CAPITAL UNIVERSITY OF SCIENCE AND TECHNOLOGY, ISLAMABAD

Financial Distress Prediction in the Pakistani Equity Market

by

Ansa Asghar

A thesis submitted in partial fulfillment for the degree of Master of Science

in the

Faculty of Management & Social Sciences
Department of Accounting & Finance

2025

This research thesis is wholeheartedly dedicated to my parents whose support and continued encouragement have been my strength and source of inspiration in all of my endeavors.

CERTIFICATE OF APPROVAL

Financial Distress Prediction in the Pakistani Equity Market

by

Ansa Asghar

(MAF231010)

THESIS EXAMINING COMMITTEE

S. No.	Examiner	Name	Organization
(a)	External Examiner	Dr. Hassan Raza	SZABIST Islamabad
(b)	Internal Examiner	Dr. Anam Tariq	CUST, Islamabad
(c)	Supervisor	Dr. Arshad Hassan	CUST, Islamabad

Dr. Arshad Hassan
Thesis Supervisor
March, 2025

Dr. Jaleel Ahmed Malik
Head
Dept. of Accounting & Finance
March, 2025

Dr. Arshad Hassan
Dean
Faculty of Management & Social Sci.
March, 2025

Author's Declaration

I, **Ansa Asghar** hereby state that my MS thesis titled "**Financial Distress Prediction in the Pakistani Equity Market**" is my own work and has not been submitted previously by me for taking any degree from Capital University of Science and Technology, Islamabad or anywhere else in the country/abroad.

At any time if my statement is found to be incorrect even after my graduation, the University has the right to withdraw my MS Degree.

(Ansa Asghar)

Registration No: MAF231010

Plagiarism Undertaking

I solemnly declare that research work presented in this thesis titled "**Financial Distress Prediction in the Pakistani Equity Market**" is solely my research work with no significant contribution from any other person. Small contribution/help wherever taken has been duly acknowledged and that complete thesis has been written by me.

I understand the zero tolerance policy of the HEC and Capital University of Science and Technology towards plagiarism. Therefore, I as an author of the above titled thesis declare that no portion of my thesis has been plagiarized and any material used as reference is properly referred/cited.

I undertake that if I am found guilty of any formal plagiarism in the above titled thesis even after award of MS Degree, the University reserves the right to withdraw/revoke my MS degree and that HEC and the University have the right to publish my name on the HEC/University website on which names of students are placed who submitted plagiarized work.

(Ansa Asghar)

Registration No: MAF231010

Acknowledgement

First and foremost, I would like to express my deepest gratitude to **Allah Almighty**, the Most Merciful and Compassionate, for His boundless blessings and guidance throughout this journey. All praise is due to Him alone, the source of all wisdom and strength, and may His blessings continue to illuminate my path. I also express my heartfelt reverence and gratitude to the **Holy Prophet Muhammad (PBUH)** for being a source of inspiration and wisdom in my life.

I would like to express my sincere appreciation to my Supervisor, **Prof. Dr. Arshad Hassan**, Dean of the Faculty of Management and Social Sciences, for his unwavering support and guidance throughout the Masters Study and the writing of this thesis. His patience, motivation, enthusiasm, and vast knowledge have been invaluable. I could not have imagined having a better advisor and mentor for my Master's journey.

I am profoundly grateful to my beloved parents, **Muhammad Asghar Khan** and my mother, whose unconditional love, unwavering encouragement, and sacrifices have been the foundation of my academic journey. Their constant support and belief in my abilities have been the driving force behind the successful completion of this thesis. To my brothers, **Zafar Iqbal, Imran Asghar, Zameer Ahmed**, and my sisters, I extend my heartfelt gratitude for your unwavering understanding, patience and encouragement throughout the challenges and triumphs of this academic endeavor. Your belief in me has been a constant source of motivation and strength.

Last but not least, I would like to extend my sincere thanks to my friends and all my well-wishers for their constant support, cooperation, and best wishes.

I am deeply grateful to my family for being an integral part of this fulfilling academic journey.

(Ansa Asghar)

Abstract

This study evaluates the effectiveness of the Altman Z-score model in predicting financial distress within the Pakistani stock market and further develops a tailored financial distress prediction model (A-score) based on indicators used by practitioners. Using a cross-sectional dataset of 124 observations comprising a matched sample 62 financially stable and 62 distressed non-financial firms listed on the Karachi Stock Exchange, the research investigates the role of operating expense ratio, interest expense to operating profit ratio leverage debt maturity structure cash flow turnover, and reinvestment ratio along with existing conventional variables. The methodology includes binary logistic regression and discriminant analysis to test the model's validity and predictive accuracy. The results of the logistic analysis showed an overall accuracy of 83.06%, while the discriminant analysis showed an overall accuracy of 95.2%.

The results of the logistic analysis of the proposed model showed an overall accuracy of 98.39%. The A-score model revealed that the debt-to-equity operating cash flow turnover and reinvestment ratio significantly influenced the financial distress. Results highlight significant limitations of the Z-score model, emphasizing the need for a market-based approach. The A-score model demonstrates improved predictive capacity, providing a robust framework for stakeholders such as investors, policymakers, and corporate managers to make informed decisions to mitigate financial risks and enhance economic stability. However, the accuracy of the A-score model was lower when discriminant analysis was applied. This study offers theoretical and practical insights into financial distress prediction, emphasizing its role in fostering corporate resilience and sustainability in emerging markets.

Keywords: Financial Distress, Altman Z-score model, proposed model A-score model, Logistic Analysis, Discriminant Analysis

Contents

Author's Declaration iv

Plagiarism Undertaking v

Acknowledgement vi

Abstract vii

List of Tables xi

Abbreviations xii

1 Introduction 1
- 1.1 Theoretical Background . . . 1
- 1.2 Gap Analysis . . . 4
- 1.3 Research Question . . . 5
- 1.4 Objective of the Study . . . 5
- 1.5 Significance of Study . . . 6
- 1.6 Organization of the Study . . . 7

2 Literature Review 8
- 2.1 Literature . . . 8

3 Data Description 23
- 3.1 Population and Sample of the Study . . . 23
- 3.2 Econometric Model . . . 24
- 3.3 Description of Variables . . . 24
  - 3.3.1 Net Working Capital to Total Assets . . . 24
  - 3.3.2 Retained Earnings to Total Assets . . . 25
  - 3.3.3 Earnings before Interest and Tax to Total Assets . . . 25
  - 3.3.4 Book Value of Equity to Total Liabilities . . . 26
  - 3.3.5 Sales to Total Assets . . . 26
- 3.4 Proposed Model . . . 26
- 3.5 Description of Variables . . . 27
  - 3.5.1 Operating Expense Ratio . . . 27
  - 3.5.2 Interest Expenses to Operating Profit Ratio . . . 28

3.5.3 Leverage Ratio 28
3.5.4 Debt Maturity Structure 29
3.5.5 Operating Cash Flow Turnover 29
3.5.6 Reinvestment Ratio 30
3.6 Data Analysis 30
3.6.1 Logit Analysis 30
3.6.2 Discriminant Analysis 31
3.6.2.1 Descriptive Statistics 31
3.6.2.2 Test of Equality of Group Means 31
3.6.2.3 Pooled Within-Group Covariance Matrices 31
3.6.2.4 Log Determinants 31
3.6.2.5 Box's M Test 32
3.6.2.6 Eigenvalues 32
3.6.2.7 Wilk's Lambda 32
3.6.2.8 Standardized Canonical Discriminant 32
3.6.2.9 Structure Matrix 32
3.6.2.10 Canonical Discriminant Function Coefficients 33
3.6.2.11 Function at Group Centroids 33
3.6.2.12 Classification Results 33

4 Results and Discussion 34
4.1 Testing and Validation of Z-score Using Logit Analysis 34
4.1.1 Descriptive Statistics 34
4.1.2 Binary Logit 36
4.1.3 ExpectationPprediction Evaluation for Binary Specification . 37
4.1.4 Goodness-of-Fit Evaluation for Binary Specification 38
4.1.5 Marginal Effect 38
4.2 Testing and Validation of Financial Distress for the Proposed Model using Logit Analysis 39
4.2.1 Descriptive Statistics 39
4.2.2 Binary Logit 41
4.2.3 Expectation-Prediction Evaluation for Binary Specification . 43
4.2.4 Goodness-of-Fit Evaluation for Binary Specification 44
4.2.5 Marginal Effect 45
4.3 Comparison of Two Tests (Logistic Analysis) 46
4.4 Testing and Validation of Z-score Using Discriminant Analysis . . . 46
4.4.1 Group Statistics 46
4.4.2 Tests of Equality of Group Means 48
4.4.3 Pooled Within-Groups Matrices 49
4.4.4 Log Determinants 49
4.4.5 Box's M Test 50
4.4.6 Eigenvalues 50
4.4.7 Wilks' Lambda 51
4.4.8 Standardized Canonical Discriminant Function Coefficients . 51
4.4.9 Structure Matrix 52
4.4.10 Canonical Discriminant Function Coefficients 53

4.4.11 Functions at Group Centroids 53
4.4.12 Classification Results 54
4.5 Testing and Validation of Financial Distr-
ess for Proposed Model Using
Discriminant Analysis 55
4.5.1 Descriptive Statistics 55
4.5.2 Test of Equality of Group Means 56
4.5.3 Pooled Within-Groups Matrices 57
4.5.4 Log Determinants 59
4.5.5 Box's M test 59
4.5.6 Eigenvalues 60
4.5.7 Wilks' Lambda 60
4.5.8 Standardized Canonical Discriminant Function Coefficients . 61
4.5.9 Structure Matrix 62
4.5.10 Canonical Discriminant Function Coefficients 63
4.5.11 Function at Group Centroids 64
4.5.12 Classification Results 65
4.6 Comparison of Two Tests (Discriminant Analysis) 66

5 Conclusion and Recommendation **67**
5.1 Altman Z-score Model 67
5.2 Proposed Model 68
5.3 Implementation and Recommendations 69
5.4 Limitations 70

References **71**

List of Tables

4.1 Descriptive Statistics 35
4.2 Binary Logit 36
4.3 Expectation-Prediction Evaluation for Binary Specification 37
4.4 Goodness-of-Fit Evaluation for Binary Specification 38
4.5 Marginal Effect 39
4.6 Descriptive Statistics 40
4.7 Binary Logit 42
4.8 Expectation-Prediction Evaluation for Binary Specification 43
4.9 Goodness-of-Fit Evaluation for Binary Specification 44
4.10 Marginal Effect 45
4.11 Comparison of Two Tests (Logistic Analysis) 46
4.12 Group Statistics 47
4.13 Tests of Equality of Group Means 48
4.14 Pooled Within-Groups Matrices 49
4.15 Log Determinants 49
4.16 Box's M Test 50
4.17 Eigenvalues 50
4.18 Wilks' Lambda 51
4.19 Standardized Canonical Discriminant Function Coefficients 51
4.20 Structure Matrix 52
4.21 Canonical Discriminant Function Coefficients 53
4.22 Functions at Group Centroids 54
4.23 Classification Results 54
4.24 Descriptive Statistics 55
4.25 Test of Equality of Group Means 57
4.26 Pooled Within-Groups Matrices 58
4.27 Log Determinants 59
4.28 Box's M test 59
4.29 Eigenvalues 60
4.30 Wilks' Lambda 61
4.31 Standardized Canonical Discriminant Function Coefficients 61
4.32 Structure Matrix 62
4.33 Canonical Discriminant Function Coefficients 63
4.34 Functions at Group Centroids 64
4.35 Classification Results 65
4.36 Comparison of Two Tests (Discriminant Analysis) 66

