stronger returns from the equity invested in the business, which can provide a positive signal about its financial position. However, profitability does not operate on its own, as a company can still face financial difficulties because of weak liquidity or high debt. Based on the overall evidence from the literature, the study expects stronger profitability to be associated with a lower likelihood of financial distress.

H1: Higher Return on Equity (ROE) is associated with a lower likelihood of financial distress among Indian non-financial listed companies.

A company with stronger liquidity is generally in a better position to make its payments on time, while weak liquidity may indicate financial difficulties. From the perspective of Signalling Theory, a strong liquidity position can give a positive signal about the company's financial health, whereas poor liquidity may raise concerns among investors and lenders.

Previous studies have generally found that stronger liquidity is associated with a lower likelihood of financial distress. Therefore, the present study expects companies with a higher Quick Ratio to have a lower likelihood of financial distress.

H2: Higher Quick Ratio is associated with a lower likelihood of financial distress among Indian non-financial listed companies.

Total Asset Turnover is included because the efficient use of assets can provide information about a company's operating performance. The ratio measures the sales generated from the company's total assets, meaning that a higher ratio generally indicates that the company is using its asset base more efficiently to generate revenue. However, the level of asset turnover can naturally differ between industries because companies have different asset requirements. This is particularly relevant to the present study because the sample includes companies from Chemicals, Industrials, Pharmaceuticals and Auto Parts. Despite these differences, the study expects greater asset efficiency to be associated with a lower likelihood of financial distress.

H3: Higher Total Asset Turnover is associated with a lower likelihood of financial distress among Indian non-financial listed companies.

Debt can create additional financial pressure because borrowed funds have to be repaid and may involve regular interest payments. A company with a high level of debt may therefore be more exposed to financial difficulties if its profitability or cash flows decline. At the same time, debt is not necessarily negative because companies may use borrowing to finance investment and growth. What matters is whether the company can generate enough returns and cash flows to manage its financial obligations. In this study, Debt Ratio is used to measure the proportion of total assets financed through debt. Based on the relationship identified in previous research, a higher Debt Ratio is expected to increase the likelihood of financial distress.

H4: Higher Debt Ratio is associated with a higher likelihood of financial distress among Indian non-financial listed companies.

Previous research has produced mixed findings when comparing financial distress prediction models. Some studies have reported stronger results from Logistic Regression, while others have found useful results from Altman's Z-Score or modified versions of the model. These differences may be linked to the companies studied, the variables included, the definition of financial distress and the period used for testing. This makes it difficult to say that one model is always better than the other.

In the present study, both models are compared using the same group of Indian listed non-financial companies and the same financial distress classification. This provides a more consistent basis for assessing their performance. Since Logistic Regression can estimate the relationship between several financial variables and the probability of distress using data from the study sample, the study expects it to provide higher predictive accuracy than the original Altman Z-Score.

H5: Logistic Regression demonstrates greater predictive accuracy in identifying financial distress among Indian non-financial listed companies than the original Altman Z-Score model.

CONCLUSIVE NOTE:

The literature reviewed in this chapter shows that financial distress is influenced by several aspects of a company's financial position, rather than by one financial measure alone. Profitability, liquidity, asset efficiency and debt have all been considered important indicators of financial health, although their relationships with distress are not always consistent across studies. The present study builds on this literature by examining Indian listed non-financial companies from the Chemicals, Industrials, Pharmaceuticals and Auto Parts sectors. The study examines the relationship between ROE, Quick Ratio, Total Asset Turnover and Debt Ratio and financial distress, while also comparing the performance of Logistic Regression with the original Altman Z-Score.

The following chapter explains the data, variable measurement, distress classification and empirical methods used to carry out this analysis. The present study addresses this gap by applying both approaches to Indian listed non-financial companies from the Chemicals, Industrials, Pharmaceuticals and Auto Parts sectors. A consistent financial distress classification is used so that the two models can be compared under the same conditions. The literature provides the basis for examining the relationship between ROE, Quick Ratio, Total Asset Turnover and Debt Ratio and financial distress, while the mixed evidence on model performance provides the basis for comparing Logistic Regression with the original Altman Z-Score. The next chapter explains how the data were collected and how financial distress was defined and how the variables and models were measured and tested.

CH-03 DATA & METHODOLOGY

RESEARCH PHILOSOPHY

The present study follows a positivist research philosophy because it is based mainly on numerical data and statistical analysis. Positivism is based on the idea that knowledge can be obtained through the observation and measurement of facts. It focuses on using objective data and statistical methods to examine relationships and test hypotheses. In this study, financial information collected from Indian non-financial listed companies is used to measure variables such as Return on Equity, Quick Ratio, Total Asset Turnover and Debt Ratio. These variables are then analysed using statistical methods to examine their relationship with financial distress.

The choice of positivism is also suitable because the study does not aim to understand the personal opinions or experiences of managers, investors or other stakeholders. Instead, it focuses on measurable financial information and uses the same measures across all companies in the sample. The financial distress status of each company is identified using a defined classification, while Altman's Z-Score and Logistic Regression are used to make predictions. The results are then compared using common measures of prediction performance. This allows the researcher to test the proposed hypotheses using numerical evidence rather than personal judgement. The study also follows a deductive approach, which is closely related to the positivist philosophy. A deductive approach starts with existing theories and findings from previous research and uses them to develop hypotheses that can then be tested using data.

In this study, previous research on financial distress, Signalling Theory and financial distress prediction models provides the basis for developing the five hypotheses. The hypotheses relating to ROE, Quick Ratio, Total Asset Turnover and Debt Ratio are tested through Logistic Regression, while the fifth hypothesis compares the prediction performance of Logistic Regression with the original Altman Z-Score.

Therefore, the positivist philosophy is appropriate for this research because the study is based on objective financial data, measurable variables, statistical testing and comparison of prediction models. It provides a suitable framework for examining financial distress among Indian non-financial listed companies and allows the findings to be based on evidence obtained from the collected data rather than subjective opinions.

The research philosophy therefore supports the overall aim of the study, which is to examine the factors associated with financial distress and determine whether Logistic Regression provides better prediction performance than the original Altman Z-Score.

QUANTITATIVE APPROACH

The present study follows a quantitative research approach because it uses numerical financial data to examine financial distress among Indian non-financial listed companies. A quantitative approach is suitable for this study as it allows financial variables to be measured and tested using statistical methods. The study uses secondary financial data collected from the London Stock Exchange Group (LSEG) database, which provides company-level financial information for the selected firms and years. The collected data were organised and prepared for further analysis using EViews. The study uses four main financial variables in the Logistic Regression model: Return on Equity (ROE), Quick Ratio, Total Asset Turnover and Debt Ratio. These variables are measured using financial information obtained from the companies' financial statements. Financial distress is represented using a binary variable, where companies are classified into distressed and non-distressed groups based on the definition used in this study. This allows the relationship between the financial variables and the likelihood of financial distress to be examined using Logistic Regression.

The quantitative approach is also used to compare the prediction performance of Logistic Regression and the original Altman Z-Score model. The Altman Z-Score is calculated for the companies in the sample and used to classify their financial condition. Logistic Regression is then used to estimate the probability of financial distress based on the selected financial variables.

The predictions from both models are compared using measures such as classification accuracy, sensitivity, specificity and other relevant performance measures. Using a quantitative approach also helps ensure that the same measures and procedures are applied consistently across all companies in the sample. This reduces the role of personal judgement when analysing the results and allows the findings to be supported by statistical evidence. The results obtained from the analysis are then used to test the five hypotheses developed in Chapter 2 and to determine whether the expected relationships are supported by the data.

Therefore, a quantitative approach is appropriate for this study because the research is based on measurable financial data, statistical testing and model comparison. It allows the study to examine the financial factors associated with distress and to make a direct comparison between the original Altman Z-Score and Logistic Regression among Indian non-financial listed companies.

DATA SOURCE

The study uses secondary financial data collected from the London Stock Exchange Group (LSEG) Refinitiv database. The data were collected for Indian listed non-financial companies for the period from 2015 to 2025. The study focuses on companies from four selected non-financial sectors, namely Chemicals, Industrials, Pharmaceuticals and Auto Parts.

These sectors were selected to provide companies from different areas of the Indian non-financial corporate sector while keeping the sample focused and manageable for the analysis. The financial information collected includes the data required to calculate the variables used in the study, including Return on Equity (ROE), Quick Ratio, Total Asset Turnover and Debt Ratio. The data required to calculate the original Altman Z-Score were also collected from the same source.

The sample was selected using specific inclusion and exclusion criteria. The study includes Indian listed non-financial companies for which the required financial information was available during the study period. Financial companies such as banks, insurance companies and other financial institutions were excluded because their financial structure and reporting practices are different from those of non-financial companies. Companies for which the financial information required to calculate the main variables was not available were also excluded from the final analysis. This was done to ensure that the same variables could be calculated consistently across the companies included in the study. The final dataset contains 195 companies covering the period from 2015 to 2025. As the availability of financial information differs between companies and years, the final dataset is an unbalanced panel, rather than a balanced panel where every company has observations for every year. After applying the data availability requirements for the main variables, the final analysis contains 1,853 observations.

The financial data were used to calculate the four main explanatory variables used in the Logistic Regression model. ROE is used to measure profitability, Quick Ratio is used to measure liquidity, Total Asset Turnover is used to measure asset efficiency, and Debt Ratio is used to measure the level of debt. The financial information was also used to calculate the original Altman Z-Score. A binary financial distress variable was used to classify companies into distressed and non-distressed groups for the Logistic Regression analysis. To make the comparison between the two prediction models fair, the same final sample and study period are used for both the original Altman Z-Score and Logistic Regression. The prediction results from both models are then compared using the same measures of performance. This approach allows the study to examine whether Logistic Regression provides better prediction results than the original Altman Z-Score without the comparison being affected by differences in the companies or observations used in the two models.

VARIABLE MEASUREMENT

The variables used in this study were selected based on the previous literature on financial distress prediction and the requirements of the Logistic Regression model. The study uses four independent variables, namely Return on Equity (ROE), Quick Ratio, Total Asset Turnover and Debt Ratio.

These variables represent profitability, liquidity, asset efficiency and leverage respectively. A binary financial distress variable is used as the dependent variable in the Logistic Regression model. The financial information required to calculate these variables was obtained from the LSEG database.

1. RETURN ON EQUITY (ROE)

Return on Equity is used to measure the profitability of a company. It shows the amount of profit generated from shareholders' equity. A higher ROE generally indicates better profitability. In this study, ROE is included as an independent variable in the Logistic Regression model, and a negative relationship with financial distress is expected.

$$ROE = Net\ Income / Shareholders'\ Equity$$

2. QUICK RATIO

Quick Ratio is used to measure the liquidity of a company. It shows the company's ability to meet its short-term obligations using its more liquid assets. A higher Quick Ratio generally indicates a stronger short-term financial position. Therefore, a negative relationship between Quick Ratio and financial distress is expected.

$$Quick\ Ratio = (Current\ Assets - Inventory) / Current\ Liabilities$$

3. TOTAL ASSET TURNOVER

Total Asset Turnover measures how efficiently a company uses its assets to generate sales. A higher ratio indicates that the company is generating more sales from its assets. In this study, it is used as a measure of asset efficiency, and a negative relationship with financial distress is expected.

$$Total\ Asset\ Turnover = Sales / Total\ Assets$$

4. DEBT RATIO

Debt Ratio measures the proportion of a company's assets that are financed through debt. A higher Debt Ratio indicates greater reliance on debt financing and may increase the financial pressure on a company. Therefore, a positive relationship between Debt Ratio and financial distress is expected.

$$Debt\ Ratio = Total\ Debt / Total\ Assets$$

FINANCIAL DISTRESS DEFINITION AND CLASSIFICATION

Financial distress is the dependent variable used in the Logistic Regression model and also provides the common actual outcome against which the predictions of Logistic Regression and the original Altman Z-Score are evaluated. A clear and consistent definition is therefore important because the performance of both models depends on how financially distressed and non-distressed companies are identified. In this study, financial distress is not determined using one financial indicator alone. Instead, four indicators are considered together: **Return on Assets (ROA), Current Ratio, Interest Coverage Ratio (ICR), and Operating Cash Flow (OCF)**. Each indicator represents a different aspect of a company's financial position, allowing financial weakness to be assessed from more than one perspective. The first condition is **negative ROA (ROA < 0)**. ROA measures the return generated from the assets used by a company. A value below zero means that the company is generating a negative return from its asset base during the financial year. A value of zero is therefore used as the threshold because it provides a clear distinction between a positive and negative return. The second condition is a **Current Ratio below 1**. A ratio below 1 means that current liabilities are greater than current assets, which may indicate difficulty in meeting short-term obligations. The third condition is an **Interest Coverage Ratio below 1**. This indicates that the company's earnings are not sufficient to cover its interest expenses for that year, creating additional financial pressure.

The fourth condition is **negative Operating Cash Flow**, which indicates that the company's core operations are not generating positive cash flows during the financial year. The use of these four conditions is intended to capture different forms of financial weakness rather than relying on a single measure. A company may have a temporary weakness in one financial ratio without necessarily being in overall financial distress. For instance, profitability may be negative in one year while the company still has sufficient liquidity and operating cash flow. Similarly, a company may have weak liquidity but continue to generate positive operating cash flow.

Considering several indicators together therefore provides a broader assessment of the company's financial condition. A **2-out-of-4 classification rule** is applied to create the final distress variable. A company is classified as financially distressed when **at least two of the four indicators meet their respective distress conditions within the same financial year**. The observation is then assigned a value of **1**. Where fewer than two conditions are met, the observation is classified as non-distressed and assigned a value of **0**.

The rule can therefore be summarised as: **two or more distress signals = 1 (financially distressed), while zero or one distress signal = 0 (non-distressed)**. This approach provides a consistent rule that requires evidence of financial weakness across more than one area rather than classifying a company as distressed because of a single weak ratio.

The use of the two-out-of-four rule also provides a practical balance between the two extremes of using only one indicator and requiring all four indicators to show distress. Requiring only one condition could classify companies as distressed because of an isolated or temporary weakness, while requiring all four conditions would be much more restrictive and could exclude companies experiencing genuine financial difficulties that are not reflected in every indicator. The two-out-of-four approach therefore allows the study to identify companies showing weakness across at least two financial dimensions while maintaining a clear and consistent classification rule across the sample. An important distinction is also made between **ROA and ROE** in the research design. Both ratios are measures of profitability and are naturally related because they assess returns generated by a company. However, they have different roles in this study. **ROA is used as one of the four conditions for constructing the financial distress dependent variable, whereas ROE is used as an independent variable in the Logistic Regression model.** Therefore, ROA is part of the process used to determine the outcome being predicted, while ROE is used to examine whether profitability is associated with the likelihood of that outcome Because ROA and ROE are related profitability measures, the distinction between the two variables is considered when interpreting the model, while multicollinearity among the actual explanatory variables is assessed separately using the appropriate diagnostic tests. This distinction allows the study to retain ROE as an explanatory measure while using ROA as part of the broader distress classification.

The financial distress classification is created separately for **each company and each financial year**. The four conditions are assessed for the relevant year, the number of conditions met is counted, and the resulting value is converted into the binary distress variable. This variable is then used as the dependent variable in the Logistic Regression model. It also provides the common actual classification required to evaluate whether the predicted outcomes from Logistic Regression and the original Altman Z-Score correctly identify financially distressed and non-distressed observations.

5. ALTMAN'S Z SCORE

The original Altman Z-Score is used as the second prediction model in this study. The score combines several financial ratios into a single measure of financial health. The required financial information was obtained from LSEG, and the original Altman Z-Score was calculated for the companies included in the study. The resulting score was then used to generate the Altman prediction, which is compared with the Logistic Regression prediction.

ALTMAN'S Z SCORE MODEL

The original Altman Z-Score is used as one of the two financial distress prediction models in this study. The original specification is retained without changing its coefficients because the purpose of the study is to assess the performance of the original model when applied to Indian listed non-financial companies. The required financial information was obtained from LSEG and used to calculate the Z-Score for each company and financial year in the sample.

The model is calculated using five financial ratios: Working Capital to Total Assets, Retained Earnings to Total Assets, Earnings Before Interest and Tax to Total Assets, Market Value of Equity to Total Liabilities, and Sales to Total Assets. The original formula is:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5$$

where:

X_1 = Working Capital / Total Assets

X_2 = Retained Earnings / Total Assets

X_3 = Earnings Before Interest and Tax / Total Assets

X_4 = Market Value of Equity / Total Liabilities

X_5 = Sales / Total Assets where each ratio represents a different aspect of the company's financial position, including liquidity, accumulated earnings, operating performance, financial structure and asset efficiency.

After calculating the score for each observation, the original Altman classification ranges are applied. A score above **2.99** is classified as the safe zone, a score between **1.81 and 2.99** as the grey zone, and a score below **1.81** as the distress zone. For the model comparison, the Altman classification is converted into a binary prediction so that it can be compared with the actual financial distress classification used in the study. The treatment of the grey zone and the construction of the prediction variable are kept consistent across the analysis so that the Altman and Logistic Regression results can be compared using the same performance measures.

The five ratios represent different areas of a company's financial position. Working Capital to Total Assets reflects liquidity, Retained Earnings to Total Assets reflects the accumulated earnings of the company, and EBIT to Total Assets reflects operating performance. Market Value of Equity to Total Liabilities provides an indication of the company's financial structure, while Sales to Total Assets measures how efficiently the company uses its assets to generate sales. After calculating the Z-Score for each company and year, the companies were classified according to the original Altman classification ranges. A Z-Score above 2.99 indicates the safe zone, while a score below 1.81 indicates the distress zone. Scores between 1.81 and 2.99 fall within the grey zone, where the financial condition of the company is less certain. For the purpose of the present study, the Altman score was then converted into the prediction variable "altmanprediction" on EViews used for the model comparison. Companies classified in the distress zone were treated as predicted distressed firms, while the remaining observations were treated as predicted non-distressed firms according to the classification procedure used in the study. This allowed the Altman prediction to be compared with the actual financial distress classification and with the predictions obtained from the Logistic Regression model.

LOGISTIC REGRESSION MODEL

Logistic Regression is used in this study to examine the factors that are associated with financial distress and to estimate the probability that a company will experience financial distress. It is suitable for the present study because the dependent variable has two possible outcomes, where a company is classified as either financially distressed or non-distressed. The model uses four financial variables, namely ROE, Quick Ratio, Total Asset Turnover and Debt Ratio.

The Logistic Regression model used in this study can be written as:

$$P(Financial\ Distress = 1) = 1 / [1 + e^{-z}]$$

where:

$$Z = \beta_0 + \beta_1 ROE + \beta_2 Quick\ Ratio + \beta_3 Total\ Asset\ Turnover + \beta_4 Debt\ Ratio + \varepsilon$$

Here, β_0 represents the constant, while β_1 to β_4 represent the coefficients of the four independent variables. The dependent variable takes a value of 1 when the company is classified as financially distressed and 0 when it is classified as non-distressed. The model therefore estimates the probability of financial distress based on the company's financial characteristics. ROE represents profitability, Quick Ratio represents liquidity, Total Asset Turnover represents asset efficiency, and Debt Ratio represents leverage. The expected coefficient signs are negative for ROE, Quick Ratio and Total Asset Turnover, and positive for Debt Ratio, based on the hypotheses developed in Chapter 2.

The Logistic Regression model was estimated in EViews using the final sample of Indian non-financial listed companies. The estimated probabilities were used to generate the Logistic Regression prediction variable. The coefficients and their statistical significance are used to test H1 to H4, while the predicted outcomes are later compared with the original Altman Z-Score using the common performance measures described in the following section. This comparison provides the basis for testing H5.

MODEL PREDICTION & PERFORMANCE EVALUATION

The prediction performance of Logistic Regression and the original Altman Z-Score was compared using the same 432 company-year observations for the 2023–2025 out-of-sample period. The Logistic Regression model achieved an overall accuracy of **79.86%**, while the Altman Z-Score achieved a higher accuracy of **84.03%**. This shows that the Altman model correctly classified a larger proportion of the observations during the prediction period. The difference can also be seen in the sensitivity results. Logistic Regression had a sensitivity of **61.22%**, compared with **64.63%** for the Altman model.

This means that Altman correctly identified a slightly larger proportion of the observations that were actually classified as financially distressed. The Altman model also recorded a higher specificity of **94.04%**, compared with **89.47%** for Logistic Regression, indicating that it was more successful in identifying non-distressed observations.

The classification results provide further support for this comparison. Logistic Regression recorded **90 true positives, 255 true negatives, 30 false positives and 57 false negatives**. In comparison, Altman recorded **95 true positives, 268 true negatives, 17 false positives and 52 false negatives**. Therefore, Altman produced fewer false positive and false negative classifications during the out-of-sample period. Overall, the results indicate that the original Altman Z-Score performed better than Logistic Regression for the 2023–2025 prediction period. Its higher accuracy, sensitivity and specificity suggest that it provided stronger classification performance for the sample used in this study. Therefore, the expectation that Logistic Regression would provide greater predictive accuracy than the original Altman Z-Score is **not supported**, and **H5 is not supported**.

CH-04 RESULTS & ANALYSIS

This chapter presents the results of the empirical analysis carried out to examine financial distress among Indian listed non-financial companies. The analysis is based on the final sample of companies covering the period from 2015 to 2025. The chapter first presents the descriptive statistics of the variables used in the study, followed by the correlation analysis and multicollinearity test. It then presents the results of the Logistic Regression model and examines the relationship between the selected financial variables and financial distress. The prediction results from the Logistic Regression model are then assessed. Finally, the prediction performance of Logistic Regression is compared with the original Altman Z-Score using the same sample and financial distress classification. The results are used to test the hypotheses developed in Chapter 2 and to determine which model provides better prediction performance.

DESCRIPTIVE STATISTICS

Variable	Mean	Median	Maximum	Minimum	Std. Deviation	Observations
Financial Distress	0.3886	0.0000	1.0000	0.0000	0.4876	1,853
ROE	0.4018	0.0869	485.8217	-20.0110	11.4652	1,853
Quick Ratio	2.1158	0.9443	229.5822	-30.1769	8.2896	1,853
Total Asset Turnover	0.9153	0.8503	12.7254	0.0000	0.7021	1,853
Debt Ratio	0.4840	0.1927	61.6322	-0.1257	2.2246	1,853

Table 4.1 Descriptive Statistics of regression variables

Table 4.1 presents the descriptive statistics for the variables used in the Logistic Regression analysis. The analysis is based on 1,853 observations covering the period from 2015 to 2025. The dependent variable, financial distress, has a mean of 0.3886, indicating that approximately 38.9% of the company-year observations were classified as financially distressed under the study's binary classification rule. ROE has a mean of 0.4018 and a median of 0.0869, with values ranging from -20.0110 to 485.8217. The substantial difference between the mean and median, together with the high maximum value, indicates considerable variation in profitability and suggests the presence of extreme observations. The Quick Ratio has a mean of 2.1158 and a median of 0.9443, with values ranging from -30.1769 to 229.5822. The difference between the mean and median similarly indicates substantial variation in liquidity across the observations.

Total Asset Turnover has a mean of 0.9153 and a median of 0.8503, with a minimum of 0 and a maximum of 12.7254. The relatively close mean and median suggest a less pronounced difference in the centre of the distribution compared with ROE and Quick Ratio, although the maximum value indicates that some observations have considerably higher asset turnover. Debt Ratio has a mean of approximately 0.4841 and a median of approximately 0.1927, with a maximum of 61.6323 and a negative minimum.

The large difference between the mean and median indicates substantial variation in the debt position of the companies and the presence of extreme observations. Overall, the descriptive statistics indicate considerable heterogeneity in the financial characteristics of the companies in the sample. The substantial differences between the means and medians and the relatively high maximum values for some variables suggest that the distributions are affected by extreme observations. These characteristics are important when interpreting the subsequent regression results.

CORRELATION ANALYSIS

Variable	Financial Distress	ROE	Quick Ratio	Total Asset Turnover	Debt Ratio
Financial Distress	1.0000	-0.0205	-0.0593	-0.3325	0.1725
ROE	-0.0205	1.0000	-0.0030	0.0099	0.0025
Quick Ratio	-0.0593	-0.0030	1.0000	-0.1309	-0.0411
Total Asset Turnover	-0.3325	0.0099	-0.1309	1.0000	0.1781
Debt Ratio	0.1725	0.0025	-0.0411	0.1781	1.0000

Table 4.2 Correlation matrix

Table 4.2 presents the correlation matrix for the financial distress variable and the four independent variables used in the Logistic Regression model. The purpose of the correlation analysis is to examine the direction and strength of the relationships between the variables and to identify whether there are any strong relationships between the independent variables that may indicate a potential multicollinearity problem. The correlation between financial distress and ROE is **-0.0205**, indicating a very weak negative relationship.

The correlation with Quick Ratio is also negative at **-0.0593**, suggesting a weak negative relationship. Total Asset Turnover has a stronger negative correlation with financial distress at **-0.3325**, while Debt Ratio has a positive correlation of **0.1725**. These directions are generally consistent with the expected relationships developed in the hypotheses. However, correlation measures the strength and direction of association only and does not indicate whether the relationships are statistically significant or imply causation.

The correlations between the four independent variables are relatively low. The highest correlation is between Total Asset Turnover and Debt Ratio at **0.1781**, while the correlations between the remaining independent variables are close to zero. This suggests that there are no strong linear relationships among the explanatory variables. However, correlation coefficients alone are not sufficient to rule out multicollinearity, so this is assessed more directly using the **Variance Inflation Factor (VIF)** results in the following section.

MULTICOLLINEARITY TEST

Variable	Centered VIF
ROE	1.0001
Quick Ratio	1.0178
Total Asset Turnover	1.0494
Debt Ratio	1.0331

Table 4.3 Variance Inflation Factors

A Variance Inflation Factor (VIF) test was carried out to assess whether multicollinearity was present among the independent variables used in the Logistic Regression model. As shown in Table 4.3, the centred VIF values for ROE, Quick Ratio, Total Asset Turnover and Debt Ratio are 1.0001, 1.0178, 1.0494 and 1.0331, respectively. All the centred VIF values are very close to 1, indicating that the explanatory variables do not exhibit a problematic level of multicollinearity.

Therefore, multicollinearity does not appear to be a problem in the Logistic Regression model. The VIF results support the inclusion of all four explanatory variables in the final model and indicate that their estimated coefficients are unlikely to be materially distorted by strong linear dependence among the regressors.

The VIF results therefore support the use of all four independent variables in the final regression model. This means that the coefficient and significance results discussed in the next section can be interpreted without a major concern that the variables are strongly overlapping with each other.

OLS REGRESSION

Variable	Coefficient	p-value	Interpretation
ROE	-0.000747	0.4055	Negative, insignificant
Quick Ratio	-0.005902	0.0000	Negative, significant
Total Asset Turnover	-0.269228	0.0000	Negative, significant
Debt Ratio	0.052038	0.0000	Positive, significant

Table 4.4: OLS regression table

Pooled OLS was initially estimated to examine the relationship between financial distress and the four financial variables used in the study. The model was estimated using **1,853 observations from 195 companies over the 2015–2025 period**. The results provide an initial indication of how profitability, liquidity, asset efficiency and leverage are associated with financial distress before considering differences across individual companies. The coefficient for ROE is **-0.000747** with a p-value of **0.4055**, indicating a negative relationship with financial distress, but the relationship is not statistically significant. Quick Ratio has a coefficient of **-0.005902** and is statistically significant at the 1% level ($p < 0.001$). This indicates that higher liquidity is associated with a lower level of financial distress. Total Asset Turnover also has a negative and statistically significant coefficient of **-0.269228** ($p < 0.001$), suggesting that companies with greater asset efficiency tend to have lower financial distress.

Debt Ratio has a positive and statistically significant coefficient of **0.052038** ($p < 0.001$), indicating that higher leverage is associated with greater financial distress. The model has an **R-squared of 0.1762**, meaning that approximately 17.62% of the variation in the financial distress variable is explained by the four financial ratios in the pooled model.

The overall F-statistic is **98.7986** with a probability value of **0.0000**, indicating that the explanatory variables are jointly significant in the model. However, because pooled OLS does not account for unobserved differences between individual companies, the results are treated as an initial benchmark. Fixed Effects and Random Effects models are therefore estimated next to determine whether accounting for company-specific effects provides a more appropriate specification.