Abbreviations

BVOETL	Book Value of Equity to Total Liabilities
EBITTA	Earnings Before Interest and Tax to Total Assets
NWCTA	Net Working Capital to Total Assets
RETA	Retained Earnings to Total Assets
STA	Sales to Total Assets

Chapter 1

Introduction

1.1 Theoretical Background

Financial distress occurs when a company is unable to meet its financial obligations, such as paying off debts, interest, or trade payables. If companies are unable to handle these financial pressures, it can lead to bankruptcy, loss of investor confidence, and even the collapse of the business. This situation is critical for all stakeholders involved investors management and policymakers as it can severely affect the company's ability to function and grow (Hoepner, Oikonomou, Scholtens, & Schröder, 2016). A firm's capital structure, with debt, raises the risk of default, impacting cash flow and profitability. This risk intensifies if debt exceeds a certain level, leading to financial distress which can force firms to shut down, particularly in emerging economies (Waqas & Md-Rus, 2018). Emerging economies like Pakistan are often subject to higher levels of volatility in their markets compared to more stable, developed economies. In the context of Pakistan's equity markets stakeholders such as investor's management and policymakers must understand and anticipate financial distress. This knowledge enables them to make more informed decisions that help mitigate risks and promote long-term corporate sustainability.

Predicting financial distress across multiple companies simultaneously plays a crucial role in stabilizing the economy by safeguarding investors, preventing systemic risk, and allowing regulators to act swiftly when necessary (Kamran & Saleem, 2023). Identifying early-stage indicators of financial distress in organizations is critical, as timely detection allows for more effective intervention and the implementation of remedial measures to address the situation (Asif, Saxena, Padmaja, Tiwari, & Chaturvedi, 2024). Auditors have a vital role in evaluating a company's future viability by providing an opinion on its ability to continue as a going concern. The financial statements that auditors examine are prepared by the company's management and reflect its financial status and future outlook (Hiong, Jalil, & Seng, 2021).

Pradhan, Shrestha, Manandhar, and Poudel (2002) financial distress does not always lead to the complete collapse or dissolution of firms. From an economic perspective, it simply indicates that the company is facing financial difficulties, such as losing money because its revenues are insufficient to cover its operating costs. Lumbantobing (2020) financial ratios, such as liquidity, leverage, activity, and profitability ratios are vital tools for diagnosing business health, forecasting financial performance, and predicting financial distress. This study explores the effect of these ratios on forecasting financial distress in Indonesian manufacturing firms (2015-2017). Cash flow volatility can disrupt operations, investment, and debt repayment, affecting key financial metrics. Macroeconomic factors like unemployment, inflation, and interest rates are beyond control but must be anticipated to mitigate their impact on future performance (Shaheen, Hussain, & Bhatti, 2021). Singh and Singla (2024) predicting financial distress is crucial in corporate finance, as it helps in identifying risks that could harm a company's market value and operations. Distressed firms often face reduced market value, stricter supplier terms, and canceled customer orders.

Azizah and Ramli (2023) listed companies facing significant threats to their sustainability may show signs such as delayed financial reporting, continuous losses, inadequate operating income, and large long-term debt. Legal issues and an inability to continue the operation further worsen the situation. These factors can lead to the company being at risk of delisting from the stock exchange. Insolvency in financial institutions is not a sudden event but rather a complex process that develops over time, often revealing signs of financial mismanagement and instability long before the actual collapse. These warning signs may include poor risk management practices, inadequate capital buffers, and unsustainable lending strategies, which gradually erode the institution's financial health (Lee & Lee, 2018).

Pakistan's economic landscape is marked by significant volatility and uncertainty presenting numerous challenges for businesses and investors. High inflation rates erode purchasing power increase operational costs, and reduce consumer demand, while political instability disrupts economic growth by creating uncertainty in policy and governance. Additionally, Pakistan's unsustainable external debt burden continues to strain foreign reserves, limiting the country's ability to invest. As reported by the United States Institute of Peace (2023), Pakistan's external debt obligation amounts to $77.5 billion from April 2023 to June 2026, which poses a substantial risk to its economic stability. This precarious situation necessitates that business owners develop backup plans and approaches to ensure continued operations and analyze critical factors contributing to financial distress (Manh & Nguyen, 2024).

In this context, signaling theory emerges as a crucial framework for understanding how companies can communicate effectively with financial statement users. Positive signals can significantly contribute to a company's survival for instance firms with favorable information often choose to voluntarily disclose their financial statements to build public trust and enhance their value. This theory emphasizes that managers provide signals to mitigate information asymmetry, which arises when they possess more internal information than external stakeholders. Such asymmetry can lead to financial distress, as investors may feel disadvantaged by undisclosed information. Effective communication through voluntary disclosures not only helps alleviate investor concerns but also reinforces the company's credibility in the market (Toly, Permatasari, & Wiranata, 2019).

Furthermore, agency theory highlights the relationship between stakeholders and management. Agents may sometimes prioritize their interests over those of the company, leading them to intentionally or unintentionally conceal information related to corporate finances.

This disparity in information creates an environment of information asymmetry where the agent holds more information than principals and external parties. Such a situation can negatively affect the company's sustainability and overall performance.

Therefore, the organization needs to monitor their agents closely to ensure that information is distributed fairly, allowing principals to understand the company's actual state. If left unchecked these agency problems may contribute significantly to financial distress within the organization (Abdullah, Mirosea, Aswati, & Santi, 2023).

1.2 Gap Analysis

The Altman Z-score model developed by American finance professor Edward Altman in 1968, has been a cornerstone in predicting corporate bankruptcy for over five decades. This model utilizes five financial ratios to assess a firm's likelihood of financial distress, making it widely applicable across various markets, including those in India China, and Malaysia.

However, while the Z-score is a valuable tool for assessing bankruptcy risk, it falls short in addressing the unique complexities and characteristics of the Pakistani market. However, it overlooks factors such as operating expenses, debt cost leverage debt maturity structure operating cash flow turnover, and reinvestment requirements which are particularly pertinent in the Pakistani market. These omissions can lead to inaccuracies when assessing financial distress in Pakistan.

Despite the widespread use of the Altman Z-score, its predictive accuracy diminishes in contexts like Pakistan Research indicates that while the Z-score is a useful tool it may not fully capture the financial distress signals in Pakistani firms.

A study focusing on Pakistani non-financial firms found that the Z-score model's predictive power was limited highlighting the need for a tailored approach (Ahmad, Ali, & Usman, 2018).

The Pakistani market is characterized by a range of challenges that exacerbate financial distress risks, making it difficult for the Z- score to provide a reliable forecast of bankruptcy risk. For instance, transparency issues in corporate financial reporting are widespread with many firms lacking clear and consistent disclosure practices. This lack of transparency leads to misinformed investment decisions, as investors struggle to obtain accurate and reliable information about a company's financial health.

These transparency issues coupled with a weak regulatory framework make it even harder for traditional models like the Z-score to function effectively in the Pakistani context. The economic conditions in Pakistan including fluctuating inflation rates economic instability and political uncertainty further complicate the use of the Z-score model (Rashid & Abbas, 2011).

Moreover, regulatory frameworks in Pakistan may not always provide the necessary support for corporate governance. Weak corporate governance practices and regulatory oversight can lead to mismanagement inefficiencies and increased risks of financial distress. These shortcomings can further undermine the predictive power of traditional models like the Z-score, which rely on the assumption of a stable regulatory environment. Developing a country-specific model would enable investors and decision-makers to make more informed choices enhancing firm performance assessment and investment decisions. Such a model would consider local economic indicators regulatory frameworks and market dynamics providing a more accurate tool for predicting financial distress in Pakistan.

1.3 Research Question

1. Does the Z-score model predict financial distress in the Pakistani stock market?
2. Does alternative model confirm the results of Z-score model?

1.4 Objective of the Study

The objective of this study is,

1. To test the Z-score model in the Pakistani stock market.
2. To develop a model based on financial variables for the prediction of financial distress.
3. To evaluate the performance of the Z-score using alternative techniques.

1.5 Significance of Study

This study is significant as it addresses a critical gap in the financial management landscape of Pakistan by developing a locally adapted financial distress prediction model. It provides a practical and theoretical foundation for various stakeholders, lenders, investors, government, policymakers, and corporate management, in making well-informed decisions.

This study equips stakeholders with a reliable tool to assess and measure financial risks before committing to business transactions or investments. By identifying potential distress early stakeholders can minimize the likelihood of financial losses and make strategic decisions to mitigate risk. The model serves as a critical resource for analyzing market dynamics and assessing the overall financial health of companies, ultimately fostering a more stable and resilient business ecosystem.

Financial institutions such as banks and credit agencies can benefit significantly from this study. The adapted Z-score model allows lenders to evaluate the financial distress of borrowers more accurately. It provides an early warning system to identify companies at risk of default, enabling lenders to implement appropriate measures, such as renegotiating loan terms or reducing exposure to high-risk clients. This leads to more prudent credit management and a reduction in non-performing loans thereby contributing to the overall stability of the financial sector.

The study offers investors a robust mechanism to assess the financial stability of potential investment opportunities. By using the Z-score model investors can identify businesses at risk of financial distress and make more informed decisions regarding capital allocation. This helps in avoiding high-risk investments and identifying better opportunities to improve portfolio performance.

The study plays a crucial role in supporting the government and policymakers in fostering economic stability and growth. A locally adapted financial distress model provides insights into sectorial vulnerabilities and systemic risk enabling the government to implement targeted economic policies. Policymakers can use this model to assess and monitor firms or industries at risk of distress, facilitating timely interventions, such as providing financial support restructuring assistance, or policy adjustments.

This study is highly valuable for corporate managers as it offers an early detection mechanism for financial distress. By identifying warning signs at an early stage, managers can take corrective measures to improve the company's financial health such as optimizing operational efficiency, managing costs, and restructuring debt. This enables businesses to avoid bankruptcy and ensure sustainable growth.