Variable	Coefficient	Std. Error	t-Statistic	p-value
Constant	0.503503	0.028376	17.74374	0.0000
ROE	-0.001885	0.000223	-8.444245	0.0000
Quick Ratio	-0.002553	0.001258	-2.028773	0.0699
Total Asset Turnover	-0.129297	0.033029	-3.914610	0.0029
Debt Ratio	0.019754	0.010394	1.900457	0.0866
R-squared	0.7080			
AdjustedR-squared	0.6731			
F-statistic	20.2579			
Prob(F-statistic)	0.0000			

Table 4.5: Fixed effects regression

A Fixed Effects model was then estimated to account for characteristics that differ between companies but remain relatively stable over time. This was used to examine whether the relationships observed in the pooled OLS model remain after controlling for company-specific differences. The model uses 1,853 observations from 195 companies over 2015–2025, with White period (cross-section cluster) standard errors and covariance. The results show that ROE has a **negative and statistically significant** relationship with financial distress (coefficient = -0.001885, $p < 0.001$).

Total Asset Turnover is also negative and statistically significant (coefficient = -0.129297, p = 0.0029). Quick Ratio remains negative but is **not statistically significant at the 5% level** (p = 0.0699), while Debt Ratio is positive but also not significant at the 5% level (p = 0.0866).

The model reports an **R-squared of 0.7080** and an adjusted R-squared of **0.6731.** The F-statistic is 20.2579 with a probability value of 0.0000, indicating that the model is jointly statistically significant. This indicates that accounting for company-specific effects changes some of the relationships observed in the pooled model. The Random Effects model is considered next before using the Hausman test to determine the more appropriate panel specification.

Variable	Coefficient	Std. Error	t-Statistic	p-value
Constant	0.529556	0.028446	18.61585	0.0000
ROE	-0.001789	0.000592	-3.024185	0.0025
Quick Ratio	-0.002973	0.001057	-2.814102	0.0049
Total Asset Turnover	-0.155908	0.015298	-10.19110	0.0000
Debt Ratio	0.025219	0.003914	6.444125	0.0000

Table 4.6: Cross-section random effects model

The Random Effects model was then estimated as an alternative to the Fixed Effects specification. Unlike the Fixed Effects model, the Random Effects approach treats the company-specific effects as random rather than allowing each company to have its own fixed effect. The model was estimated using the same **1,853 observations from 195 companies over 2015–2025**. All four explanatory variables are statistically significant in the Random Effects model. ROE has a negative coefficient of **-0.001789** (p = 0.0025), while Quick Ratio has a negative coefficient of **-0.002973** (p = 0.0049). Total Asset Turnover also has a negative and statistically significant coefficient of **-0.155908** (p < 0.001). In contrast, Debt Ratio has a positive and statistically significant coefficient of **0.025219** (p < 0.001). The signs are consistent with the expected relationships, although the strength and significance of some variables differ from the Fixed Effects results.

The weighted R-squared is **0.0639**, while the overall F-statistic is **31.5588** with a probability value below 0.001, indicating that the variables are jointly significant. Since both Fixed Effects and Random Effects provide different results, the **Hausman test is used next to determine which model is more appropriate for the analysis**.

Test	Chi-square Statistic	df	p-value	Decision
Cross-section random effects	31.6845	4	0.0000	Reject H_0; Fixed Effects preferred

Table 4.7: Hausman test

The Hausman test was used to determine whether the Fixed Effects or Random Effects model was more appropriate for the panel data. The test compares the estimates from the two models and assesses whether the company-specific effects are related to the explanatory variables. The test produced a **Chi-square statistic of 31.6845 with 4 degrees of freedom and a p-value of 0.0000**. As the p-value is below the 5% significance level, the null hypothesis is rejected. This indicates that the Random Effects assumptions do not hold for the data, and that the company-specific effects are related to the explanatory variables. Therefore, the **Fixed Effects model is preferred** for the analysis.

The Fixed Effects model is retained as the preferred panel specification and provides supplementary evidence on the relationships between the financial variables and financial distress.

Heteroskedasticity Test

Test	Likelihood Ratio	df	p-value	Decision
Cross-section	48,142.61	195	0.0000	Reject H_0
Period	8.0056	195	1.0000	Do not reject H_0

Table 4.8: Panel Heteroskedasticity test table

A panel heteroskedasticity test was conducted to examine whether the variance of the residuals was constant across companies and over time. The cross-section test produced a likelihood ratio of **48142.61** with a p-value of **0.0000**. Since the p-value is below the 5% significance level, the null hypothesis of homoscedastic residuals is rejected, indicating the presence of **cross-sectional heteroskedasticity**. The period test, however, produced a likelihood ratio of **8.005622** with a p-value of **1.0000**. This means that the null hypothesis cannot be rejected for the time dimension, providing no evidence of period heteroskedasticity. The results therefore suggest that the main issue is differences in error variance across companies rather than across time. In response to the cross-sectional heteroskedasticity, the final Fixed Effects estimation uses **White period (cross-section cluster) standard errors and covariance**. This provides more reliable standard errors and statistical inference while retaining the Fixed Effects specification selected by the Hausman test.

Following the diagnostic tests, the Fixed Effects specification with White period (cross-section cluster) standard errors and covariance was retained as the preferred panel model. The results continue to show negative and significant relationships for ROE and Total Asset Turnover, while Quick Ratio and Debt Ratio are not significant at the 5% level. These panel results are treated as supplementary evidence, with Logistic Regression providing the formal tests of H1–H4.

UNIT ROOT TEST

Variable	Levin, Lin & Chu	Im, Pesaran & Shin	ADF-Fisher	PP-Fisher	Conclusion
ROE	0.0000	0.0000	0.0000	0.0000	Stationary
Quick Ratio	0.0000	0.0077	0.0004	0.0000	Stationary
Total Asset Turnover	0.0177	0.0000	0.0000	0.0000	Stationary
Debt Ratio	0.0000	0.0000	0.0000	0.0000	Stationary

Table 4.9: Unit root test on all 4 variables

Unit root test roe

Before estimating the panel regression models, panel unit root tests were conducted to examine whether the financial variables were stationary over the study period. Four tests were considered: Levin, Lin and Chu, Im, Pesaran and Shin, ADF-Fisher and PP-Fisher. The null hypothesis for these tests is that the series contains a unit root. As shown in Table 4.9, the results provide evidence that all four variables are stationary at the 5% significance level. For ROE, all four tests have p-values of **0.0000**.

The Quick Ratio also rejects the unit-root null across all four tests, with p-values ranging from **0.0000 to 0.0077**. For Total Asset Turnover, the Levin, Lin and Chu test reports a p-value of **0.0177**, while the remaining tests report p-values of **0.0000**. Debt Ratio also has p-values of **0.0000** across all four tests. Overall, the results indicate that the variables used in the panel regression do not show evidence of a unit root at the 5% level. This supports proceeding with the panel regression analysis without the need to difference the variables.

LOGISTIC REGRESSION

Variable	Coefficient	Std. Error	z-Statistic	p-value
Constant	0.260161	0.135736	1.916676	0.0553
ROE	-0.031786	0.026929	-1.180361	0.2379

Variable	Coefficient	Std. Error	z-Statistic	p-value
Quick Ratio	-0.024657	0.009719	-2.537044	0.0112
Total Asset Turnover	-1.832381	0.133119	-13.76494	<0.001
Debt Ratio	3.059239	0.246942	12.38851	<0.001

Statistic	Value
McFadden R-squared	0.2619
LR statistic	648.4805
Prob(LR statistic)	<0.001
Observations	1,853
Observations with Y = 0	1,133
Observations with Y = 1	720
Convergence	7 iterations

Table 4.10 Logistic regression results

Table 4.10 presents the results of the Logistic Regression model used to examine the relationship between the selected financial variables and financial distress. The model is based on 1,853 observations covering the period from 2015 to 2025. The model achieved convergence after seven iterations, indicating that the estimation was successfully completed.

The coefficient for ROE is -0.0318, with a p-value of 0.2379. The coefficient is negative, which is in the expected direction, but the p-value is above 0.05. Therefore, ROE does not have a statistically significant relationship with financial distress in this model. Quick Ratio has a coefficient of -0.0247 and a p-value of 0.0112. This shows a negative and statistically significant relationship at the 5% level. This suggests that companies with higher liquidity are less likely to be classified as financially distressed.

Total Asset Turnover has a coefficient of -1.8324 and a p-value of 0.0000. The coefficient is negative and statistically significant. This indicates that companies with higher asset turnover are associated with a lower likelihood of financial distress. In contrast, Debt Ratio has a coefficient of 3.0592 and a p-value of 0.0000. The positive coefficient and very low p-value indicate a statistically significant positive relationship with financial distress. This suggests that companies with higher levels of debt relative to assets are more likely to experience financial distress.

The constant has a coefficient of 0.2602 and is significant at the 10% level, with a p-value of 0.0553. However, the focus of the analysis is on the four explanatory variables. The overall model is statistically significant, as shown by the LR statistic of 648.4805 and a probability value of 0.0000. This indicates that the Logistic Regression model provides useful information for explaining financial distress. The model has a McFadden R-squared of 0.2619, which indicates that the model has reasonable explanatory power for a binary outcome. Overall, the results provide support for the expected relationships for Quick Ratio, Total Asset Turnover and Debt Ratio, while the expected relationship for ROE is not statistically significant. The formal decisions on H1 to H4 will be presented later after considering the results together.

LOGISTIC REGRESSION PREDICTION RESULTS

Prediction outcome	**Actual Non-Distressed (Y=0)**	**Actual Distressed (Y=1)**	**Total**
Predicted Non-Distressed (Y=0)	1,041	262	1,303
Predicted Distressed (Y=1)	92	458	550
Total	**1,133**	**720**	**1,853**

Measure	Result
Accuracy	80.90%
Sensitivity	63.61%
Specificity	91.88%
Incorrect Classification Rate	19.10%
Total Gain	19.75%
Percentage Gain	50.83%
Classification Cut-off	0.50

Table 4.11 Logistic regression prediction performance

Table 4.11 presents the prediction performance of the Logistic Regression model using a classification cut-off of 0.50. Of the 1,133 observations that were non-distressed, 1,041 were correctly classified, while 92 were incorrectly classified as distressed. Of the 720 observations that were distressed, 458 were correctly identified and 262 were incorrectly classified as non-distressed. Overall, the model correctly classified 1,499 of the 1,853 observations, resulting in an accuracy of 80.90%.

The model achieved a specificity of 91.88%, indicating that it was effective at identifying non-distressed observations. However, its sensitivity was lower at 63.61%, showing that a greater proportion of financially distressed observations were incorrectly classified as non-distressed. The overall incorrect classification rate was 19.10%. The model also recorded a total gain of 19.75% and a percentage gain of 50.83% relative to the constant probability specification. These results indicate that the Logistic Regression model provides useful predictive information, although its ability to identify distressed observations is weaker than its ability to identify non-distressed observations.

Classification Outcome	Number of Observations
True Positives (TP)	458
True Negatives (TN)	1,041
False Positives (FP)	92
False Negatives (FN)	262
Total Observations	**1,853**

Table 4.12 Logistic regression classification result

Table 4.12 provides further detail on the individual classification outcomes of the Logistic Regression model. The model recorded **458 True Positives (TP)**, meaning that 458 observations that were financially distressed were correctly classified as distressed. It also recorded **1,041 True Negatives (TN)**, showing that 1,041 non-distressed observations were correctly classified. There were **92 False Positives (FP)**, where non-distressed observations were classified as distressed, and **262 False Negatives (FN)**, where financially distressed observations were classified as non-distressed. The higher number of false negatives than false positives indicates that the model had greater difficulty identifying financially distressed observations than non-distressed observations.

Variable	Coefficient	Std. Error	z-Statistic	p-value
Constant	0.589821	0.163081	3.616733	0.0003
ROE	-0.008708	0.014282	-0.609686	0.5421
Quick Ratio	-0.030359	0.011178	-2.716024	0.0066
Total Asset Turnover	-2.000788	0.158144	-12.65168	<0.001
Debt Ratio	2.543684	0.276866	9.187422	<0.001

Statistic	Value
McFadden R-squared	0.2606
LR statistic	499.4213
Prob(LR statistic)	<0.001
Observations	1,421
Observations with Y = 0	848
Observations with Y = 1	573
Convergence	6 iterations

Table 4.13: 2015–2022 Logistic Regression estimation

To assess the model's out-of-sample prediction performance, a separate Logistic Regression was estimated using observations from 2015 to 2022. This approach follows the distinction between estimating the model using earlier observations and subsequently using the estimated model to predict outcomes for a later period. The estimation included 1,421 observations after accounting for observations with missing values. The coefficient for ROE was negative (-0.0087) but was not statistically significant ($p = 0.5421$). Quick Ratio had a negative and statistically significant coefficient of -0.0304 ($p = 0.0066$), while Total Asset Turnover also had a negative and statistically significant coefficient of -2.0008 ($p < 0.001$). Debt Ratio had a positive and statistically significant coefficient of 2.5437 ($p < 0.001$). The overall model was statistically significant, with an LR statistic of 499.4213 ($p < 0.001$) and a McFadden R-squared of 0.2606. These results provide the estimated Logistic Regression model that was subsequently used to generate out-of-sample predictions for the 2023–2025 period.

OUT-OF-SAMPLE LOGISTIC REGRESSION PREDICTION: 2023–2025

Performance Measure	Result
Accuracy	79.86%
Sensitivity	61.22%
Specificity	89.47%
Total Observations	432

Table 4.14 Logit accuracy, specificity & sensitivity (2023-2025)

Prediction Outcome	Actual Non-Distressed (Y=0)	Actual Distressed (Y=1)	Total
Predicted Non-Distressed (Y=0)	255	57	312
Predicted Distressed (Y=1)	30	90	120
Total	**285**	**147**	**432**

Table 4.15: Logit TP, TN, FP & FN

To assess the out-of-sample prediction performance of the Logistic Regression model, the model was estimated using data from 2015 to 2022 and subsequently used to predict financial distress for the 2023–2025 period. The prediction was based on the estimated probability of financial distress, with a cut-off of 0.50 used to classify observations as either distressed or non-distressed. The prediction period contained 432 observations.

The model correctly classified 90 financially distressed observations as distressed (true positives) and 255 non-distressed observations as non-distressed (true negatives). It incorrectly classified 30 non-distressed observations as distressed (false positives) and failed to identify 57 observations that were distressed (false negatives). Overall, the model correctly classified 345 out of 432 observations, resulting in an accuracy of 79.86%.