1.6 Organization of the Study

This study is structured into five detailed chapters. The first chapter provides an overview of the topic and includes an introduction theoretical background and research gap. Additionally, it outlines the research questions objectives, and significance of the study. The second chapter presents an in-depth review of the relevant literature. The third chapter focuses on the methodology of the study, including an explanation of the variables and the econometric model employed. The econometric models utilized in this study are logistic analysis and discriminant analysis. Chapter Four discusses the findings of the study in detail. Chapter Five concludes the study, summarizing the key findings and providing recommendations and limitations of the study.

Chapter 2

Literature Review

2.1 Literature

According to (Say, 2024), financial distress is a phase of deterioration in the financial situation of a firm prior to insolvency or dissolution taking place. Management cannot assess the financial condition of the company, which causes increased business risk. This research aims to assess the financial failure degrees of the corporations. The research targets the chemical, pharmaceutical, petroleum, rubber, and plastic products sectors with shares listed on Bursa Istanbul. Applied the Z-score model to evaluate the health and corporate risk within this sector. The result acquired from the study, most of the enterprises are either in the risky zone or in the gray zone for the studied 3- year's period.

Mehmood and De Luca (2023) state that the motive of the study is to create a model for the forecasting of insolvency risk. This research employed a sample of 312 struggling and 312 non-struggling companies including 231 Italian 60 French, and 21 Spanish, firms across both solvency and insolvency categories.

The findings of the study are Z-score model particularly for forecasting financial distress represents greater prediction accuracy. Ullah, Shah, Khan, and Ali (2023) examine the impact of corporate social responsibility on the financial distress of non-financial publicly traded Pakistani companies. Altman Z-score model was employed to evaluate the bankruptcy risk of non-financial listed firms. The study used 100 non-financial Pakistani listed companies from 2015 to 2019. The researcher establishes that there is an inverse relationship among CSR practices and bankruptcy risk level.

Another study utilizes the Altman Z-score model to assess a corporation's financial condition and estimate the probability that it will experience financial troubles within two years. The study seeks to predict insolvency in non-financial publicly listed firms. The study chooses 84 companies registered on the Kuala Lumpur Stock Exchange, with 52 classified as high risk and 32 as low risk. The research concludes that the Z-score model is efficient in forecasting a company's financial instability and predicting its potential bankruptcy (Hiong et al., 2021).

(Manh & Nguyen, 2024) argue that measuring the likelihood of financial instability is a significant element of efficient management as it assists enterprises in making sound financial choices mitigating potential risks, and enhancing business operations. The research aims to examine how assessing financial distress risk improves decision making mitigates potential risks, and improves business operations. The study used a sample of 30 firms that were delisted from UPCOM due to financial difficulties and 30 firms with a Z-score exceeding 4.35 on the Ho Chi Minh City Stock Exchange over the 5 years from 2018 to 2022. The research finds a substantial affiliation among the Z-score and the bankruptcy levels in two groups of companies. Specifically, firms that were delisted from UPCOM due to financial difficulties exhibited lower Z-scores, indicating higher levels of financial distress.

Asif et al. (2024) conducted a comprehensive study that utilized the Altman Z-score model to forecast the default risk of corporations registered on the Equity Market of India. The primary aim of this study was to assess how efficiently the Altman Z-score model can forecast the default risk of Indian firms. The findings underscored the model's ability to effectively identify companies at risk of insolvency, making it a valuable instrument for traders, corporate decision-makers, and financial advisors in India.

Al-Manaseer and Al-Oshaibat (2018) explore the reliability of the Altman Z-score model in forecasting the financial downfall of insurance corporations registered on the Amman Equity Market between 2011 and 2016. The study employs multiple linear regressions to assess the effectiveness of the Z-score model. The study found that the Z-score model has strong forecasting ability. The results suggest that the Z-score model might be a significant influential indicator for various operators of financial statements.

Rahman, Rahman, and Subat (2020) find that non-bank financial institutions (NBFI) are identified as the fundamentals of a financial market as they complement the banking sector. NBFI plays a dynamic contribution to the economic development of Bangladesh. The study analyzes the financial soundness of selected NBFI by utilizing the Altman Z-score model using 20 NBFIs out of 23 organizations registered on the Dhaka Equity Market from 2014 to 2018. The outcomes show that during this period, 95% of the NBFIs were in distress while only 5% were in the safe zone.

The research investigates the financial performance of organizations registered on the Karachi Equity Market in Pakistan from 2006 to 2011. Four firms from the private sector of the Karachi Stock Exchange were selected for the study. The Z-score model is utilized to assess the financial health of these private firms. The study found that, based on profitability liquidity solvency and there were no bankruptcies among these firms (Khan, 2015).

The study explores the likelihood of financial instability in Indonesia's publicly traded firms within the manufacturing sector. The research used data from 139 companies for the years 2016 to 2018. The Z-score model was applied to forecast insolvency. The variables used in the Z-score model, include the retained earnings to total assets, book value to total liabilities, EBIT to total assets, and net working capital to total assets ratio. The study suggests that the model employed has a favorable impact on financial distress (Toly et al., 2019). Pradhan et al. (2002) financial distress among enterprises in Nepal is a significant concern as highlighted by a study that analyzed the decline in financial ratios during such periods. Distressed firms show higher operating expense ratios, lower profitability, reduced liquidity turnover labor productivity, and coverage ratios. The study emphasizes that liquidation of privatization of public enterprise can be avoided if stakeholders including labor supplier's debt holders (like banks) and shareholders are willing to make sacrifices during the restructuring process. Lumbantobing (2020) conducted a study that examines the impact of financial ratios on the likelihood of financial instability among manufacturing firms registered on the Indonesia Equity Market. The study focused on a sample of 30 firms from the period of 2015 to 2017. The findings indicated that the activity ratios do not significantly influence the likelihood of financial trouble. In contrast, the liquidity ratio was found to have a significant negative effect, suggesting that improved liquidity reduces the probability of distress. The research concludes that liquidity and debt ratios are the most effective metrics for predicting financial distress. This research endorses that profit ratios particularly in conjunction with liquidity ratios should be included in financial statements to assist stakeholders in making informed decisions during potential financial distress situations.

The research explores the effect of insolvency risk and currency crises on the association among financial leverage and financial health. The study picked data from 200 corporations listed on the Istanbul Stock Exchange over the span from 2009 to 2019. The research employs several analytical models to test its hypothesis and capture the complexities of the data. These models include Pooled ordinary least squares, random effects, and a Generalized Method of Moments. The results indicate that financial leverage negatively and significantly affects financial performance. Additionally, it finds that currency crises can exacerbate the negative effects of leverage, particularly in emerging markets. The study's results suggest that reducing financial leverage is a key strategy for improving financial performance, especially for firms in economically volatile regions. By managing debt more prudently and reducing leverage, companies can enhance their resilience to external shocks such as financial crises and currency devaluation, thereby improving their overall performance and long-term stability (Kalash, 2023).

This study provides an in-depth exploration of the effects of macroeconomic elements on the connection between cash flow volatility and debt maturity among non-financial corporations listed in Pakistan. The study spans 19 years (1999 to 2018), focusing on 380 non-financial firms. The key purpose of research is to analyze how cash flow volatility influences a firm's decision regarding its debt maturity structure. The study uses advanced econometric techniques such as ordered probit regression, two-way fixed effects model, and GMM to investigate the data and verify the hypotheses. The study finds that macroeconomic factors significantly alter the magnitude and direction of the association among cash flow volatility and debt maturity structure. This study offers valuable practical implications for firms operating in emerging markets where macroeconomic volatility is more pronounced. Firms should align debt maturity with cash flow stability and macroeconomic conditions favoring short-term debt when cash flow is volatile. Policymakers can enhance economic stability to reduce volatility and support long-term debt viability for firms (Shaheen et al., 2021).

Putri (2021) investigates the impact of sales growth operating capacity, and operating cash flow on forecasting default risk in manufacturing enterprises registered on the Indonesia Equity Market throughout the time frame between 2017 and 2019. This study employs SPSS to analyze data collected from various manufacturing firms, focusing on identifying factors that could potentially lead to financial instability. The results show that operating cash flow and sales growth are key contributors to greater financial stability. In contrast, operating capacity is positively correlated with bankruptcy, implying that expanding operational capacity would increase the risk of financial difficulties.

Utami, Atmaja, and Hirawati (2021) aim to explore the impacts of leverage, liquidity, and profitability on financial distress within enterprises operating in the agricultural basic industry, and chemical sectors. The research draws a sample of 380 observations, collected through purposive sampling, and utilizes logistic regression analysis to examine the connection among these financial indicators and the occurrence of financial distress. The outcomes revealed that substantial connection between profitability and liquidity and the likelihood of financial distress across all three sectors. Specifically higher levels of profitability and liquidity are found to be associated with a lower profitability of financial distress. On the other hand, the study identifies leverage as a significant factor influencing financial distress, particularly in the basic industry and chemical sectors. A high level of leverage increases the risk of insolvency by raising financial obligations and the potential of default.

This study investigates the factors influencing financial distress in Ethiopian insurance companies by analyzing equally structured panel data from eleven insurers spanning the years 2008 to 2019. The research utilized secondary data obtained from the annual reports of the designated insurance firms and employed a random effects regression model, along with descriptive statistics, to examine the connection among various financial metrics and the occurrence of bankruptcy risk. The findings reveal that leverage firm size, profitability, and company age have a substantial adverse impact on financial distress. These factors serve as proactive mechanisms to help insurance companies weather financial challenges and reduce their vulnerability to distress. In contrast, the loss ratio and asset tangibility exhibit a positive and substantial relationship with insolvency (Isayas, 2021).

Waqas and Md-Rus (2018) seek to classify the key predictors of financial distress among firms in Pakistan. It examines various financial indicators, including leverage, profitability, cash flows, and liquidity alongside two important market variables, the idiosyncratic standard deviation of stock returns (SIG) and firm size. The population includes 290 companies in the period between 2007 & 2016. The outcomes indicate that liquidity, cash flow, profitability, leverage ratios, and firm size are significant predictors, while SIG does not show a significant impact. The findings from the logit models show consistent predictive accuracy.

This study explores the connection between financial metrics and bankruptcy focusing on firms registered on the Indonesia Equity Market in the time frame between 2013 and 2015. The population comprised 40 subsidiaries across various industries offering a broad spectrum of insights into how financial metrics can influence the risk of financial distress within Indonesian companies. The study employed descriptive statistics and logistic regression techniques. The research found that EBITTA and ROE significantly influence financial distress, with higher values reducing distress likelihood. Conversely, the current ratio, RETA debt to assets, and total assets turnover showed no significant impact. This study suggests profitability and operational efficiency are crucial factors while other ratios may not effectively mitigate financial risk (Restianti & Agustina, 2018).

Supriyanto and Darmawan (2018) evaluate the bankruptcy risk of mining corporations registered on the Indonesia Equity Market from 2011 to 2014. The research utilized the modified Altman model and the sample comprised 119 mining firms. The results of the research showed that all four ratios positively influence financial distress. Kamaluddin, Ishak, and Mohammed (2019) address the critical issue of financial distress emphasizing its potential to lead to bankruptcy which in turn has negative repercussions on the broader economy. Identifying indicators that can predict financial distress is therefore of great significance. This study explores the association among cash flow ratios and the prediction of insolvency in corporations, focusing on industrial and consumer product firms listed on Bursa Malaysia. The Altman Z-score is employed to evaluate the extent of financial instability. The study found varied results for the solvency ratio, indicating it's important but not the sole predictor of distress. A significant adverse affiliation was observed between the profitability's roles in stability. The efficiency ratio showed no clear correlation suggesting external factors may have a stronger impact on distress than efficiency alone.

The objective of this research is to assess the efficiency of the Z-score model in predicting bankruptcy among Lebanese Alpha banks from 2009 to 2018. The investigators employed Eviews software to conduct a detailed analysis of the key financial variables, utilizing both descriptive statistics and a Pearson correlation matrix. The correlation analysis revealed that NWCTA had a strong positive association with the Z-score, while RETA and EBITTA showed weaker correlations indicating limited predictive power for distress. The market value of equity to the book value of debt also displayed a low correlation suggesting that market sentiment has less impact on predicting distress. The findings revealed that most of the Alpha banks fell below the threshold suggesting that these banks experienced financial distress during the period from 2009 to 2018 (Elia, Toros, & Sawaya, 2021).

The study aims to develop a robust model for forecasting insolvency in non-financial corporations registered on the Equity Market of Thai land. The study utilized stepwise logistic regression analysis. The dataset used for this analysis consisted of four pairs of financially distressed and financially stable companies over the period from January 20000 to March 2009.

The final predictive model developed from the analysis incorporates four key financial ratios debt to equity, ROA, ratio of cash flow from operations to net income, and current ratio. In addition, three corporate governance factors, CEO duality, managerial ownership, and institutional ownership, are identified as significant variables in predicting financial distress. The model demonstrates strong predicting power, achieving an overall classification accuracy rate of 95.65% in identifying firms at risk of financial distress. The study also concludes that macroeconomic variables do not show a considerable impact on forecasting future financial instability for the firms in the dataset (Suntraruk, 2009).

The purpose of this research is to assess the effect of financial metrics and macroeconomic variables on financial instability. The sample for this research contains 285 non-financial companies registered on the Pakistani Equity Market, drawn from a population of 559 firms covering the timeframe from 2013 to 2017. Logistic regression was employed for the evaluation. The results indicate that profitability, as measured by EBITA, has an inverse and significant connection with financial strain, while RETA shows a strong and meaningful connection with financial distress. The liquidity metrics, WCTA, are negatively and significantly related to financial distress, whereas CA and CL show a positive but insignificant relationship. Additionally, inflation was found to have a positive and substantial association with insolvency (Muien, Nordin, & Badru, 2022).

This research aimed to forecast financial instability in Kenyan registered firms by evaluating the role of financial ratios and the effectiveness of logistic regression. This study compared predictive accuracy before and during the financial crises (2004-2006 vs. 2007-2009). The results indicated that higher ratios of working capital, retained earnings to total assets EBIT, and current liabilities, increased financial distress, while debt-to-assets had a marginal effect. The study concluded that key financial ratios, especially EBIT-to-assets, significantly influence financial distress and recommended firms maintain liquidity, balanced leverage, and profitability to mitigate risk (Koech, 2018).

Singh and Singla (2019) aim to evaluate the sensitivity of Altman's models to differences in time and methodology. The study utilizes a group of 74 Indian manufacturing firms, equally split between firms that experienced default and those that remained solvent, spanning from 2011 to 2015. The objective is to examine how time influences the predictive power of Altman's model and how methodological adjustments, such as re-estimating the model coefficient with recent data and applying logistic regression, can enhance its accuracy in bankruptcy prediction. The results reveal that the classification rate for Altman's model in 2015 was 66.21% indicating moderate accuracy. However, the classification rate declines further in the years preceding 2015, suggesting a reduction in the model's effectiveness over time. The study concludes that after recalibrating the model, the classification rate increases significantly to 81.10% demonstrating that incorporating newer data leads to improved predictive accuracy.

Malakauskas and Lakštutienė (2021) conducted a comprehensive study to forecast the financial instability of small and medium-sized enterprises in France using various predictive techniques. The research evaluated several machine learning and statistical models, including the Artificial Neural Networks Support Vector Machine, Partial least Squares, Logit model, and a hybrid model combining SVM and PLS. The study utilized a data set consisting of financial data from French SMEs focusing on identifying distress one year and two years before it occurs. The analysis employed a range of techniques to compare their performance in accurately predicting financial distress. The findings indicate that the Support Vector Machine achieved the highest accuracy of 88.57% in predicting financial distress one year in advance. However, for predictions made two years before financial instability, the hybrid model combining SVM and PLS outperformed all other methods with an impressive accuracy rate of 94.28% showing superior capacity to predict distress at an earlier stage. The findings suggest that distressed SMEs tend to be smaller more leveraged and exhibit poor financial health including low liquidity profitability and solvency. The findings offer practical implications for managers, investors, and creditors. For managers, the results provide early warning signals of performance deterioration, enabling corrective actions to mitigate financial distress risk. For investors, considering the key aspects driving financial stress helps in avoiding high-risk firms, while creditors can use these insights to gauge the financial health of firms and manage counterpart risk effectively.

This research investigates the impact of Altman models on forecasting non-financial institutions in Egypt. Using a deductive approach, analyzed a sample of 44 firms from the EGX 70 index over the span from 2016 to 2020. The research utilized both the modified (1993) and original (1968) Altman Z-score models. The outcomes reveal that the application of these models significantly enhances the predictability of financial distress, with the modified model demonstrating superior performance (Elewa, 2022).

The study examines the financial ratios of saving banks and their impact on bankruptcy risk through a quantitative empirical analysis of a forecasting model. The research design involved the integration of several financial indicators, including two growth indices, three liquidity indices, five profitability indices, and four activity indices within the CAMEL rating framework. These indicators are derived from both the income statements and balance sheets of 30 savings banks that ceased operations between 2011 and 2015. The findings reveal that certain financial variables significantly influenced the bankruptcy prediction models. Key variables included the operating income growth ratio and the total assets growth ratio from the growth index, along with the liquidity ratio, tangible equity ratio, and sales-to-account-receivable ratio, from the liquidity index (Lee & Lee, 2018).

Ijaz, Hunjra, Hameed, Maqbool, and Azam (2013) researched to assess the financial health of sugar sector firms registered on the Karachi Stock Exchange, using two key financial indicators the current ratio and Z-score. The study included all thirty-five sugar sector companies registered on the Karachi Equity Market. The analysis focused on financial data from 2009 and 2010, which was sourced from the State Bank of Pakistan's balance sheet analysis and the company's financial statements. The study concluded that both the Z-score and the current ratio were reliable and effective indicators of the financial performance of sugar sector companies.

Khawaja (2023) emphasizes the importance of early prediction in identifying financial distress, particularly within the banking sector as it allows stakeholders including investors, regulators, and bank management to intervene before a bank's financial situation deteriorates to the point of insolvency. This study specifically investigates the predictability of financial failure among commercial banks in Pakistan, focusing on two widely recognized financial indicators, the Altman Z-score and the current ratio.

The study employs financial data from commercial banks operating in Pakistan from the period of 2016 to 2021. The results of the research indicate that both the current ratio and the Z-score model are effective tools for identifying signs of financial distress in Pakistani commercial banks. The study results indicate that commercial banks exhibit a significant risk of financial failure.

Pindado and Rodrigues (2005) provide international evidence on the costs linked to financial distress. To achieve this, the author constructed a model that determines financial distress costs through two main avenues first, by utilizing a refined pointer of the likelihood of financial distress, and second by incorporating a collection of variables that financial theory suggests influence the magnitude of costs incurred by firms experiencing financial distress. The findings underscore the significance of our enhanced probability indicator, which consistently shows a positive correlation with financial distress costs across all countries examined. Furthermore, results indicate an adverse affiliation between distress costs and liquid assets, suggesting that the benefits derived from holding liquid assets more than compensate for their opportunity costs.

This research aims to explore the impact of key financial indicators namely profitability working capital and free cash flow on the occurrence of insolvency among manufacturing firms registered on the Indonesia Equity Market from 2018 to 2020. The study utilized a purposive sampling method, selecting 71 manufacturing firms, resulting in a total of 213 observations over the three years.

The analysis reveals that profitability has a positive and substantial impact on bankruptcy, suggesting that more profitable companies may face higher financial risk. Similarly, working capital is positively linked to financial distress, indicating that inefficient asset management could increase financial strain. In contrast free cash flow shows an adverse but insignificant relationship with financial distress, implying that it does not significantly influence financial risk (Junior & Bangun, 2024).

This study examines the impact of leverage, liquidity, free cash flow, company size, and profitability on bankruptcy. It investigates secondary data gathered from the annual reports of manufacturing institutions listed on the Indonesia Equity Market, spanning the years 2016 to 2018. The findings indicate that profitability has a positive impact on bankruptcy, while free cash flow, leverage, and liquidity do not significantly influence bankruptcy. In contrast, company size is negatively associated with bankruptcy (Dirman, 2020).

The Islamic banking sector has increasingly been recognized as a crucial component of the Islamic financial system, steadily gaining global attention due to its unique financial principles that align with Islamic law. This study focuses on assessing the performance of Bangladesh's Islamic banking sector by examining the insolvency risks faced by its major Islamic banks. The research covers seven out of the eleven full-fledged Islamic banks operating in the country from the period of 2014 to 2019.

To evaluate the bankruptcy risks, the study employs the Emerging Economy Z-score model and the Altman model. The results reveal that three out of seven banks are categorized as financially stable, while three other banks are heading toward insolvency. Using the Emerging Economy Z-score model, the analysis shows that a notable 86% of the banks are considered to be in a secure position, further confirming the relative stability of the sector (Majumder & Moonmoon, 2020).

This study explores the insolvency risk of firms registered on the Indonesia Equity Market using the Z-score model for analysis. The study adopts a descriptive positive approach, focusing on secondary information derived from the financial statements of the firms. The findings indicate that all five firms are within the precautionary to distress zones. This study emphasizes significant financial challenges for these firms as they navigate the threat of delisting (Azizah & Ramli, 2023).

The objectives of this research to evaluate the efficiency of the Altman model in predicting company failures within Pakistani's textile sector. The empirical analysis encompasses 21 textile corporations listed on the Karachi Equity Market from 2000 to 2010, comprising 12 stable firms and 9 that went bankrupt. The results suggest that the Z-score model is highly effective in accurately forecasting the outcomes for both bankrupt and non-bankrupt companies.