The sensitivity was 61.22%, indicating that the model correctly identified approximately 61% of the observations that were actually financially distressed. The specificity was 89.47%, showing that the model was more successful in identifying non-distressed observations. These results indicate that the Logistic Regression model had reasonable discriminatory performance during the out-of-sample period, although its lower sensitivity suggests that it was less effective at detecting financial distress than at identifying non-distressed observations. The results are subsequently compared with the corresponding Altman Z-Score predictions for the same 2023–2025 observations.

ALTMAN PREDICTION ANALYSIS

Prediction Outcome	**Actual Non-Distressed (Y=0)**	**Actual Distressed (Y=1)**	**Total**
Predicted Non-Distressed (Y=0)	1,071	103	1,174
Predicted Distressed (Y=1)	62	617	679
Total	**1,133**	**720**	**1,853**

Performance Measure	Result
Accuracy	91.10%
Sensitivity	85.69%
Specificity	94.53%
Incorrect Classification Rate	8.90%
Total Gain	29.95%
Percentage Gain	77.08%
Classification Cut-off	0.50

Table 4.16 Altman z score prediction results

The prediction performance of the original Altman Z-Score was assessed by converting the model's classifications into a binary outcome for comparison with the Logistic Regression model. As shown in Table 4.16, the model correctly classified 1,688 out of 1,853 observations, resulting in an overall accuracy of 91.10%. Of the 1,133 observations that were non-distressed, 1,071 were correctly classified, giving a specificity of 94.53%. Of the 720 observations that were financially distressed, 617 were correctly identified, giving a sensitivity of 85.69%. These results indicate that the original Altman Z-Score performed strongly in distinguishing between distressed and non-distressed observations across the full 2015–2025 sample.

The model recorded 617 true positives, 1,071 true negatives, 62 false positives and 103 false negatives. The number of false negatives was higher than the number of false positives, although both represented a relatively small proportion of the total observations. Overall, 8.90% of observations were incorrectly classified. The model also recorded a total gain of 29.95% and a percentage gain of 77.08% compared with the constant probability specification. These results indicate strong full-sample classification performance and provide a basis for the subsequent out-of-sample comparison with Logistic Regression.

OUT-OF-SAMPLE COMPARISON OF LOGISTIC REGRESSION AND ALTMAN Z-SCORE

Prediction Outcome	Actual Non-Distressed (Y=0)	Actual Distressed (Y=1)	Total
Predicted Non-Distressed (Y=0)	268	52	320
Predicted Distressed (Y=1)	17	95	112
Total	**285**	**147**	**432**

Table 4.17: Altman TP, TN, FP & FN (2023-2025)

Performance Measure	Result
Accuracy	84.03%
Sensitivity	64.63%
Specificity	94.04%
Total Observations	432

Table 4.18: Altman Accuracy, sensitivity & specificity

The out-of-sample performance of the two models was evaluated using the same 432 company-year observations for the 2023–2025 period. The Logistic Regression model correctly classified 90 financially distressed observations and 255 non-distressed observations, while 30 observations were incorrectly classified as distressed and 57 distressed observations were not identified. This resulted in an overall accuracy of 79.86%, with sensitivity of 61.22% and specificity of 89.47%.

The original Altman Z-Score performed better on the same observations. It correctly classified 95 financially distressed observations and 268 non-distressed observations, while producing 17 false positives and 52 false negatives. The model achieved an overall accuracy of 84.03%, with sensitivity of 64.63% and specificity of 94.04%. Therefore, the original Altman Z-Score outperformed Logistic Regression across all three performance measures considered in this study.

The difference in accuracy shows that the original Altman Z-Score correctly classified a larger proportion of observations during the 2023–2025 prediction period. Its higher sensitivity indicates that Altman was also more effective at identifying observations that were actually financially distressed, while its higher specificity indicates stronger performance in identifying non-distressed observations. Based on these results, H5 is not supported. Contrary to the expectation that Logistic Regression would provide greater predictive accuracy, the original Altman Z-Score achieved higher out-of-sample accuracy than Logistic Regression (84.03% compared with 79.86%). This suggests that, for the sample and prediction period examined, the original Altman model provided stronger predictive performance.

MODEL COMPARISON

The results show that the original Altman Z-Score performed better than Logistic Regression in the sample used in this study. The Altman model correctly classified 91.10% of the observations, while Logistic Regression correctly classified 80.90%. This gives Altman a higher overall accuracy by 10.20 percentage points. The difference is also clear when looking at the identification of financially distressed companies. The Altman model correctly identified 85.69% of the distressed observations, compared with 63.61% for Logistic Regression. This means that Altman was able to identify a larger proportion of the companies that were classified as financially distressed.

Altman also performed slightly better in identifying non distressed companies. Its specificity was 94.53%, compared with 91.88% for Logistic Regression. The incorrect classification rate was also lower for Altman, at 8.90%, compared with 19.10% for Logistic Regression. Overall, the results from the prediction analysis show that the original Altman Z-Score provided better classification results than the Logistic Regression model for the sample used in this study.

Therefore, based on the results obtained, the original Altman Z-Score appears to be more effective in predicting financial distress in the companies included in this study.

HYPOTHESIS TESTING

The first four hypotheses were tested using the Logistic Regression results because these hypotheses examine the relationship between the selected financial variables and the probability of financial distress. A 5% significance level was used to determine whether the relationships were statistically significant. The fifth hypothesis was assessed separately using the out-of-sample prediction results of Logistic Regression and the original Altman Z-Score.

H1: ROE and Financial Distress

H1 proposed a negative relationship between Return on Equity (ROE) and financial distress, based on the expectation that higher profitability would be associated with a lower likelihood of financial distress. The Logistic Regression coefficient for ROE is -0.0318, indicating the expected negative direction. However, the p-value of 0.2379 is above the 5% significance level. Therefore, the relationship is not statistically significant, and H1 is not supported.

H2: Quick Ratio and Financial Distress

H2 proposed a negative relationship between Quick Ratio and financial distress. The Logistic Regression coefficient is -0.0247, indicating that higher liquidity is associated with a lower probability of financial distress. The p-value of 0.0112 is below the 5% significance level, indicating that the relationship is statistically significant. Therefore, H2 is supported.

H3: Total Asset Turnover and Financial Distress

H3 proposed a negative relationship between Total Asset Turnover and financial distress. The Logistic Regression coefficient is -1.8324 and is statistically significant ($p < 0.001$). The negative coefficient indicates that higher asset turnover is associated with a lower probability of financial distress. Therefore, H3 is supported.

H4: Debt Ratio and Financial Distress

H4 proposed a positive relationship between Debt Ratio and financial distress. The Logistic Regression coefficient for Debt Ratio is 3.0592 and is statistically significant ($p < 0.001$).

The positive coefficient indicates that higher debt relative to assets is associated with a higher probability of financial distress. Therefore, H4 is supported.

H5: Logistic Regression and Altman Z-Score Prediction

H5 proposed that Logistic Regression would provide greater predictive accuracy than the original Altman Z-Score. This hypothesis was assessed using the out-of-sample prediction results for 2023–2025, based on the same 432 company-year observations. Logistic Regression achieved an overall accuracy of 79.86%, while the original Altman Z-Score achieved a higher accuracy of 84.03%. Altman also recorded higher sensitivity (64.63% compared with 61.22%) and specificity (94.04% compared with 89.47%). Therefore, the results do not support the expectation that Logistic Regression would provide greater predictive accuracy than the original Altman Z-Score. **H5 is not supported.**

Overall, the results support **H2, H3 and H4**, while **H1 and H5 are not supported**. The Logistic Regression results indicate that Quick Ratio, Total Asset Turnover and Debt Ratio have statistically significant relationships with financial distress, while the relationship between ROE and financial distress is not statistically significant. The out-of-sample comparison further shows that the original Altman Z-Score achieved stronger predictive performance than Logistic Regression during the 2023–2025 prediction period.

CH-05 CONCLUSION

INTRODUCTION

This chapter concludes the study by bringing together the main findings from the empirical analysis and considering what they mean in relation to the research objectives and questions. The chapter first summarises the key findings of the study before directly answering the research questions. It then discusses the theoretical and practical implications of the findings, followed by recommendations, limitations of the study and suggestions for future research. The chapter ends with an overall conclusion based on the evidence obtained from the analysis of Indian non-financial listed companies.

SUMMARY OF THE STUDY

This study examined financial distress prediction among Indian non-financial listed companies by comparing the original Altman Z-Score model with Logistic Regression. The study focused on four sectors: Chemicals, Industrial Goods, Pharmaceuticals and Medical Research, and Automobiles and Auto Parts. The analysis covered the period from 2015 to 2025 and used financial information obtained from LSEG Workspace. Financial distress was identified using a classification based on four financial conditions: negative Return on Assets (ROA), a Current Ratio below 1, an Interest Coverage Ratio below 1, and negative Operating Cash Flow. An observation was classified as financially distressed when at least two of these conditions occurred in the same financial year. This approach was used to provide a broader measure of financial distress rather than relying on a single financial indicator.

The study then applied the original Altman Z-Score and Logistic Regression to examine financial distress and compare their predictive performance. Logistic Regression used ROE, Quick Ratio, Total Asset Turnover and Debt Ratio as explanatory variables. Panel regression techniques were also used to examine the relationships between these variables and financial distress. Pooled OLS, Fixed Effects and Random Effects models were considered, with the Hausman test identifying Fixed Effects as the more appropriate specification. The final Fixed Effects model used robust two-way clustered standard errors.

The predictive performance of the two models was assessed using accuracy, sensitivity and specificity. In addition to the full-sample classification results, an out-of-sample prediction period covering 2023–2025 was used to provide a more meaningful comparison between Logistic Regression and the original Altman Z-Score. Both models were evaluated using the same 432 observations during this prediction period.

KEY EMPIRICAL FINDINGS

The empirical findings provide evidence that the relationship between financial characteristics and financial distress depends on the variable examined and the modelling approach used. The formal hypothesis tests are based on the Logistic Regression results, while the Fixed Effects model provides supplementary evidence on the panel relationships after controlling for company-specific effects. The Logistic Regression results show that Quick Ratio, Total Asset Turnover and Debt Ratio are statistically significant, whereas ROE has the expected negative coefficient but is not statistically significant. These findings are considered below in relation to the previous literature.

ROE and financial distress: The Logistic Regression results show a negative relationship between ROE and financial distress (β = -0.0318), but the relationship is not statistically significant (p = 0.2379). The negative direction is consistent with the expectation developed from previous research.

Nair and Sachdeva (2016) identified profitability as an important factor in financial distress among Indian textile companies, while Balasubramanian et al. (2019) also found profitability-related measures useful in predicting distress among Indian listed companies. Similar evidence has been reported by Savery et al. (2024) and Singh and Singla (2024). However, the present study does not statistically confirm the expected relationship for ROE. This difference may reflect the specific profitability measure used, the definition of financial distress, the sectors included and the period examined. Therefore, the finding is consistent with the literature in direction but provides weaker statistical evidence than the general relationship reported in previous research. H1 is therefore not supported.

Quick Ratio and financial distress: Quick Ratio has a negative and statistically significant coefficient (β = -0.0247, p = 0.0112). This result is consistent with the literature, which generally identifies liquidity as an important characteristic when assessing financial distress.

Nair and Sachdeva (2016), Balasubramanian et al. (2019) and Mahesh et al. (2025) all considered liquidity-related measures in their studies, although the specific ratios and their importance differed between research settings. The present finding therefore agrees with the expected direction and provides statistical support for the view that stronger short-term liquidity is associated with a lower likelihood of financial distress. H2 is supported.

Total Asset Turnover and financial distress: Total Asset Turnover has a negative and statistically significant relationship with financial distress ($\beta = -1.8324$, $p < 0.001$). This finding agrees with the expected relationship and is also supported by previous research that has considered asset efficiency as a financial distress indicator. Mahesh et al. (2025) included Total Asset Turnover in their analysis of Indian small enterprises, while Sethi and Mahadik (2024) included asset turnover in their Logistic Regression analysis of Indian non-financial companies. The result suggests that companies generating greater sales relative to their asset base tend to have a lower probability of financial distress. At the same time, previous research indicates that the importance of asset turnover can vary between industries because companies have different asset structures and operating requirements. The present finding therefore supports the literature while also providing evidence from a broader group of Indian non-financial sectors. H3 is supported.

Debt Ratio and financial distress: Debt Ratio has a positive and statistically significant relationship with financial distress ($\beta = 3.0592$, $p < 0.001$). This result is consistent with the expected relationship and with previous studies that have identified leverage as an important factor in financial distress. Balasubramanian et al. (2019), Savery et al. (2024) and Mahesh et al. (2025) all considered debt or leverage in their financial distress analyses. The finding suggests that greater reliance on debt is associated with a higher probability of financial distress, potentially because higher debt creates greater financial obligations when profitability or cash flows weaken.

However, the literature also recognises that debt is not necessarily harmful, as borrowing can be used to finance investment and growth. Its effect depends partly on the company's ability to generate sufficient returns and cash flows to meet its obligations. The significant positive relationship found in the present study therefore supports the expected direction in the literature. H4 is supported.

Comparison of Logistic Regression and the original Altman Z-Score: The most important model-comparison finding is that the original Altman Z-Score outperformed Logistic Regression during the 2023–2025 out-of-sample period. Using the same 432 company-year observations, Altman achieved an accuracy of 84.03%, compared with 79.86% for Logistic Regression. Altman also recorded higher sensitivity (64.63% compared with 61.22%) and higher specificity (94.04% compared with 89.47%). The result therefore does not support H5.

This finding differs from some previous research. Singh and Singla (2023), for example, reported stronger performance from a newly developed Logistic Regression model compared with a re-estimated Altman model in the Indian corporate sector. However, their comparison involved a re-estimated Altman model, rather than the original Altman coefficients used in the present study. This distinction is important because changing the coefficients changes the model being evaluated. Similarly, Sethi and Mahadik (2024) found strong performance from Logistic Regression when comparing it with Linear Discriminant Analysis and Artificial Neural Networks, but their study examined Indian non-financial service companies and did not provide the same direct comparison between Logistic Regression and the original Altman model used here.

On the other hand, previous Indian research has also reported strong performance from Altman's Z-Score. Ahamed and Ahammed (2024), for example, reported 96.6% accuracy for the Z-Score among 41 Indian logistics companies, although their study was restricted to a single industry and therefore is not directly comparable with the present multi-sector sample. The present study therefore adds to the mixed evidence by showing that the original Altman Z-Score can outperform Logistic Regression when both are evaluated on the same Indian non-financial company-year observations and under a common distress classification.