These results were significant as they can inform management decisions related to financing, assist regulatory authorities, and guide portfolio managers in stock selection within Pakistan's textile sector (Hussain, 2014).Sareen and Sharma (2021) utilized the Z-score model for forecasting financial instability and stock prices, specifically within India's automotive sector. This comprehensive research is divided into two main sections the first focuses on analyzing the financial distress faced by the automotive industry during periods of financial crises and the introduction of Goods and Services Tax, while the second part uses panel data modeling to forecast stock prices over a period from 2000 to 2020. The study employs econometric growth curves to better understand the significant impacts that both financial crises and the GST (Goods and Services Tax) regime have had on the automotive sector. The study's findings reveal that both financial crises and GST had significant impacts on the bankruptcy risk levels of companies in India's automotive sector.

Almamy, Aston, and Ngwa (2015) present an in-depth examination of the extended applications of the Altman Z-score model focusing specifically on its capability to forecast the financial performance of enterprises in the United Kingdom. The primary goal of the research is to enhance the forecasting accuracy of the original Z-score model by introducing a new variable, cash flow, into the analysis.

The study spans the period from 2000 to 2013. The methodology includes discriminant analysis and performance ratio techniques to identify which financial ratios most significantly contribute to assessing a company's financial performance. The findings reveal that the integration of cash flow significantly improves the predictive power of the Z-score model. When cash flow is added to the original variables the enhanced model referred to as the J-UK model, achieves a predictive accuracy of 82.9% representing a notable improvement over the original model.

The study examines the influence of two financial indicators return on assets and current ratio on financial distress within the automotive and component manufacturing sectors specifically focusing on firms registered on the Indonesia Equity Market between 2015 and 2020. The primary objective of this study is to evaluate which of these two financial metrics plays a more significant role in determining the level of financial distress, as assessed by the Altman model. A sample of 10 firms was selected using non-probability sampling. Data analyzed utilizing multiple linear regression analysis, alongside hypothesis testing is carried out via t-tests to evaluate the significance of individual predictors. The findings of the study reveal that both return on assets and current ratio exhibit a statistically significant positive impact on bankruptcy risk level (Karlina & Rahman, 2023). Tinoco and Wilson (2013) explores the effectiveness of combining accounting, market-based, and macroeconomic data to evaluate corporate credit risk. The dataset includes 23,218 firm-year observations from publicly registered corporations spanning the years 1980 to 2011. The research aims to develop predictive models for forecasting bankruptcy by integrating various accounting metrics, stock market indicators, and macroeconomic proxies. The study emphasizes the benefits of incorporating a broad spectrum of data accounting, market, and macroeconomic factors into financial distress prediction models for publicly traded companies. This study further evaluates the performance of these integrated models in comparison to alternative approaches including a neural network model and Altman Z-score model. This comparative analysis highlights the potential for significantly improved predictive power when adopting a multifaceted approach to corporate credit risk assessment.

This study assesses the efficiency of the Z-score model in forecasting insolvency between retail enterprises registered on the Indonesia Equity Market during the period from 2021 to 2023. A total of 31 retail firms were analyzed. The research utilized the modified Altman Z-score model for data analysis. The findings revealed that the majority of the companies 17 out of 31 were categorized as strong, indicating that these firms were financially stable and not at immediate risk of bankruptcy, 3 companies were categorized as weak, suggesting that these firms were facing financial challenges. The remaining 11 companies were identified as being at high risk of bankruptcy (Rohim, Sandy, Ramadhan, & Hidayat, 2024).

This study assesses the financial health of PT Matahari Prima from 2018 to 2022, utilizing the Zmijewski, Grover, and Springate models to predict potential bankruptcy. By applying a descriptive approach to analyze the company's financial data over the specified period, the study examines key financial ratios and trends to evaluate its stability and ability to navigate financial difficulties.

The findings reveal that one firm has experienced financial distress during the selected time frame. These models suggest a decline in the company's financial position, with increasing risk factors that could potentially lead to bankruptcy if not addressed (Fitriyah & Prasasti, 2025). Balasubramanian, GS, P, and Natarajan (2019) state that the objective of this study is to create a corporate financial instability model for Indian publicly traded firms by incorporating both financial and non-financial factors employing a conditional logit regression method. The research analyzed a group of 96 firms 48 of which were classified as financially distressed, over the period from 2014 to 2016. Performance was assessed using a confusion matrix, specificity precision, and sensitivity. The results revealed that models based solely on financial variables achieved prediction accuracies of 85.19% and 86.11%.

Hanafi, Md-Rus, and Mohd (2021) the rising number of financially troubled companies in the Malaysian market highlights the need for effective financial distress prediction. This study predicts financial distress in Malaysian firms by using financial ratios and applying hazard models and logistic regression. It analyzes listed companies on the Malaysian stock market from 2000 to 2018, creating two datasets a primary Sample and a holdout sample to compare the predictive effectiveness of both models. The findings suggest that the hazard model outperforms both models, offering better identification of significant variables and greater accuracy consistency. This research highlights the superior predictive capability of hazard models in addressing financial distress challenges faced by Malaysian firms and underscores their value in improving financial distress prediction and early warning systems.

This study creates a model to forecast corporate financial distress for registered companies in India, utilizing binary logistic regression and financial ratios. The sample contains 51 companies from the Bombay Stock Exchange categorized into insolvent and solvent groups. Explanatory variables are classified into liquidity solvency efficiency and profitability ratios. A t-test identified significant variables, revealing that some ratios such as fixed assets turnover and interest coverage were non-significant, while others were significant. The model demonstrated a forecasting strength of 96.8% validated by the Hosmer and Lemeshow test (Kumar, Kumar, Verma, & Sharma, 2021).

Chapter 3

Data Description

The purpose of this study is to evaluate the effectiveness of the existing Z-score model in predicting business failure in Pakistan. Additionally, the study aims to develop a tailored model specifically for the Pakistani market to predict financial failure or bankruptcy.

3.1 Population and Sample of the Study

The study utilizes secondary quantitative cross-sectional data sourced from the annual reports of companies registered on the Karachi Stock Exchange (KSE).

The focus is on non-financial companies in Pakistan, specifically those that have reported a negative book value. Data collection targets the fiscal year in which these companies exhibited a negative book value.

This research includes a representative, matched sample of 124 observations, consisting of 62 financially strong companies and 62 companies with a negative book value. For these companies, a reverse calculation was conducted to assess their financial performance and implications.

This approach aims to provide insights into the characteristics and trends of firms experiencing negative equity within the context of the KSE.

3.2 Econometric Model

This study uses the Altman Z-score model developed by Edward Altman in 1968. The Z-score model combines five financial ratios to measure a company's financial health. In this study, the Z-score model was used to examine the financial distress of the companies in the non-financial sector of Pakistan.

$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1X_5$

The robustness of the model will be confirmed by using logistic regression analysis.

$P = 1/1 + e^{-z}$

Where:

X_1= Net working capital to total assets

X_2 = Retained earnings to total assets

X_3 = Earnings before interest and tax to total assets

X_4 = Book value of equity to total liabilities

X_5 = Sales to total assets

3.3 Description of Variables

This study uses five variables to test the existing Z-score model for predicting financial distress in the non-financial sector of Pakistan.

3.3.1 Net Working Capital to Total Assets

The NWCTA ratio is a key financial indicator that will be used to assess a company's liquidity position and its ability to meet short-term financial obligations. This ratio measures the difference between a company's current assets and current liabilities relative to its total assets. Current assets include cash in hand, accounts receivable, and inventories. Current liabilities include short-term debt, and accounts payable (Toly et al., 2019). A higher NWCTA ratio is favorable as it suggests that the company has more current assets than liabilities, indicating a strong liquidity position and the ability to meet its short-term obligations. In contrast, a lower ratio signals potential liquidity problems which means the company might struggle to cover its short-term liabilities.

If liquidity is insufficient, the company could face challenges that may ultimately lead to financial distress.

$$X_1 = \frac{\text{Net Working Capital}}{\text{Total Assets}}$$

3.3.2 Retained Earnings to Total Assets

The RETA ratio measures the growth of the business. This ratio estimates a business's capability/proficiency to generate retained earnings from its assets. Hussain (2014) retained earnings represent the company's cumulative profits or losses over its entire existence. A higher ratio of retained earnings to total assets indicates good financial health, while a lower ratio shows weak profitability or limited retained earnings, potentially reflecting financial distress.

$$X_2 = \frac{\text{Retained Earnings}}{\text{Total Assets}}$$

3.3.3 Earnings before Interest and Tax to Total Assets

EBIT designates operating profit before interest and tax. This ratio is used to measure a business's profitability and productivity. Earnings before interest and tax to total assets tell us how much cash is available to pay creditors, the government, and shareholders (Al-Manaseer & Al-Oshaibat, 2018). A higher ratio of earnings before interest and tax to total assets shows strong positive profitability and efficient use of assets to generate earnings. A lower ratio suggests inefficiency in asset utilization and lower profitability.

$$X_3 = \frac{\text{Earnings Before Interest and Tax}}{\text{Total Assets}}$$

3.3.4 Book Value of Equity to Total Liabilities

The BVOETL ratio points toward the range in which companies' assets are financed by debt. The book value of equity is calculated by dividing total company equity by the number of outstanding shares (Hiong et al., 2021). A higher ratio of book value of equity to total liabilities indicates financial stability and lower reliance on debt. A lower ratio signals higher leverage indicating that the company depends more on liabilities than equity.

$$X4 = \frac{\text{Book Value of Equity}}{\text{Total Liabilities}}$$

3.3.5 Sales to Total Assets

The STA referred to as the asset turnover ratio, is a financial indicator that determines a company's capacity to efficiently use its assets to generate sales (Khan, 2015). The sales to total assets higher ratio reflects the efficient utilization of assets to generate revenue, while the lower ratio suggests inefficiency in using assets to generate sales.

$$X5 = \frac{\text{Sales}}{\text{Total Assets}}$$

To determine the Z-score model, use the following criteria:

If the Z-score is greater than 2.99, the company is considered in the safe zone with low bankruptcy risk. Companies with Z-scores lying on 1.81 to 2.99 are in the gray zone, indicating a potential bankruptcy risk. Z-scores below 1.81 suggest a high risk of bankruptcy or being in the distress zone.

3.4 Proposed Model

The Altman Z-score was developed to predict financial distress in firms and is widely used worldwide. However, the Pakistani market is an emerging market, and the proposed model is specifically designed to predict financial distress or bankruptcy within this context. The ratios used in the proposed model are derived from financial statement red flags as proposed by Even Buffet and Charles Munger. Investment experts Even Buffet and Charles Munger identified key financial ratios to assess the quality of the stock. They consider these measures as red flags. This proposed model is called the A-score, and its equation is:

A-score $= \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \epsilon$

Where:

$\mathrm{X}_1 = \frac{\mathrm{OPE}_t - \mathrm{OPE}_{t-1}}{\mathrm{OPE}_{t-1}}$

$\mathrm{X}_2 = \frac{\text{Interest Expenses}_t}{\text{Earnings Before Interest and Tax}_t}$

$\mathrm{X}_3 = \frac{\text{Debt}}{\text{Equity}}$

$\mathrm{X}_4 = \frac{\text{Short Term Debt}}{\text{Short Term Debt+Long Term Debt}}$

$\mathrm{X}_5 = \frac{\text{Earnings Before Interest and Tax}}{\text{Operating Cash Flow}}$

$\mathrm{X}_6 = \frac{\text{Capital Expenditure}}{\text{Free Cash Flow}}$

It is important to examine these ratios used by market practitioners for academic perspective.

3.5 Description of Variables

This study uses six variables to develop the A-score model for predicting financial distress in the non-financial sector of Pakistan.

3.5.1 Operating Expense Ratio

Operating expense ratio is a financial metric used to measure the effectiveness of a firm's operations. It compares the firm operating expenses at time t (current period) minus operating expenses at time t-1 (previous period) to its operating expenses at time t-1.

Operating expenses include all costs related to running a business. When operating expenses increase, the profitability of the business decreases, and it leads to financial distress. This means that the company's spending is more than its generating profit. The operating expense ratio has a positive relationship with financial distress. Pradhan et al. (2002) analyzing firms in Nepal found that financially distressed companies had significantly higher operating expense ratios, suggesting that inefficiencies in managing operating expenses are a precursor to financial difficulties.

$$X_1 = \frac{\text{OPE}_t - \text{OPE}_{t-1}}{\text{OPE}_{t-1}}$$

3.5.2 Interest Expenses to Operating Profit Ratio

The interest expenses to operating profit ratio measures how well earnings can cover interest expenses. It compares a company's interest expenses at time t to its earnings before interest and tax at time t. An increase in interest expenses tells us the business is relying too much on debt. This can weaken the company's financial position. Increase in interest expenses, business going to weak, and its lead to financial distress. Interest expenses to operating profit ratio is positively associated with financial distress. Lumbantobing (2020) indicates that firms with higher interest expenses to operating profit ratios are more likely to experience financial distress. The increased burden of interest payments can lead to liquidity issues, forcing companies to liquidate assets at unfavorable prices or default on obligations.

$$X_2 = \frac{\text{Interest Expenses}_t}{\text{EBIT}_t}$$

3.5.3 Leverage Ratio

The leverage ratio is a critical financial indicator used to assess how much a firm depends on debt to finance its operations. This ratio compares debt to shareholders' equity. If the internal funds of the firm are insufficient to meet its needs, a business turns to debt financing. When the company cannot generate enough income to cover its debt, it could lead to bankruptcy. The leverage ratio has a positive impact on bankruptcy. Kalash (2023) explores the connection between financial leverage and financial performance. This suggests that as corporations increase their reliance on debt to finance their operations, their overall performance tends to decline.

$$X_3 = \frac{\text{Debt}}{\text{Equity}}$$

3.5.4 Debt Maturity Structure

The debt-maturity structure ratio indicates how well a business's operating profits can handle the burden of debt. When a business cannot meet its current operational expenses, it relies on short-term borrowing to cover its costs. Business operations depend on borrowing.

A high debt maturity structure ratio indicates that a significant portion of the firm's debt is short-term, which can lead to bankruptcy. The debt maturity structure is positively correlated with financial distress. Shaheen et al. (2021) their study provides evidence that companies experiencing high cash volatility are more inclined to rely on short-term borrowing. Short-term debt exposes firms to frequent refinancing risks and interest rate fluctuations, both of which can exacerbate financial instability.

$$X_4 = \frac{\text{Short term debt}}{\text{Short term debt} + \text{Long term debt}}$$

3.5.5 Operating Cash Flow Turnover

The operating cash flow turnover ratio is utilized to evaluate how effectively a company generates cash from its core operating activities about its revenue or expenses. This ratio is a key indicator of a business's ability to produce enough cash flow from its operations to cover its ongoing operating costs. Essentially it measures how well a company can convert its earnings into actual cash that can be used to fund its activities. The high figure indicates that this business has in problem high amount of cash in non-cash form. Operating cash flow has a positive relationship with financial distress. Putri (2021) investigated the impact of operating cash flow on financial distress among manufacturing firms listed on the Indonesia Stock Exchange. The research reveals that higher operating cash flow is linked to a reduced likelihood of financial distress, emphasizing that generating cash efficiently from operations plays a critical role in maintaining financial stability.

$$X_5 = \frac{\text{EBIT}}{\text{Operating cashflow}}$$

3.5.6 Reinvestment Ratio

The reinvestment ratio helps to measure the balance between a business's ability to generate cash and its need to reinvest in future growth. A business that continuously requires a high proportion of free cash flow for reinvestment faces challenges. A capital expenditure low ratio indicates the business going profit, when this ratio is high, it indicates the business is going towards financial distress. The reinvestment ratio has a positive impact on financial distress. Utami et al. (2021) investigate various financial ratios, including reinvestment ratios, and their impact on predicting financial distress. It emphasizes that a high proportion of capital expenditure relative to free cash flow can indicate potential financial difficulties for firms.

$$X_6 = \frac{\text{Capital expenditure}}{\text{Free cashflow}}$$

3.6 Data Analysis

3.6.1 Logit Analysis

The data analysis through a logit model using Eviews software includes the following components, Binary logit estimation prediction, evaluation for binary specification, and goodness-of-fit evaluation for binary specification. Singh and Singla (2024) Binary logit refer to a statistical model used to describe the relationship between a binary dependent variable (a variable with two possible outcomes, often coded as 0 or 1) and one or more independent variables (predictors).

Prediction and Evaluation for Binary Specification involves assessing how well the model predicts the actual outcomes, typically using metrics like classification accuracy. Goodness-of-fit Evaluation for Binary specification tests how well the model fits the data. Common tests for evaluating the goodness of fit in binary logit models include R-squared, Likelihood Ratio Test, and Hosmer-Lemeshow Test.

3.6.2 Discriminant Analysis

Discriminant analysis is used to test the Z-score model and A-score model using SPSS. Soni (2019) this statistical technique helps in determining how well these models classify cases into predefined groups, such as distinguishing between financial distress and non-distress situations. The analysis includes several key components.

3.6.2.1 Descriptive Statistics

Descriptive statistics were computed to summarize the basic characteristics of the predictor variables, such as their means and standard deviations across the different groups.

3.6.2.2 Test of Equality of Group Means

The test of equality of group means is used to evaluate whether the means of the predictor variables differ significantly across the groups. If the p-value is low, it indicates that the variables can effectively separate the groups.

3.6.2.3 Pooled Within-Group Covariance Matrices

The pooled within-group covariance matrices are matric that combines the covariance matrices of multiple groups assuming that the covariance structure (variability and relationship between variables) is the same across all groups.

3.6.2.4 Log Determinants

The natural logarithm of the determinant of the covariance matrices for each class or group is referred to as the log determinant.

3.6.2.5 Box's M Test

Box's M test is used to assess the equality of covariance matrices across multiple groups or populations. The null hypothesis that the covariance matrices are equal is tested.

3.6.2.6 Eigenvalues

The eigenvalues from the discriminant function are analyzed to understand how much variance is explained by each discriminant function in separating the groups. It is suggested by larger eigenvalues that the function is more effective at distinguishing between groups.

3.6.2.7 Wilk's Lambda

The overall significance of the discriminant functions is assessed by Wilk's Lambda statistic. It is indicated by smaller values of Wilk's lambda that the discriminant functions significantly differentiate the groups.

3.6.2.8 Standardized Canonical Discriminant

The influence of each predictor variable on the discriminant function is indicated by the standardized canonical discriminant function coefficients when the variables are measured on different scales. The data is transformed by the standardization process so that each variable has a mean of zero and a standard deviation of one, making them comparable.

The equation of the discriminant function is used to calculate discriminant scores for each case using these coefficients. The group (bankrupt or non-bankrupt) is determined by these scores.

3.6.2.9 Structure Matrix

The structure matrix shows the correlations between the predictors and the discriminant functions indicating which variables are most strongly associated with the group separation.

3.6.2.10 Canonical Discriminant Function Coefficients

The canonical discriminant function coefficients are used to calculate the discriminant scores for each case.

3.6.2.11 Function at Group Centroids

The function at group centroids represents the mean discriminant scores for each group, and examining the distance between these centroids helps assess how well the groups are separated.

3.6.2.12 Classification Results

The classification results provide the most direct measure of the model's effectiveness. SPSS generates a classification matrix, which shows the number of correctly and incorrectly classified cases. The overall accuracy is also reported, reflecting how well the model predicts group membership. If cross-validation is performed, it further assesses the model's ability to generalize to new unseen data.

Chapter 4

Results and Discussion

4.1 Testing and Validation of Z-score Using Logit Analysis

The Altman Z score model is utilized to evaluate the distress and non-distress and the same classification is employed to assess the validity of the model using binary logistic analysis.

4.1.1 Descriptive Statistics

Descriptive statistics summarize and describe the key features of the data under study, providing insights into its central tendency, variability, and distribution.

This table presents key measures, including the mean, median, minimum, and maximum values, which highlight the central tendency and range of the data. Standard deviation indicates the level of variability showing how much each variable deviates from its mean. Skewness and kurtosis describe the distribution shape, helping to assess whether the data follows a normal distribution.

Kurtosis provides information about the peakedness or flatness of the data. If its value is greater than three, the distribution is leptokurtic. If its value is less than three, it is platykurtic. The data may be left skewed, indicating higher values that pull the mean to the left. If it is right skewed, large values on the right side pull the mean to the right.

Table 4.1: Descriptive Statistics

	NWCTA	RETA	EBITTA	BVOETL	STA
Mean	-0.322848	-0.082792	0.028229	0.676353	1.058707
Median	-0.092100	-0.005017	0.017578	0.205810	0.665784
Maximum	0.595600	0.319294	0.575202	4.976365	4.806925
Minimum	-3.238300	-1.157032	-0.586251	-0.971140	0.000000
Std. Dev.	0.753816	0.238924	0.173967	1.406727	0.991110
Skewness	-1.227556	-2.098260	0.052705	1.478011	1.345106
Kurtosis	4.542963	8.018180	4.459335	4.429347	4.449866
Jarque-Bera	43.44294	221.0967	11.06065	55.70235	48.25330
Probability	0.000000	0.000000	0.003965	0.000000	0.000000

“NWCTA represents Networking capital to total assets. RETA represents Retained earnings to total assets. EBITTA represents Earnings before interest and tax to total assets. BVOETL represents the Book value of equity to total liabilities. STA represents Sales to total assets.” Mean represents the average value of each variable. NWCTA -0.322848 negative mean indicating that some firms may have high current liabilities. RETA -0.082792 negative mean suggesting some firms have accumulated losses. EBITTA has a low positive mean of 0.028229 reflecting limited profitability. BVOETL and STA have a positive mean value indicating relatively stronger equity positions and operational efficiency. The range of NWCTA -3.238300 to 0.5959600 suggests a disparity in working capital efficiency. STA exhibits a broad range of 0.000000 to 4.806925 suggesting differing levels of asset efficiency. RETA and EBITTA have smaller ranges but still highlight firms with negative retained earnings and operating losses. Standard deviation measures the spread of data. NWCTA and STA have higher values suggesting greater variability in these variables. The Skewness indicates asymmetry of the data distribution. NWCTA, RETA, and EBITTA show negative skewness meaning a longer tail on the left. BVOETL and STA show positive skewness meaning a longer tail on the right. Kurtosis measures the peakedness of the data distribution. RETA and

EBITTA have a high kurtosis indicating the presence of heavy tails and numerous outliers.