The difference between the present findings and some earlier studies highlights the importance of research design when comparing financial distress models. Previous research has used different industries, company sizes, periods, financial variables, distress definitions and modified versions of Altman's model. Therefore, the results do not imply that Altman will always outperform Logistic Regression. Instead, they suggest that model performance is context dependent. In the present study, the original Altman model provided stronger out-of-sample performance during 2023–2025, while Logistic Regression provided useful evidence on the individual financial variables associated with the probability of distress.

ANSWERS TO RESEARCH QUESTION

The main research question of this study asked: **"How effective is the original Altman's Z-Score in predicting financial distress among Indian non-financial listed companies compared with Logistic Regression?"**

The findings indicate that the original Altman Z-Score was more effective than Logistic Regression in the out-of-sample prediction period examined in this study. Using the same 432 company-year observations for 2023–2025, the original Altman Z-Score achieved an accuracy of 84.03%, compared with 79.86% for Logistic Regression. Altman also achieved higher sensitivity (64.63% compared with 61.22%) and specificity (94.04% compared with 89.47%). Therefore, Altman performed better not only in overall classification accuracy but also in identifying both distressed and non-distressed observations.

The result provides an interesting contrast with parts of the previous literature. Some Indian studies have reported strong results from Logistic Regression, including Singh and Singla (2023), who found that their newly developed Logistic Regression model outperformed a re-estimated Altman model. Sethi and Mahadik (2024) also reported strong performance from Logistic Regression in their comparison with LDA and ANN. However, these studies used different samples, variables and model specifications, and the Altman model considered by Singh and Singla (2023) was re-estimated rather than the original specification.

The present study therefore provides a different result by testing the original Altman Z-Score against Logistic Regression under the same research conditions. The finding suggests that the greater flexibility of Logistic Regression does not necessarily result in superior predictive performance. In this sample, the established Altman model provided stronger out-of-sample classification performance.

However, the result should not be interpreted as evidence that Altman will always outperform Logistic Regression. Previous research has shown that model performance can vary according to the industry, company size, period, variables included and definition of financial distress. The conclusion is therefore specific to the Indian listed non-financial companies and the 2023–2025 prediction period examined in this study.

Overall, the research question is answered by finding that the original Altman Z-Score was more effective than Logistic Regression in predicting financial distress during the out-of-sample period used in this study. This finding does not diminish the usefulness of Logistic Regression, as the model also identified significant relationships between financial variables and distress. Rather, it demonstrates that model effectiveness depends on the empirical setting and that a more flexible model does not automatically produce better predictions.

THEORETICAL IMPLICATIONS

The findings of this study contribute to the financial distress literature in several ways. First, the results provide further evidence that financial distress is associated with several dimensions of a company's financial condition rather than with a single financial measure. The Logistic Regression results show that liquidity, asset efficiency and debt are significantly related to financial distress, while profitability, measured by ROE, has the expected negative direction but is not statistically significant. This broadly supports the view in previous research that profitability, liquidity, efficiency and leverage can provide useful information about financial distress, while also showing that the importance of individual variables can differ across research settings. Previous studies have similarly found differences in the significance and strength of financial variables across industries and samples.

Second, the significant negative relationship between Quick Ratio and financial distress provides support for the role of liquidity in explaining financial difficulty. This is consistent with previous research that has incorporated liquidity measures into financial distress models, including Nair and Sachdeva (2016), Balasubramanian et al. (2019) and Mahesh et al. (2025). The result suggests that the ability to meet short-term obligations remains relevant when assessing financial distress among the Indian non-financial companies examined in this study.

Third, the significant negative relationship between Total Asset Turnover and financial distress provides evidence that asset efficiency is also relevant to financial distress prediction. This supports previous research by Mahesh et al. (2025) and Sethi and Mahadik (2024), which included asset turnover or asset efficiency in their financial distress analyses.

At the same time, the literature indicates that asset turnover can vary naturally between industries because companies have different asset structures and operating requirements. The finding therefore supports the relevance of asset efficiency while recognising that its effect may be context dependent.

Fourth, the positive and statistically significant relationship between Debt Ratio and financial distress supports the argument that greater reliance on debt can increase financial pressure. This is consistent with previous research that has identified leverage as an important factor in financial distress, including Balasubramanian et al. (2019), Savery et al. (2024) and Mahesh et al. (2025). However, the finding should not be interpreted as suggesting that all borrowing is inherently harmful. The effect of debt depends on whether companies can generate sufficient returns and cash flows to meet their financial obligations.

The non-significant relationship between ROE and financial distress provides an additional theoretical point. Although the coefficient was negative, as expected, the relationship was not statistically significant. This means that the present study does not provide sufficient evidence to confirm that higher ROE independently reduces the probability of financial distress within the Logistic Regression model. The finding does not contradict the broader literature on profitability completely but instead suggests that the importance of profitability may depend on the profitability measure used, the distress definition and the characteristics of the companies examined. Previous studies have identified profitability as relevant to distress, but the strength of the relationship has varied across settings.

The study also contributes to the literature on financial distress prediction models by directly evaluating the original Altman Z-Score rather than relying on a modified or re-estimated version. This is important because previous Indian research has often involved modified Altman models or comparisons with other statistical and machine-learning approaches. Singh and Singla (2023), for example, compared a newly developed Logistic Regression model with a re-estimated Altman model, meaning that their comparison was not equivalent to testing the original Altman coefficients. The present study instead retains the original Altman specification and evaluates it against Logistic Regression using the same companies, distress classification and out-of-sample observations.

The out-of-sample finding also contributes to the ongoing discussion about whether more flexible statistical models necessarily provide better prediction. Logistic Regression did not outperform the original Altman model in the present study. Instead, Altman achieved higher accuracy, sensitivity and specificity during 2023–2025. This finding is important because previous literature has produced mixed evidence regarding the relative performance of traditional and statistical prediction models. The present study therefore supports the view that model performance is context-dependent rather than determined simply by model complexity.

Finally, the study reinforces the importance of out-of-sample evaluation in financial distress research. The original Altman model achieved 91.10% accuracy when the wider 2015–2025 sample was classified, but its accuracy fell to 84.03% when evaluated on the separate 2023–2025 prediction period. This difference demonstrates why strong classification of historical observations should not automatically be interpreted as evidence of future predictive ability. The use of a separate prediction period in this study therefore provides a stronger basis for evaluating the practical predictive performance of the two models.

PRACTICAL IMPLICATIONS

The findings have practical relevance for managers, investors, lenders and financial analysts. The significant relationships identified in the Logistic Regression model for Quick Ratio, Total Asset Turnover and Debt Ratio suggest that liquidity, asset efficiency and leverage can provide useful signals when monitoring financial condition. The negative direction of ROE also provides a consistent profitability signal, although its relationship was not statistically significant in the formal Logistic Regression test.

For investors and lenders, the findings suggest that financial ratios and established financial distress models can provide useful early-warning information. The original Altman Z-Score may be particularly useful as an initial screening tool because it performed better than Logistic Regression in the 2023–2025 out-of-sample comparison. However, neither model should be used as the sole basis for investment or lending decisions. Their results should instead be considered alongside company-specific financial information, industry conditions and other relevant factors.

The findings also highlight the importance of evaluating prediction models using out-of-sample observations. A model that performs well within the estimation sample may not necessarily provide the strongest predictions when applied to later observations. Therefore, organisations using financial distress models should periodically assess their predictive performance and consider whether the model remains appropriate for the companies and economic environment being analysed.

RECOMMENDATIONS

Based on the findings of the study, several recommendations can be made. First, companies should regularly monitor key financial indicators associated with financial distress. In particular, liquidity, asset efficiency and leverage should be included within regular financial risk monitoring, as Quick Ratio, Total Asset Turnover and Debt Ratio were statistically significant in the Logistic Regression analysis. Monitoring these indicators may help management identify changes in financial condition at an earlier stage. Second, investors, lenders and financial analysts should use financial distress models as early-warning and screening tools rather than relying on a single financial indicator. The original Altman Z-Score may be particularly useful for initial screening in the context examined in this study, given its stronger out-of-sample performance. However, its results should be considered together with wider financial information, company-specific circumstances and industry conditions before making investment or lending decisions.

Third, organisations applying financial distress prediction models should regularly evaluate their predictive performance using observations that were not used to estimate the model. The findings of this study demonstrate the importance of out-of-sample assessment, as the model that performed better within the estimation sample was not necessarily the model that achieved the strongest later-period prediction. Finally, researchers and practitioners should avoid if a more flexible or statistically complex model will always produce better predictions. Model selection should consider the characteristics of the firms, the definition of financial distress, the variables available and the economic environment in which the model is applied. Where appropriate, established models such as the original Altman Z-Score can be retained alongside newer approaches and evaluated based on their actual predictive performance.

LIMITATIONS OF THE STUDY

This study has several limitations that should be considered when interpreting the findings. First, the analysis focuses on Indian listed non-financial companies from four selected sectors. Therefore, the findings may not be directly applicable to companies from other industries or to unlisted firms. The study also covers the period 2015–2025, meaning that the results reflect the economic and financial conditions observed during this period. Second, financial distress was identified using the study's defined combination of four financial conditions: negative ROA, Current Ratio below 1, Interest Coverage Ratio below 1 and negative Operating Cash Flow. An observation was classified as financially distressed when at least two of these conditions occurred in the same financial year. Although this approach provides a broader measure of distress than relying on a single indicator, alternative definitions of financial distress could produce different classifications and consequently different model results.

Third, the Logistic Regression model was based on four financial ratios: ROE, Quick Ratio, Total Asset Turnover and Debt Ratio. Other financial, market and non-financial factors that may influence financial distress were not included. The predictive comparison was also based on the 2023–2025 out-of-sample period. Although this provides a separate period for evaluating predictive performance, it remains relatively limited for assessing longer-term model stability. Finally, the original Altman Z-Score was developed using companies from a different economic and market environment. Its application to Indian companies therefore involves a difference between the original development context and the context examined in this study. The findings should consequently be interpreted specifically within the sample, sectors and period examined rather than being generalised to all companies, industries or markets.

SUGGESTIONS FOR FUTURE RESEARCH

Future research could extend this study in several ways. First, a larger sample covering more industries and both listed and unlisted companies could provide a broader understanding of financial distress in India. Extending the study period could also help examine whether the predictive performance of Altman Z-Score and Logistic Regression changes across different economic and financial conditions. Second, future studies could incorporate additional financial, market and non-financial variables.

Variables relating to corporate governance, firm size, market performance, macroeconomic conditions and other company-specific characteristics could be examined to determine whether they improve the prediction of financial distress. Third, alternative definitions of financial distress could be tested. Comparing the present two-out-of-four classification approach with other distress definitions would help determine how sensitive model performance is to the way financial distress is identified. Fourth, future research could compare the original Altman Z-Score and Logistic Regression with other statistical and machine-learning approaches. Models such as Linear Discriminant Analysis, decision trees, random forests or other classification techniques could provide further evidence on whether more flexible approaches offer predictive advantages in different settings.

Finally, future studies could evaluate the models across individual sectors and over longer out-of-sample periods. Sector-specific analysis may reveal whether the relative performance of Altman and Logistic Regression differs according to industry characteristics. Longer prediction periods would also provide stronger evidence regarding the stability and reliability of the models over time.

OVERALL CONCLUSION

This study examined financial distress prediction among Indian listed non-financial companies by comparing the original Altman Z-Score model with Logistic Regression. The study used company-year observations from four sectors over the period 2015–2025 and defined financial distress using a combination of four financial conditions: negative ROA, Current Ratio below 1, Interest Coverage Ratio below 1 and negative Operating Cash Flow. An observation was classified as distressed when at least two of these conditions were present in the same financial year. The formal Logistic Regression analysis provided evidence that Quick Ratio, Total Asset Turnover and Debt Ratio were significantly associated with financial distress, while the relationship between ROE and financial distress was not statistically significant. Therefore, H2, H3 and H4 were supported, while H1 was not supported. These findings broadly agree with previous literature in terms of the expected direction of the significant relationships, while the non-significant ROE result shows that the relevance of individual financial indicators can vary across samples and research settings.

The comparison of the two prediction models provides the main contribution of the study. Using the same 432 company-year observations for the 2023–2025 out-of-sample period, the original Altman Z-Score achieved an accuracy of 84.03%, compared with 79.86% for Logistic Regression. Altman also achieved higher sensitivity (64.63% compared with 61.22%) and specificity (94.04% compared with 89.47%). Therefore, H5 was not supported. These findings provide context-specific evidence that the original Altman Z-Score can remain useful for financial distress screening among the Indian listed non-financial companies examined in this study. At the same time, the results should not be interpreted as showing that Altman will always outperform Logistic Regression. Previous research has reported different results depending on the model specification, sample, distress definition and prediction period. The findings of this study therefore suggest that the effectiveness of a financial distress prediction model depends not only on the statistical technique used, but also on the characteristics of the companies, variables, classification method and period of prediction.

Overall, the study contributes to the financial distress literature by providing a direct comparison of the unchanged original Altman Z-Score and Logistic Regression using the same distress definition and the same out-of-sample observations. The results demonstrate that a well-established model can remain competitive against a more flexible statistical approach and highlight the importance of testing prediction models using data outside the estimation period.

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APPENDICES

LIST OF COMPANIES ALONG WITH THEIR SECTORS AND COMPANY CODE

(APPENDIX A)

Note: Appendix A presents the final company sample used in the study, organised according to the four selected sectors: Chemicals, Industrial Goods, Pharmaceuticals & Medical Research, and Automobiles & Auto Parts. The intended sample consisted of 200 companies, with 50 companies selected from each sector. Following the application of the study's inclusion criteria and data availability requirements, the final sample comprised 195 companies. The sector-wise company lists below show the companies included in the final dataset. The resulting dataset contains 1,853 usable company-year observations over the 2015–2025 study period.

A.1 Chemicals (50 companies)

No.	Company Name	Ticker / Company Code	Sector
1	Shalimar Paints Ltd	SHLP.NS	Chemicals
2	Vinati Organics Ltd	VNTI.NS	Chemicals
3	Bharat Agri Fert & Realty Ltd	BFER.BO	Chemicals
4	Primo Chemicals Ltd	PIMO.NS	Chemicals
5	Laffans Petrochemicals Ltd	LAFP.BO	Chemicals
6	Organic Coatings Ltd	ORCO.BO	Chemicals
7	Alkyl Amines Chemicals Ltd	ALKY.NS	Chemicals
8	Vinyl Chemicals (India) Ltd	VNYL.NS	Chemicals
9	Shree Hari Chemicals Export Ltd	SHCE.BO	Chemicals
10	National Oxygen Ltd	NTOX.BO	Chemicals
11	Manali Petrochemicals Ltd	MNLI.NS	Chemicals

12	Kesoram Industries Ltd	KSRM.NS	Chemicals
13	Plastiblends India Ltd	PLST.NS	Chemicals
14	Uniphos Enterprises Ltd	UNPH.NS	Chemicals
15	Hindustan Organic Chemicals Ltd	HOCL.BO	Chemicals
16	Sudarshan Chemical Industries Ltd	SDCH.NS	Chemicals
17	Asian Paints Ltd	ASPN.NS	Chemicals
18	Supreme Industries Ltd	SUPI.NS	Chemicals
19	Supreme Petrochem Ltd	SPTL.NS	Chemicals
20	Polyplex Corp Ltd	PLYP.NS	Chemicals
21	Rashtriya Chemicals and Fertilizers Ltd	RSTC.NS	Chemicals
22	Nagarjuna Fertilizers and Chemicals Ltd	NGFR.NS	Chemicals
23	Shreyas Intermediates Ltd	SRNG.BO	Chemicals
24	Rallis India Ltd	RALL.NS	Chemicals
25	Solar Industries India Ltd	SLIN.NS	Chemicals
26	Indo Borax and Chemicals Ltd	IBCH.NS	Chemicals
27	Vikas WSP Ltd	VWSP.BO	Chemicals
28	Kanoria Chemicals and Industries Ltd	KNRC.NS	Chemicals
29	Tuticorin Alkali Chemicals and Fertilizers Ltd	TUTI.BO	Chemicals
30	Poddar Pigments Ltd	PODR.NS	Chemicals
31	ULTRAMARINE & PIGMENTS Ltd	ULTR.NS	Chemicals
32	Aries Agro Ltd (CN)	ARAI.NS	Chemicals
33	Sumeet Industries Ltd	SUIN.NS	Chemicals
34	Jaysynth Orgochem Ltd	JAYO.BO	Chemicals

35	Citurgia Biochemicals Ltd	CITR.BO	Chemicals
36	Madras Fertilizers Ltd	MDFT.NS	Chemicals
37	Standard Surfactants Ltd	STDS.BO	Chemicals
38	Asian Petro Products and Exporters Ltd	APTR.BO	Chemicals
39	Prima Plastics Ltd	PRIP.BO	Chemicals
40	Padmanabh Industries Ltd	PADI.BO	Chemicals
41	Polylink Polymers (India) Ltd	PPLY.BO	Chemicals
42	Rama Petrochemicals Ltd	RMPT.BO	Chemicals
43	Polycon International Ltd	POIN.BO	Chemicals
44	Teesta Agro Industries Ltd	TEES.BO	Chemicals
45	Bloom Dekor Ltd	BLOD.BO	Chemicals
46	Agarwal Industrial Corporation Ltd	AGWL.NS	Chemicals
47	Aviva Industries Ltd	AVID.BO	Chemicals
48	Shaily Engineering Plastics Ltd	SEPL.NS	Chemicals
49	Mena Mani Industries Ltd	MNAM.BO	Chemicals
50	Vipul Organics Ltd	VIPU.BO	Chemicals

A.2 Industrial Goods (47 companies)

No.	Company Name	Ticker / Company Code	Sector
51	Batliboi Ltd	BTLI.NS	Industrial Goods
52	LEEL Electricals Ltd	LEEL.NS	Industrial Goods
53	Cosmo Ferrites Ltd	CSFR.BO	Industrial Goods
54	HBL Engineering Ltd	HBLO.NS	Industrial Goods
55	Kabra Extrusion Technik Ltd	KBRE.NS	Industrial Goods
56	Manugraph India Ltd	MNUG.NS	Industrial Goods
57	BEML Ltd	BEML.NS	Industrial Goods
58	Elgi Equipments Ltd	ELGE.NS	Industrial Goods
59	Indian Card Clothing Company Ltd	IDIC.NS	Industrial Goods
60	Premier Ltd	PRMI.NS	Industrial Goods
61	TIL Ltd	TILL.NS	Industrial Goods
62	Finolex Cables Ltd	FNXC.NS	Industrial Goods
63	ABB India Ltd	ABB.NS	Industrial Goods
64	Alfa Transformers Ltd	ALFT.BO	Industrial Goods
65	Veejay Lakshmi Engineering Works Ltd	VLEW.BO	Industrial Goods
66	Honda India Power Products Ltd	HOND.NS	Industrial Goods
67	IMP Powers Ltd	IMPP.NS	Industrial Goods
68	Apar Industries Ltd	APAR.NS	Industrial Goods
69	Bharat Electronics Ltd	BAJE.NS	Industrial Goods
70	Bhagyanagar India Ltd	BHIL.NS	Industrial Goods
71	Havells India Ltd	HVEL.NS	Industrial Goods

72	Jyoti Ltd	JYTI.BO	Industrial Goods
73	Galada Power and Telecommunication Ltd	GALA.BO	Industrial Goods
74	Amara Raja Energy & Mobility Ltd	AMAR.NS	Industrial Goods
75	HMT Ltd	HMTL.NS	Industrial Goods
76	AIA Engineering Ltd	AIAE.NS	Industrial Goods
77	Switching Technologies Gunther Ltd	SWTE.BO	Industrial Goods
78	Rishi Laser Ltd	RILC.BO	Industrial Goods
79	Aurique Ltd	AURQ.BO	Industrial Goods
80	Skyline Millars Ltd	SLMI.BO	Industrial Goods
81	Clenon Enterprises Ltd	CLEN.BO	Industrial Goods
82	Delta Manufacturing Ltd	DLTA.NS	Industrial Goods
83	Envair Electrodyne Ltd	ENEL.BO	Industrial Goods
84	Cenlub Industries Ltd	CENL.BO	Industrial Goods
85	Fluidomat Ltd	FLUD.BO	Industrial Goods
86	Mid India Industries Ltd	MIDU.BO	Industrial Goods
87	Frontier Springs Ltd	FRON.NS	Industrial Goods
88	Galaxy Bearings Ltd	GLXB.BO	Industrial Goods
89	ITL Industries Ltd	IDRE.BO	Industrial Goods
90	Miven Machine Tools Ltd	KRWR.BO	Industrial Goods
91	Swan Defence and Heavy Industries Ltd	SWAE.NS	Industrial Goods
92	Sturdy Industries Ltd	STUD.BO	Industrial Goods
93	Isgec Heavy Engineering Ltd	ISGE.NS	Industrial Goods
94	Cords Cable Industries Ltd	CCIL.NS	Industrial Goods

95	Integra Switchgear Ltd	INTS.BO	Industrial Goods
96	Anirit Ventures Ltd	ANIR.BO	Industrial Goods
97	Modern Insulators Ltd	MDIS.BO	Industrial Goods

A.3 Pharmaceuticals & Medical Research (49 companies)

No.	**Company Name**	**Ticker / Company Code**	**Sector**
98	Sun Pharma Advanced Research Co Ltd	SPRC.NS	Pharmaceuticals & Medical Research
99	Coral Laboratories Ltd	CORL.BO	Pharmaceuticals & Medical Research
100	Krebs Biochemicals and Industries Ltd	KREB.NS	Pharmaceuticals & Medical Research
101	Lincoln Pharmaceuticals Ltd	LINP.NS	Pharmaceuticals & Medical Research
102	Vista Pharmaceuticals Ltd	VIPH.BO	Pharmaceuticals & Medical Research
103	Jenburkt Pharmaceuticals Ltd	JENA.BO	Pharmaceuticals & Medical Research
104	Hester Biosciences Ltd	HEST.NS	Pharmaceuticals & Medical Research
105	Divi's Laboratories Ltd	DIVI.NS	Pharmaceuticals & Medical Research
106	Aurobindo Pharma Ltd	ARBN.NS	Pharmaceuticals & Medical Research
107	Bharat Immunologicals and Biologicals Corporation Ltd	BIBC.BO	Pharmaceuticals & Medical Research

108	Cipla Ltd	CIPL.NS	Pharmaceuticals & Medical Research
109	Orchid Pharma Ltd	ORCD.NS	Pharmaceuticals & Medical Research
110	Ambalal Sarabhai Enterprises Ltd	AMBL.NS	Pharmaceuticals & Medical Research
111	KOBO Biotech Ltd	KOBO.BO	Pharmaceuticals & Medical Research
112	Unichem Laboratories Ltd	UNLB.NS	Pharmaceuticals & Medical Research
113	Parenteral Drugs (India) Ltd	PADG.NS	Pharmaceuticals & Medical Research
114	Godavari Drugs Ltd	GDRU.BO	Pharmaceuticals & Medical Research
115	Abbott India Ltd	ABOT.NS	Pharmaceuticals & Medical Research
116	IPCA Laboratories Ltd	IPCA.NS	Pharmaceuticals & Medical Research
117	Wockhardt Ltd	WCKH.NS	Pharmaceuticals & Medical Research
118	Marksans Pharma Ltd	MARK.NS	Pharmaceuticals & Medical Research
119	Shamrock Industrial Company Ltd	SHMR.BO	Pharmaceuticals & Medical Research
120	Transgene Biotek Ltd	TRBL.BO	Pharmaceuticals & Medical Research

121	Aarti Drugs Ltd	ADRG.NS	Pharmaceuticals & Medical Research
122	Panacea Biotec Ltd	PNCA.NS	Pharmaceuticals & Medical Research
123	Amrutanjan Health Care Ltd	AJAN.NS	Pharmaceuticals & Medical Research
124	Suven Life Sciences Ltd	SUVP.NS	Pharmaceuticals & Medical Research
125	Lyka Labs Ltd	LYKA.NS	Pharmaceuticals & Medical Research
126	Zenotech Laboratories Ltd	ZENL.BO	Pharmaceuticals & Medical Research
127	Medicamen Biotech Ltd	MEBI.NS	Pharmaceuticals & Medical Research
128	Gufic Biosciences Ltd	GUFI.NS	Pharmaceuticals & Medical Research
129	BDH Industries Ltd	BDHI.BO	Pharmaceuticals & Medical Research
130	Anuh Pharma Ltd	ANUH.NS	Pharmaceuticals & Medical Research
131	Vivimed Labs Ltd	VVMD.NS	Pharmaceuticals & Medical Research
132	Ajanta Pharma Ltd	AJPH.NS	Pharmaceuticals & Medical Research
133	Aarey Drugs and Pharmaceuticals Ltd	ADPH.NS	Pharmaceuticals & Medical Research

134	Ishita Drugs and Industries Ltd	ISHI.BO	Pharmaceuticals & Medical Research
135	Bacil Pharma Ltd	BACP.BO	Pharmaceuticals & Medical Research
136	Maximaa Systems Ltd	MXSY.BO	Pharmaceuticals & Medical Research
137	Oxygenta Pharmaceutical Ltd	OXPH.BO	Pharmaceuticals & Medical Research
138	Biofil Chemicals and Pharmaceuticals Ltd	BIOF.NS	Pharmaceuticals & Medical Research
139	Gennex Laboratories Ltd	GNXL.BO	Pharmaceuticals & Medical Research
140	Norris Medicines Ltd	NORI.BO	Pharmaceuticals & Medical Research
141	Colinz Laboratories Ltd	CLAB.BO	Pharmaceuticals & Medical Research
142	Pharmaids Pharmaceuticals Ltd	PPHM.BO	Pharmaceuticals & Medical Research
143	Adline Chem Lab Ltd	ADLN.BO	Pharmaceuticals & Medical Research
144	Bafna Pharmaceuticals Ltd	BAFP.NS	Pharmaceuticals & Medical Research
145	Vivanza Biosciences Ltd	VIVN.BO	Pharmaceuticals & Medical Research
146	Desh Rakshak Aushdhalaya Ltd	DESH.BO	Pharmaceuticals & Medical Research

A.4 Automobiles & Auto Parts (49 companies)

No.	Company Name	Ticker / Company Code	Sector
147	Talbros Automotive Components Ltd	TALB.NS	Automobiles & Auto Parts
148	Munjal Auto Industries Ltd	MUAU.NS	Automobiles & Auto Parts
149	Menon Pistons Ltd	MEPI.NS	Automobiles & Auto Parts
150	LG Balakrishnan & Bros Ltd	LGB.NS	Automobiles & Auto Parts
151	Kinetic Engineering Ltd	KNTE.BO	Automobiles & Auto Parts
152	Shivam Autotech Ltd	SHAU.NS	Automobiles & Auto Parts
153	Gabriel India Ltd	GABR.NS	Automobiles & Auto Parts
154	Unimers India Ltd	UNMR.BO	Automobiles & Auto Parts
155	India Nippon Electricals Ltd	INEL.NS	Automobiles & Auto Parts
156	Igarashi Motors India Ltd	IGAM.NS	Automobiles & Auto Parts
157	Sundaram Brake Linings Ltd	SBKL.NS	Automobiles & Auto Parts

158	Hero MotoCorp Ltd	HROM.NS	Automobiles & Auto Parts
159	Mahindra and Mahindra Ltd	MAHM.NS	Automobiles & Auto Parts
160	Sundram Fasteners Ltd	SNFS.NS	Automobiles & Auto Parts
161	Tata Motors Passenger Vehicles Ltd	TAMO.NS	Automobiles & Auto Parts
162	TVS Holdings Ltd	TVSH.NS	Automobiles & Auto Parts
163	Automotive Axles Ltd	ATOA.NS	Automobiles & Auto Parts
164	Machino Plastics Ltd	MCPL.BO	Automobiles & Auto Parts
165	Menon Bearings Ltd	MENO.NS	Automobiles & Auto Parts
166	MRF Ltd	MRF.NS	Automobiles & Auto Parts
167	Omax Autos Ltd	OMXA.NS	Automobiles & Auto Parts
168	IP Rings Ltd	IPRI.BO	Automobiles & Auto Parts
169	UCAL Ltd	UCAI.NS	Automobiles & Auto Parts
170	Cummins India Ltd	CUMM.NS	Automobiles & Auto Parts