4.1.2 Binary Logit

A binary logit is a statistical output that summarizes the results of a binary logistic regression analysis. The table provides coefficients, statistical significance, and diagnostic metrics that describe the relationship between the predictors and the probability of an event occurring.

TABLE 4.2: Binary Logit

Variable	**Coeff**	**Std. Error**	**z-Stats**	**P.**
NWCTA	3.784220	1.000614	3.781898	0.0002
RETA	3.932617	2.431531	1.617342	0.1058
EBITTA	1.783994	2.294634	0.777463	0.4369
BVOETL	-0.019449	0.195675	-0.099394	0.9208
STA	-0.109089	0.200682	-0.543593	0.5867
Mean dependent var	0.306452	S.D. dependent var		0.462890
S.E. of regression	0.341588	Akaike info criterion		0.766765
Sum squared resid	13.88517	Schwarz criterion		0.880486
Log-likelihood	-42.53942	Hannan-Quinn criter.		0.812961
Deviance	85.07884	Restr. Deviance		152.8255
Avg. log-likelihood	-0.343060			
Obs with Dep=0	86	Total obs		124
Obs with Dep=1	38			

Binary logit analysis depicts that the NWCTA (Net Working Capital Total Assets) has a probability value of 0.0002, which is statistically significant. A positive coefficient indicates that as NWCTA increases, the likelihood of the increases in Z score. RETA (Retain Earnings to Total Assets) has a probability value of 0.1058 statistically insignificant, which suggests that RETA does not have a strong predictive power for the distress. EBITTA probability value of 0.4369 is statistically insignificant and does not provide strong evidence of influencing the outcome. BVOETL has a probability value of 0.9208 statistically negligible, and the negative coefficient suggests little to no effect. STA (Sales to Total Assets) has a probability value of 0.05867 is statistically insignificant, suggesting no strong predictive influence on the outcome.

The Akaike information criterion, 0.766765, helps assess model fit lower values of the Akaike information criterion indicate a better model. There are 124 total observations, 86 of which have a dependent = 0 and 38 of which have a dependent = 1, which means 86 cases are classified as financial distress.

4.1.3 ExpectationPprediction Evaluation for Binary Specification

The Expectation-Prediction Evaluation table measures the predictive accuracy of the binary logistic regression model by comparing the predicted and actual outcomes for the dependent variable.

Table 4.3: Expectation-Prediction Evaluation for Binary Specification

	Estimated Equation			**Constant Probability**		
	Dep=0	**Dep=1**	**Total**	**Dep=0**	**Dep=1**	**Total**
P(Dep=1)<=C	66	1	67	86	38	124
P(Dep=1)>C	20	37	57	0	0	0
Total	86	38	124	86	38	124
Correct	66	37	103	86	0	86
% Correct	76.74	97.37	83.06	100.00	0.00	69.35
% Incorrect	23.26	2.63	16.94	0.00	100.00	30.65

Estimated equation performance Dep = 0 (Financial Distress) and Dep = 1 (non-financial distress) cases are classified with 76.74% and 97.37% accuracy respectively. Out of 86 observations 66 are correctly predicted as distress and out of 38 observations 37 are correctly predicted as non-distress. The model achieves an overall accuracy of 83.06%.

4.1.4 Goodness-of-Fit Evaluation for Binary Specification

The Goodness-of-Fit Evaluation in logistic regression evaluates how well the model predicted probabilities match the actual outcomes by using the Hosmer-Lemeshow (H-L) test and Asndrews's statistics.

Table 4.4: Goodness-of-Fit Evaluation for Binary Specification

	Quantile of Risk			**Dep=0**		**Dep=1**	**Total**	**H-L**
	Low	**High**	**Actual**	**Expect**	**Actual**	**Expect**	**Obs**	**Value**
1	8E-141	0.0015	12	11.9948	0	0.00524	12	0.00524
2	0.0016	0.0088	12	11.9384	0	0.06160	12	0.06192
3	0.0089	0.0248	13	12.7613	0	0.23866	13	0.24313
4	0.0248	0.0712	12	11.4965	0	0.50353	12	0.52558
5	0.0816	0.3368	13	10.0445	0	2.95546	13	3.82507
6	0.3519	0.5599	9	6.23523	3	5.76477	12	2.55191
7	0.5631	0.6729	6	4.55282	6	7.44718	12	0.74123
8	0.6750	0.8325	4	3.05420	9	9.94580	13	0.38283
9	0.8372	0.8726	4	1.73559	8	10.2644	12	3.45389
10	0.8792	0.9414	1	1.26233	12	11.7377	13	0.06038
		Total	86	75.0757	38	48.9243	124	11.8512
H-L Statistic			11.8512		Prob. Chi-Sq(8)		0.1580	

The data is divided into 10 quantiles, each with expected and actual frequencies for Dep = 0 and Dep =1. The H-L statistic is 11.8512 with a p-value of 0.1580. The p-value is greater than 0.05, indicating that the model does not discriminate across quantiles.

4.1.5 Marginal Effect

The Marginal Effect quantifies the impact of a one-unit change in an independent variable on the dependent variable while holding all other factors constant.

Table 4.5: Marginal Effect

Variables	X	β	L=X*β	βP	Marginal Effect
NWCTA	-0.322848	3.78422	-1.2217	0.5963	0.5024
RETA	-0.082792	3.93262	-0.3256	0.6197	0.5221
EBITTA	0.028229	1.78399	-0.0005	0.2811	0.2368
BVETL	0.676353	-0.01945	-0.0131	-0.0031	-0.0026
STA	1.058707	-0.10909	-0.1154	-0.0172	-0.0145
		L	-1.6763		
		P	0.1576		

The column variables represent different variables that are included in the logit model. X shows the mean values of variables extracted from descriptive statistics of the model. Beta shows the coefficients taken out from binary logit analysis and represents the impact of each predictor on the dependent variable. L shows the linear prediction for each variable. NWCTA has a significant marginal effect. A one-unit increase in NWCTA decreases the probability of financial distress by 0.5024. RETA, EBITTA, BVETL, and STA have a P-value greater than 0.05, an insignificant marginal effect of these variables exists. Therefore, this specific work indicates that the reliability of the model is questionable.

4.2 Testing and Validation of Financial Distress for the Proposed Model using Logit Analysis

Distress and non-distress are estimated by using the Altman Z score model, and then the proposed model is tested using logistic analysis.

4.2.1 Descriptive Statistics

Descriptive statistics summarize and describe the key features of the data under the study providing insights into its central tendency, variability, and distribution.

TABLE 4.6: Descriptive Statistics

	Operating-Expense Ratio	**Interest-Expense-to Operating Profit-Ratio**	**Debt-to-Equity**	**Debt-Maturity-Structure**	**Operating-Cash-Flow Turnover**	**Reinvestment Ratio**
Mean	1.064644	-0.295580	-2.475091	0.867171	1.583958	-0.212798
Median	0.957250	0.001456	0.222400	0.967029	0.892230	0.003282
Maximum	5.040474	7.497621	6.724400	1.000000	72.74207	5.231916
Minimum	-0.484132	-14.72452	-38.29590	0.163727	-78.72148	-18.26581
Std. Dev.	0.652008	2.051200	7.463258	0.173406	14.73373	2.526101
Skewness	3.031162	-4.297547	-3.226545	-1.285969	0.004302	-4.939117
Kurtosis	16.07177	33.35516	14.09902	4.109319	18.94057	32.53747
Jarque-Bera	1072.719	5142.444	851.6246	40.53483	1312.859	5011.882
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

The mean values indicate the average performance of each metric, with the Operating expense ratio averaging 1.065, suggesting that companies generally have relatively high operating expenses compared to their revenues. The median of 0.957 indicates that half of the observations fall below this value reflecting a skew towards higher operating expenses. The Interest expense to operating profit ratio has a mean of -0.296, indicating that many companies experience negative or low costs associated with their debt.

The range of values highlights significant variability among metrics the operating expense ranges from a minimum of -0.484 to a maximum of 5.040, revealing that some companies incur very high operational costs relative to their income. The Debt-equity ratio spans from -38.296 to 6.724, suggesting substantial differences in leverage among firms.

The standard deviations further illustrate this variability with the Interest expense to operating profit ratio showing a high standard of 2.051 and Operating Cash Flow Turnover exhibiting an even higher standard deviation of 14.734, indicating considerable difference in how effectively companies convert cash flow into revenue.

Skewness values reveal that most metrics are not symmetrically distributed, the Operating Expense ratio has a skewness of 3.031 indicating a long right tail with many companies reporting high expenses, while the Interest expense to operating profit ratio shows a skewness of -4.298, reflecting numerous negative values and few positive ones.

High kurtosis values of Interest expense to operating profit ratio at 33.35 suggest that the distributions are peaked with heavy tails, indicating that extreme values are more common than in a normal distribution.

4.2.2 Binary Logit

A binary logit is a statistical output that summarizes the results of a binary logistic regression analysis.

The table provides coefficients, statistical significance, and diagnostic metrics that describe the relationship between the predictors and the probability of an event occurring.

Table 4.7: Binary Logit

Variable	**Coeff**	**Std. Error**	**z-Stats**	**P.**
Operating expense ratio	0.5388	0.695878	0.774308	0.4387
Interest expense to operating profit ratio	0.0686	0.107677	0.637123	0.5240
Debt to equity	2.3386	0.521711	4.482479	0.0000
Debt maturity structure	1.5447	0.955411	1.616739	0.1059
Operating cash flow turnover	-0.0646	0.022531	-2.867307	0.0041
Reinvestment ratio	0.2708	0.130290	2.078280	0.0377
Mean dependent var	0.5000	S.D. dependent var		0.502028
S.E. of regression	0.1409	Akaike info criterion		0.336494
Sum squared resid	2.3431	Schwarz criterion		0.472959
Log-likelihood	-14.8626	Hannan-Quinn criter.		0.391929
Deviance	29.7252	Restr. Deviance		171.9005
Avg. log-likelihood	-0.1199			
Obs with Dep=0	62	Total obs		124
Obs with Dep=1	62			

Binary logit analysis depicts that the Operating expense ratio has a probability value of 0.4387 statistically insignificant. A positive coefficient indicates a positive relationship with the dependent variable. Interest expense to operating profit ratio has a probability value of 0.5240 statistically insignificant.