171	Duncan Engineering Ltd	DUNC.BO	Automobiles & Auto Parts
172	IST Ltd	ISTL.BO	Automobiles & Auto Parts
173	Bosch Ltd	BOSH.NS	Automobiles & Auto Parts
174	Exide Industries Ltd	EXID.NS	Automobiles & Auto Parts
175	Balkrishna Industries Ltd	BLKI.NS	Automobiles & Auto Parts
176	Setco Automotive Ltd	SETC.NS	Automobiles & Auto Parts
177	Bharat Gears Ltd	BGRS.NS	Automobiles & Auto Parts
178	ELGI Rubber Co Ltd	ELGT.NS	Automobiles & Auto Parts
179	Rasandik Engineering Industries India Ltd	REIL.BO	Automobiles & Auto Parts
180	India Motor Parts & Accessories Ltd	IMPA.NS	Automobiles & Auto Parts
181	Jay Ushin Ltd	JAYY.BO	Automobiles & Auto Parts
182	Automotive Stampings and Assemblies Ltd	ASAS.NS	Automobiles & Auto Parts
183	Lumax AutoTechnologies Ltd	LUAT.NS	Automobiles & Auto Parts

184	Autoline Industries Ltd	AUIN.NS	Automobiles & Auto Parts
185	HIM Teknoforge Ltd	HMTE.BO	Automobiles & Auto Parts
186	MKP Mobility Ltd	MKPM.BO	Automobiles & Auto Parts
187	Auto Pins (India) Ltd	AUPI.BO	Automobiles & Auto Parts
188	G.S. Auto International Ltd	GSAI.BO	Automobiles & Auto Parts
189	Cochin Malabar Estates and Industries Ltd	CMEI.BO	Automobiles & Auto Parts
190	Southern Latex Ltd	SOUT.BO	Automobiles & Auto Parts
191	Eastern Treads Ltd	EASE.BO	Automobiles & Auto Parts
192	Sibar Auto Parts Ltd	SIAP.BO	Automobiles & Auto Parts
193	ZF Commercial Vehicle Control Systems India Ltd	ZFCV.NS	Automobiles & Auto Parts
194	Rane (Madras) Ltd	RAMD.NS	Automobiles & Auto Parts
195	Bajaj Auto Ltd	BAJA.NS	Automobiles & Auto Parts

EVIEWS STATISTICAL OUTPUT TABLES

Screenshots of the work done on EViews: (APPENDIX B)

Note: Appendix B presents the underlying EViews outputs supporting the empirical analysis reported in Chapters 3 and 4. The outputs are organised according to the sequence of the empirical analysis, including descriptive statistics, correlation analysis, multicollinearity, panel model estimation and selection, heteroskedasticity, unit root testing, Logistic Regression, prediction results and the final comparison of Logistic Regression and the original Altman Z-Score. The appendix is provided to improve transparency and allow the reported results to be independently traced to the corresponding statistical outputs.

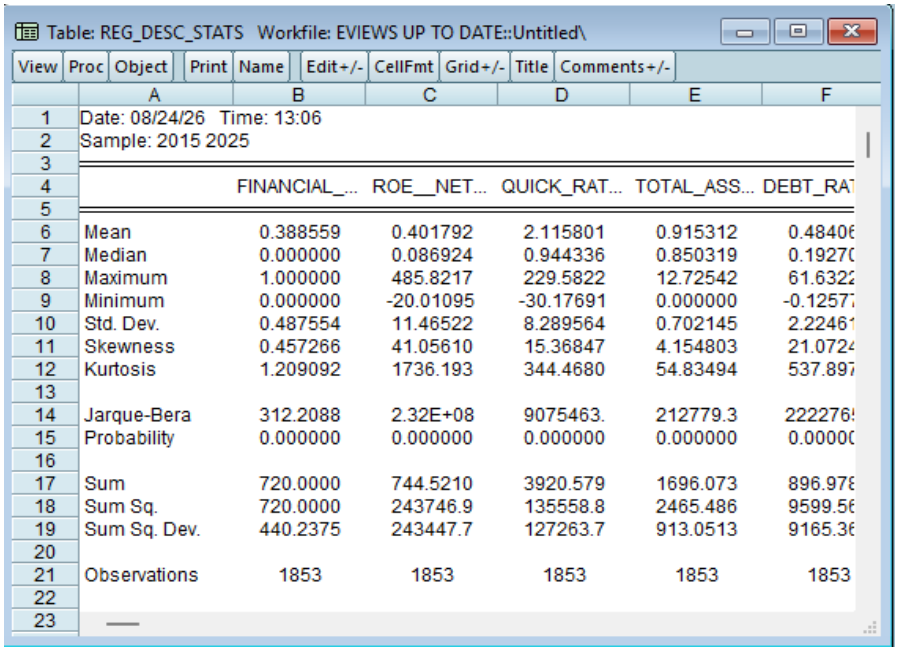


Table: REG_DESC_STATS Workfile: EVIEWS UP TO DATE::Untitled\

View | Proc | Object | Print | Name | Edit+/- | CellFmt | Grid+/- | Title | Comments+/-

Date: 08/24/26 Time: 13:06
Sample: 2015 2025

	FINANCIAL_...	ROE__NET...	QUICK_RAT...	TOTAL_ASS...	DEBT_RA
Mean	0.388559	0.401792	2.115801	0.915312	0.4840
Median	0.000000	0.086924	0.944336	0.850319	0.1927
Maximum	1.000000	485.8217	229.5822	12.72542	61.632
Minimum	0.000000	-20.01095	-30.17691	0.000000	-0.1257
Std. Dev.	0.487554	11.46522	8.289564	0.702145	2.2246
Skewness	0.457266	41.05610	15.36847	4.154803	21.072
Kurtosis	1.209092	1736.193	344.4680	54.83494	537.89
Jarque-Bera	312.2088	2.32E+08	9075463.	212779.3	22227
Probability	0.000000	0.000000	0.000000	0.000000	0.0000
Sum	720.0000	744.5210	3920.579	1696.073	896.97
Sum Sq.	720.0000	243746.9	135558.8	2465.486	9599.5
Sum Sq. Dev.	440.2375	243447.7	127263.7	913.0513	9165.3
Observations	1853	1853	1853	1853	1853

Table1: descriptive statistics

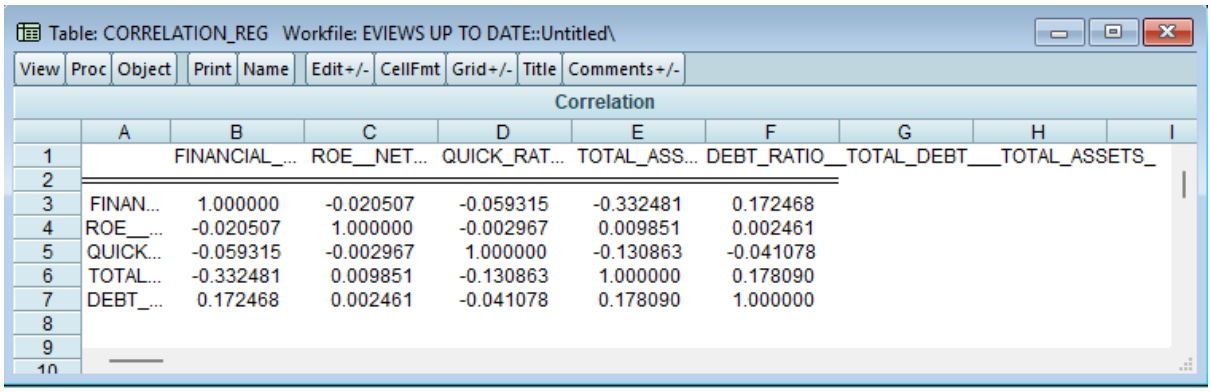


Table: CORRELATION_REG Workfile: EVIEWS UP TO DATE::Untitled\

View | Proc | Object | Print | Name | Edit+/- | CellFmt | Grid+/- | Title | Comments+/-

Correlation

	FINANCIAL_...	ROE__NET...	QUICK_RAT...	TOTAL_ASS...	DEBT_RATIO	TOTAL_DEBT__	TOTAL_ASSETS_
FINAN...	1.000000	-0.020507	-0.059315	-0.332481	0.172468		
ROE__...	-0.020507	1.000000	-0.002967	0.009851	0.002461		
QUICK...	-0.059315	-0.002967	1.000000	-0.130863	-0.041078		
TOTAL...	-0.332481	0.009851	-0.130863	1.000000	0.178090		
DEBT_...	0.172468	0.002461	-0.041078	0.178090	1.000000		

Table 2: correlation matrix

Table: REG_VIF Workfile: EVIEWS UP TO DATE::Untitled\

View | Proc | Object | Print | Name | Edit+/- | CellFmt | Grid+/- | Title | Comments+/-

Variance Inflation Factors

	A	B	C	D
1	Variance Inflation Factors			
2	Date: 08/24/26 Time: 10:59			
3	Sample: 2015 2025			
4	Included observations: 1853			
5				
6		Coefficient	Uncentered	Centered
7	Variable	Variance	VIF	VIF
8				
9	C	0.000306	2.885436	NA
10	ROE__NET_INCOME...	8.06E-07	1.001329	1.000100
11	QUICK_RATIO___CU...	1.57E-06	1.084103	1.017764
12	TOTAL_ASSET_TUR...	0.000226	2.833705	1.049415
13	DEBT_RATIO__TOTA...	2.21E-05	1.082040	1.033098
14				
15				
16				
17				

Table 3: Variance Inflation Factor

Equation: OLS_REG Workfile: EVIEWS UP TO DATE::Untitled\

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: FINANCIAL_DEPENDENT_VARIABLE_Y
Method: Panel Least Squares
Date: 08/29/26 Time: 11:40
Sample: 2015 2025
Periods included: 11
Cross-sections included: 195
Total panel (unbalanced) observations: 1853

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.622585	0.017481	35.61401	0.0000
ROE__NET_INCOME___TOTAL_SHARE...	-0.000747	0.000898	-0.832082	0.4055
QUICK_RATIO___CURRENT_ASSETS__...	-0.005902	0.001253	-4.711274	0.0000
TOTAL_ASSET_TURNOVER__REVENUE...	-0.269228	0.015019	-17.92606	0.0000
DEBT_RATIO__TOTAL_DEBT___TOTAL_...	0.052038	0.004703	11.06407	0.0000

R-squared	0.176175	Mean dependent var	0.388559
Adjusted R-squared	0.174392	S.D. dependent var	0.487554
S.E. of regression	0.443006	Akaike info criterion	1.212230
Sum squared resid	362.6786	Schwarz criterion	1.227137
Log likelihood	-1118.131	Hannan-Quinn criter.	1.217724
F-statistic	98.79868	Durbin-Watson stat	0.557026
Prob(F-statistic)	0.000000		

Table 4: OLS Regression table

Equation: OLS_FE_FINAL Workfile: EVIEWS UP TO DATE::Untitled\

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: FINANCIAL_DEPENDENT_VARIABLE_Y
Method: Panel Least Squares
Date: 08/25/26 Time: 12:34
Sample: 2015 2025
Periods included: 11
Cross-sections included: 195
Total panel (unbalanced) observations: 1853
White two-way cluster standard errors & covariance (d.f. corrected)
WARNING: estimated coefficient covariance matrix is of reduced rank
Standard error and t-statistic probabilities adjusted for clustering

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.503503	0.028376	17.74374	0.0000
ROE__NET_INCOME___TOTAL_SHARE...	-0.001885	0.000223	-8.444245	0.0000
QUICK_RATIO___CURRENT_ASSETS__...	-0.002553	0.001258	-2.028773	0.0699
TOTAL_ASSET_TURNOVER__REVENUE...	-0.129297	0.033029	-3.914610	0.0029
DEBT_RATIO__TOTAL_DEBT___TOTAL_...	0.019754	0.010394	1.900457	0.0866

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.708035	Mean dependent var	0.388559
Adjusted R-squared	0.673084	S.D. dependent var	0.487554
S.E. of regression	0.278767	Akaike info criterion	0.384295
Sum squared resid	128.5339	Schwarz criterion	0.977597
Log likelihood	-157.0498	Hannan-Quinn criter.	0.602986
F-statistic	20.25789	Durbin-Watson stat	1.383565
Prob(F-statistic)	0.000000		

Table 5: Fixed effects regression

Table: OLS_RE Workfile: EVIEWS UP TO DATE::Untitled\

View | Proc | Object | Print | Name | Edit+/- | CellFmt | Grid+/- | Title | Comments+/-

Dependent Variable: FINANCIAL_DEPENDENT_VARIABLE_Y
Method: Panel EGLS (Cross-section random effects)
Date: 08/24/26 Time: 12:01
Sample: 2015 2025
Periods included: 11
Cross-sections included: 195
Total panel (unbalanced) observations: 1853
Swamy and Arora estimator of component variances

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.529556	0.028446	18.61585	0.0000
ROE__NET_INCOME___TOTAL_SHARE...	-0.001789	0.000592	-3.024185	0.0025
QUICK_RATIO___CURRENT_ASSETS__...	-0.002973	0.001057	-2.814102	0.0049
TOTAL_ASSET_TURNOVER__REVENUE...	-0.155908	0.015298	-10.19110	0.0000
DEBT_RATIO__TOTAL_DEBT___TOTAL_...	0.025219	0.003914	6.444125	0.0000

Effects Specification

	S.D.	Rho
Cross-section random	0.335814	0.5920
Idiosyncratic random	0.278767	0.4080

Weighted Statistics

R-squared	0.063941	Mean dependent var	0.100542
Adjusted R-squared	0.061915	S.D. dependent var	0.290646
S.E. of regression	0.280985	Sum squared resid	145.9042
F-statistic	31.55877	Durbin-Watson stat	1.234015
Prob(F-statistic)	0.000000		

Unweighted Statistics

R-squared	0.140232	Mean dependent var	0.388559
Sum squared resid	378.5023	Durbin-Watson stat	0.475685

Table 6: Cross-section random effects model

Table: HAUSMAN_RE Workfile: EVIEWS UP TO DATE::Untitled\

View | Proc | Object | Print | Name | Edit+/- | CellFmt | Grid+/- | Title | Comments+/-

Correlated Random Effects - Hausman Test
Equation: OLS_REG
Test cross-section random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	31.684530	4	0.0000

Cross-section random effects test comparisons:

Variable	Fixed	Random	Var(Diff.)	Prob.
ROE__NET_INCOME___TOTAL_SHARE...	-0.001885	-0.001789	0.000000	0.0414
QUICK_RATIO___CURRENT_ASSETS__...	-0.002553	-0.002973	0.000000	0.1614
TOTAL_ASSET_TURNOVER__REVENUE...	-0.129297	-0.155908	0.000034	0.0000
DEBT_RATIO__TOTAL_DEBT___TOTAL_...	0.019754	0.025219	0.000001	0.0000

Cross-section random effects test equation:
Dependent Variable: FINANCIAL_DEPENDENT_VARIABLE_Y
Method: Panel Least Squares
Date: 08/24/26 Time: 12:03
Sample: 2015 2025
Periods included: 11
Cross-sections included: 195
Total panel (unbalanced) observations: 1853

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.503503	0.015945	31.57772	0.0000
ROE__NET_INCOME___TOTAL_SHARE...	-0.001885	0.000594	-3.175578	0.0015
QUICK_RATIO___CURRENT_ASSETS__...	-0.002553	0.001098	-2.324754	0.0202
TOTAL_ASSET_TURNOVER__REVENUE...	-0.129297	0.016364	-7.901551	0.0000
DEBT_RATIO__TOTAL_DEBT___TOTAL_...	0.019754	0.004072	4.850708	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.708035	Mean dependent var	0.388559
Adjusted R-squared	0.673084	S.D. dependent var	0.487554
S.E. of regression	0.278767	Akaike info criterion	0.384295
Sum squared resid	128.5339	Schwarz criterion	0.977597
Log likelihood	-157.0498	Hannan-Quinn criter.	0.602986
F-statistic	20.25789	Durbin-Watson stat	1.383565
Prob(F-statistic)	0.000000		

Table 7: Hausman test

Equation: LOGIT_REGRESSION Workfile: EVIEWS UP TO DATE::Untitled\

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: FINANCIAL_DEPENDENT_VARIABLE_Y
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 08/24/26 Time: 13:16
Sample: 2015 2025
Included observations: 1853
Convergence achieved after 7 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.260161	0.135736	1.916676	0.0553
ROE__NET_INCOME___TOTAL_SHARE...	-0.031786	0.026929	-1.180361	0.2379
QUICK_RATIO___CURRENT_ASSETS__...	-0.024657	0.009719	-2.537044	0.0112
TOTAL_ASSET_TURNOVER__REVENUE...	-1.832381	0.133119	-13.76494	0.0000
DEBT_RATIO__TOTAL_DEBT___TOTAL_...	3.059239	0.246942	12.38851	0.0000

McFadden R-squared	0.261909	Mean dependent var	0.388559
S.D. dependent var	0.487554	S.E. of regression	0.381743
Akaike info criterion	0.991633	Sum squared resid	269.3043
Schwarz criterion	1.006540	Log likelihood	-913.7476
Hannan-Quinn criter.	0.997127	Deviance	1827.495
Restr. deviance	2475.976	Restr. log likelihood	-1237.988
LR statistic	648.4805	Avg. log likelihood	-0.493118
Prob(LR statistic)	0.000000		

Obs with Dep=0	1133	Total obs	1853
Obs with Dep=1	720		

Table 8: Logistic regression results

Table: LOGIT_PREDICTION_SAMPLE Workfile: EVIEWS UP TO DATE:...

View | Proc | Object | Print | Name | Edit+/- | CellFmt | Grid+/- | Title | Comments+/-

	A	B	C	D	E	F	G
1	Expectation-Prediction Evaluation for Binary Specification						
2	Equation: LOGIT_REGRESSION						
3	Date: 08/25/26 Time: 13:43						
4	Success cutoff: C = 0.5						
5							
6		Estimated Equation			Constant Probability		
7		Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
8							
9	P(Dep=1)<=C	1041	262	1303	1133	720	1853
10	P(Dep=1)>C	92	458	550	0	0	0
11	Total	1133	720	1853	1133	720	1853
12	Correct	1041	458	1499	1133	0	1133
13	% Correct	91.88	63.61	80.90	100.00	0.00	61.14
14	% Incorrect	8.12	36.39	19.10	0.00	100.00	38.86
15	Total Gain*	-8.12	63.61	19.75			
16	Percent Gain**	NA	63.61	50.83			
17							
18		Estimated Equation			Constant Probability		
19		Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
20							
21	E(# of Dep=0)	845.90	287.10	1133.00	692.76	440.24	1133.00
22	E(# of Dep=1)	287.10	432.90	720.00	440.24	279.76	720.00
23	Total	1133.00	720.00	1853.00	1133.00	720.00	1853.00
24	Correct	845.90	432.90	1278.81	692.76	279.76	972.53
25	% Correct	74.66	60.13	69.01	61.14	38.86	52.48
26	% Incorrect	25.34	39.87	30.99	38.86	61.14	47.52
27	Total Gain*	13.52	21.27	16.53			
28	Percent Gain**	34.79	34.79	34.79			
29							
30	*Change in "% Correct" from default (constant probability) specification						
31	**Percent of incorrect (default) prediction corrected by equation						
32							
33							

Table 9: Logistic regression prediction performance

Scalar: LOGIT_FN Workfile: EVIEWS UP TO DATE::Untitled\

View | Proc | Object | Print | Name | Freeze | Edit+/-

262

	Value
LOGIT_FN	262.0000

Scalar: LOGIT_TN Workfile: EVIEWS UP TO DATE::Untitled\

View | Proc | Object | Print | Name | Freeze | Edit+/-

1041

	Value
LOGIT_TN	1041.000

Scalar: LOGIT_TP Workfile: EVIEWS UP TO DATE::Untitled\

View | Proc | Object | Print | Name | Freeze | Edit+/-

458

	Value
LOGIT_TP	458.0000

Scalar: LOGIT_FP Workfile: EVIEWS UP TO DATE::Untitled\

View | Proc | Object | Print | Name | Freeze | Edit+/-

92

	Value
LOGIT_FP	92.00000

Table 10: Logistic regression classification result

Equation: LOGIT_REGRESSION Workfile: EVIEWS UP TO DATE::Untitled\

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: FINANCIAL_DEPENDENT_VARIABLE_Y
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 08/29/26 Time: 10:16
Sample: 2015 2025 IF YEARS<=2022
Included observations: 1421
Convergence achieved after 6 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.589821	0.163081	3.616733	0.0003
ROE__NET_INCOME___TOTAL_SHARE...	-0.008708	0.014282	-0.609686	0.5421
QUICK_RATIO___CURRENT_ASSETS__...	-0.030359	0.011178	-2.716024	0.0066
TOTAL_ASSET_TURNOVER__REVENUE...	-2.000788	0.158144	-12.65168	0.0000
DEBT_RATIO__TOTAL_DEBT___TOTAL_...	2.543684	0.276866	9.187422	0.0000

McFadden R-squared	0.260608	Mean dependent var	0.403237
S.D. dependent var	0.490720	S.E. of regression	0.386193
Akaike info criterion	1.004185	Sum squared resid	211.1895
Schwarz criterion	1.022689	Log likelihood	-708.4731
Hannan-Quinn criter.	1.011097	Deviance	1416.946
Restr. deviance	1916.367	Restr. log likelihood	-958.1837
LR statistic	499.4213	Avg. log likelihood	-0.498574
Prob(LR statistic)	0.000000		

Obs with Dep=0	848	Total obs	1421
Obs with Dep=1	573		

Table 11: 2015-2022 logistic regression model

Scalar: LOGIT_ACCURACY_2325 Workfile: EVIEWS UP TO ...

View | Proc | Object | Print | Name | Freeze | Edit+/-

0.7986111111111111

	Value
LOGIT_A...	0.798611

Scalar: LOGIT_SENSITIVITY_2325 Workfile: EVIEWS UP TO ...

View | Proc | Object | Print | Name | Freeze | Edit+/-

0.6122448979591836

	Value
LOGIT_S...	0.612245

Scalar: LOGIT_SPECIFICITY_2325 Workfile: EVIEWS UP TO ...

View | Proc | Object | Print | Name | Freeze | Edit+/-

0.8947368421052631

	Value
LOGIT_S...	0.894737

Table 12: logit accuracy, specificity and sensitivity 2022-2025

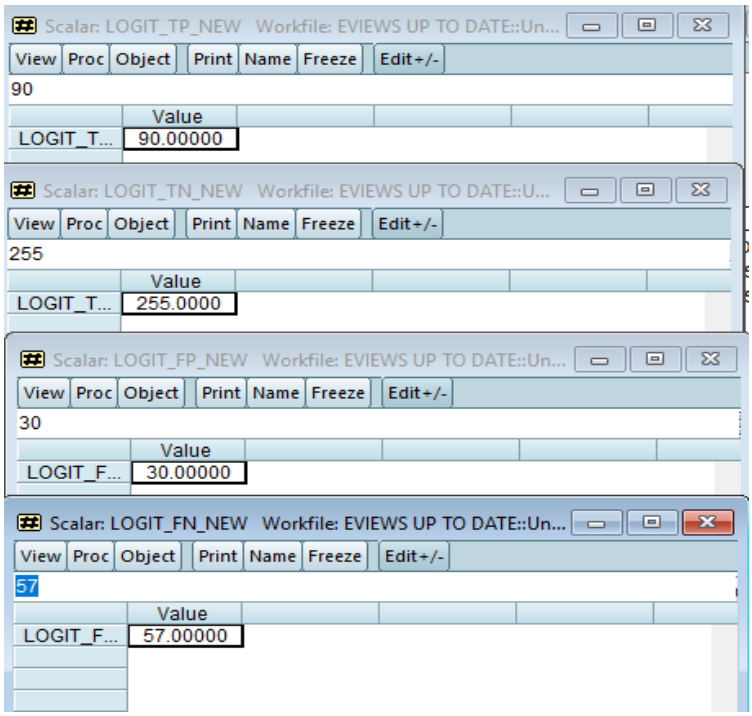


Table 13: TP, TN, FP, FN

Table: ALTMAN_PREDICTION_SAMPLE Workfile: EVIEWS UP TO DA...

View Proc Object Print Name Edit+/- CellFmt Grid+/- Title Comments+/-

	A	B	C	D	E	F	G
1	Expectation-Prediction Evaluation for Binary Specification						
2	Equation: UNTITLED						
3	Date: 08/25/26 Time: 13:41						
4	Success cutoff: C = 0.5						
5							
6		Estimated Equation			Constant Probability		
7		Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
8							
9	P(Dep=1)<=C	1071	103	1174	1133	720	1853
10	P(Dep=1)>C	62	617	679	0	0	0
11	Total	1133	720	1853	1133	720	1853
12	Correct	1071	617	1688	1133	0	1133
13	% Correct	94.53	85.69	91.10	100.00	0.00	61.14
14	% Incorrect	5.47	14.31	8.90	0.00	100.00	38.86
15	Total Gain*	-5.47	85.69	29.95			
16	Percent Gain**	NA	85.69	77.08			
17							
18		Estimated Equation			Constant Probability		
19		Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
20							
21	E(# of Dep=0)	983.27	149.73	1133.00	692.76	440.24	1133.00
22	E(# of Dep=1)	149.73	570.27	720.00	440.24	279.76	720.00
23	Total	1133.00	720.00	1853.00	1133.00	720.00	1853.00
24	Correct	983.27	570.27	1553.54	692.76	279.76	972.53
25	% Correct	86.78	79.20	83.84	61.14	38.86	52.48
26	% Incorrect	13.22	20.80	16.16	38.86	61.14	47.52
27	Total Gain*	25.64	40.35	31.36			
28	Percent Gain**	65.99	65.99	65.99			
29							
30	*Change in "% Correct" from default (constant probability) specification						
31	**Percent of incorrect (default) prediction corrected by equation						
32							
33							

Table 14: Altman z score prediction results

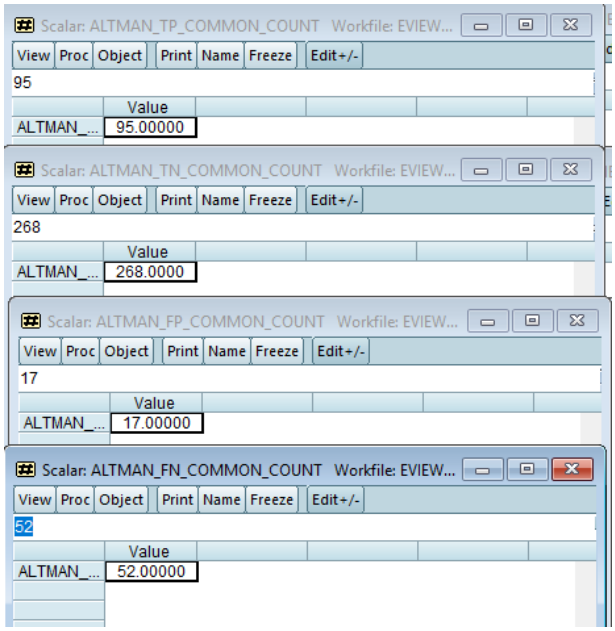


Table 15: Altman TP, TN, FP, FN

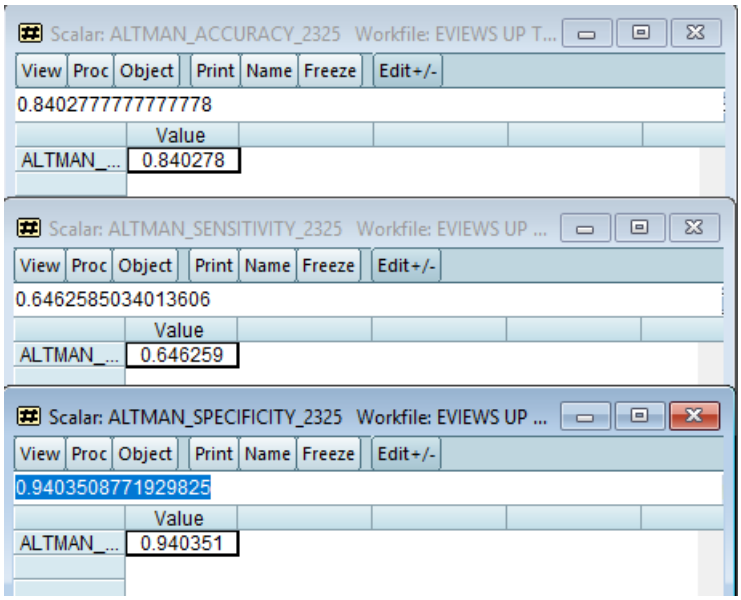


Table 16: Altman accuracy, sensitivity, specificity