The interest expense to operating profit ratio does not affect the dependent variable. Debt to equity has a coefficient of 2.339560 and a probability value of 0.0000 statistically significant indicating a positive relationship with the dependent variable.

Debt Maturity Structure has a positive and insignificant relationship with the dependent variable. Operating Cash Flow has a negative and significant relationship with the dependent variable. The reinvestment ratio has a positive and significant relationship with the dependent variable.

Standard error measures the average distance that the estimated coefficient is likely to be from the actual average value of the dependent variable. Lower standard errors show the consistency of the data. Z-Statistic measures how many standard deviations an element is from the mean. The Akaike info criterion is 0.336494 value helps in assessing the model fit. Lower values of the Akaike information criterion indicate a better model. The total observations are 124, 62 have a dependent = 0, and 62 have a dependent = 1 means 62 cases are classified with financial distress and 62 are classified with non-financial distress.

4.2.3 Expectation-Prediction Evaluation for Binary Specification

The Expectation-Prediction Evaluation table measures the predictive accuracy of the binary logistic regression model by comparing the predicted and actual outcomes for the dependent variable.

TABLE 4.8: Expectation-Prediction Evaluation for Binary Specification

	Estimated Equation			**Constant Probability**		
	Dep=0	**Dep=1**	**Total**	**Dep=0**	**Dep=1**	**Total**
P(Dep=1)<=C	61	1	62	62	62	124
P(Dep=1)>C	1	61	62	0	0	0
Total	62	62	124	62	62	124
Correct	61	61	122	62	0	62
% Correct	98.39	98.39	98.39	100.00	0.00	50.00
% Incorrect	1.61	1.61	1.61	0.00	100.00	50.00

Estimated equation performance Dep = 0 (Financial Distress) and Dep = 1 (non-financial distress). Out of 62 observations, 61 were correctly predicted as distress, and 61 observations out of 62 were classified as non-distress. The model achieved an overall accuracy of 98.39%

4.2.4 Goodness-of-Fit Evaluation for Binary Specification

The Goodness-of-Fit Evaluation in logistic regression evaluates how well the model's predicted probabilities match the actual outcomes by using the Hosmer-Lemeshow (H-L) test and Andrews's statistic.

Table 4.9: Goodness-of-Fit Evaluation for Binary Specification

	Quantile of Risk			**Dep=0**		**Dep=1**	**Total**	**H-L**
	Low	**High**	**Actual**	**Expect**	**Actual**	**Expect**	**Obs**	**Value**
1	0.0000	6.E-11	12	12.0000	0	1.0E-10	12	1.0E-10
2	2.E-10	0.0011	12	11.9976	0	0.00242	12	0.00242
3	0.0011	0.0142	13	12.9135	0	0.08651	13	0.08709
4	0.0156	0.0481	12	11.6332	0	0.36683	12	0.37840
5	0.0483	0.4035	12	10.8889	1	2.11114	13	0.69820
6	0.5945	0.9481	0	1.44701	12	10.5530	12	1.64543
7	0.9497	0.9662	0	0.48732	12	11.5127	12	0.50795
8	0.9677	0.9913	0	0.24561	13	12.7544	13	0.25034
9	0.9918	0.9975	0	0.06556	12	11.9344	12	0.06592
10	0.9980	1.0000	1	0.00656	12	12.9934	13	150.442
		Total	62	61.6852	62	62.3148	124	154.077
H-L Statistic			154.0774		Prob. Chi-Sq(8)		0.0000	

The data is divided into 10 quantiles, each with expected and actual frequencies for Dep = 0 and Dep =1. H-L Statistics measures the difference between high-risk groups, indicating how well the model distinguishes between them. A higher H-L value suggests better discrimination. The total observed and expected values

Dep = 0 62 vs 61.6852 and Dep =1 62 vs 62.3148 align closely, suggesting the model predicts well. The H-L statistic is 154.0774 indicating strong differentiation between risk levels across the quantiles.

4.2.5 Marginal Effect

The Marginal Effect shows the impact of a one-unit change in an independent variable on the dependent variable assuming all other factors remain constant.

TABLE 4.10: Marginal Effect

Variables	**X**	β	**L=X*β**	β**P**	**Marginal Effect**
Operating Expense ratio	1.0646	0.5388	0.5737	0.0092	0.0090
Interest Expenses to Operating Profit ratio	-0.2956	0.0686	-0.0203	0.0012	0.0011
Debt to Equity	-2.4751	2.3386	-5.7882	0.0398	0.0392
Debt Maturity Structure	0.8672	1.5446	1.3395	0.0263	0.0259
Operating Cash flow Turnover	1.5839	-0.0646	-0.1023	-0.0011	-0.0011
Reinvestment Ratio	-0.2128	0.2708	-0.0576	0.0046	0.0045
		L	-4.0552		
		P	0.0170		

The column variables represent different variables that are included in the logit model. X shows the mean values of variables extracted from descriptive statistics of the model. Beta shows the coefficients taken out from binary logit analysis and represents the impact of each predictor on the dependent variable. L shows the linear prediction for each variable. This table indicates the marginal contribution or the probability of change in the independent variable. The debt to equity has a marginal effect of 0.0392 indicating that as the debt to equity increases, it increases the probability of financial distress. The operating cash flow turnover has a marginal effect of -0.0011 indicating that an increase in operating cash flow turnover decreases the probability of financial distress. The reinvestment ratio has a marginal effect of 0.0045, indicating that an increase in the reinvestment ratio slightly increases the probability of financial distress.

4.3 Comparison of Two Tests (Logistic Analysis)

TABLE 4.11: Comparison of Two Tests (Logistic Analysis)

	Z-score Model	**A-score Model**
Significant variables	Net Working Capital to Total Assets	Debt-to-Equity
		Operating Cash Flow
		Turnover
		Reinvestment Ratio
Overall Accuracy	83.06%	98.39%
Hosmer-Lemeshow Test	Prob. Chi-Sq 0.1580	Prob. Chi-Sq 0.0000

The A-score model demonstrates superior accuracy and better fit by incorporating financial indicators such as Debt to equity Operating cash flow turnover Reinvestment ratio. This suggests that the A-score model is better predicted as compared to the traditional model Z-score.

4.4 Testing and Validation of Z-score Using Discriminant Analysis

4.4.1 Group Statistics

Descriptive statistics in discriminant analysis summarize key features of predictor variables (mean standard deviations) to assess normality, variance homogeneity, and group differences before modeling.

Table 4.12: Group Statistics

Z		**Mean**	**Std. Deviation**
0	NWCTA	-0.99	3.64
	RETA	-0.55	3.71
	EBITTA	-0.43	3.61
	BVOETL	0.04	0.68
	STA	0.71	0.63
1	NWCTA	0.29	0.18
	RETA	0.06	0.05
	EBITTA	0.18	0.12
	BVOETL	2.12	1.57
	STA	1.84	1.20
Total	NWCTA	-0.60	3.09
	RETA	-0.36	3.10
	EBITTA	-0.24	3.01
	BVOETL	0.68	1.41
	STA	1.06	0.99

Group Z = 0 represents the first subgroup, distressed firms and Z = 1 represents the non-distressed firms. The total represents the combined groups. NWCTA the mean for group Z=0 is negative -0.99 with a standard deviation of 3.64, indicating high variability and a negative working capital position, while group Z=1 has a mean of 0.29 with a lower standard of 0.18 showing better performance. The mean for all firms is -0.60, indicating an overall negative working capital. RETA group Z=0 has a negative mean of -0.55, while Z = 1 has a positive mean of 0.06, reflecting better earnings performance. The overall mean is -0.36, suggesting overall negative retained earnings in the sample. EBITTA the mean difference group Z = 0 showing -0.43 indicating significant losses, while group Z = 1 displays a positive mean of

0.18 highlighting profitability. The total mean of -0.24 highlights overall financial stress. The BVOETL ratio shows that group Z = 0 has a mean of 0.04 suggesting high leverage compared to 2.12 in group Z = 1 where equity sufficiently covers liabilities. The total mean of 0.68 indicates better equity coverage of liabilities in some firms. The Sales to Total Assets ratio group Z = 0 has a mean of 0.71 showing low asset turnover, while Z=1 has a higher mean of 1.84, indicating better efficiency in generating sales from assets. The overall mean is 1.06, suggesting moderate sales performance across all firms. All financial ratios are on the higher side for financially strong firms whereas all financially distressed firms have negative or lower ratios which indicate the discriminant power of the variable used. The negative or lower values average is the result of the dominant negativity of firms.

4.4.2 Tests of Equality of Group Means

The test of equality of group means estimates, whether the group means for each predictor variable, differ significantly among different groups.

Table 4.13: Tests of Equality of Group Means

	Wilks' Lambda	**F**	**df1**	**df2**	**Sig.**
NWCTA	.963	4.646	1	122	.033
RETA	.992	1.035	1	122	.311
EBITTA	.991	1.089	1	122	.299
BVOETL	.532	107.239	1	122	.000
STA	.725	46.194	1	122	.000

A p-value below 0.05 suggests significant differences between group means. The analysis shows that NWCTA $p - value = 0.033 < 0.05$suggests significant group differences. RETA has a p-value = 0.311 > 0.05 suggesting no significant group differences. EBITTA has a $p - value = 0.299 > 0.05$ no significant group differences. BVOETL has a $p - value = 0.000 < 0.05$. Strong significant group differences. STA has a $p - value = 0.000 < 0.05$ significant group differences. The F-statistics tests the null hypothesis that groups are equal. A higher F-value suggests a greater difference between groups.

4.4.3 Pooled Within-Groups Matrices

The Pooled Within-Group matrix presents the correlation between various financial metrics, indicating the strength and direction of linear relationships among them.

Table 4.14: Pooled Within-Groups Matrices

		NWCTA	**RETA**	**EBITTA**	**BVOETL**	**STA**
	NWCTA	1.000	.980	.980	.174	.099
	RETA	.980	1.000	.998	.108	.073
Correlation	EBITTA	.980	.998	1.000	.097	.081
	BVOETL	.174	.108	.097	1.000	-.444
	STA	.099	.073	.081	-.444	1.000

NWCTA is highly correlated with RETA and EBITTA (0.980 for both). BVOETL has a moderate negative correlation with sales to total assets (-0.444), indicating an inverse relationship. A STA (sale to total assets) has weak correlations with most variables except BVOETL.

4.4.4 Log Determinants

The Log Determinants table shows the logarithms of the determinants of covariance matrices for each group (distress & non-distress).

Table 4.15: Log Determinants

Z	**Rank**	**Log Determinant**
.0	5	-3.915
1.0	5	-14.058
Pooled within-groups	5	-3.166

"The ranks and natural logarithms of determinants printed are those of the group covariance matrices."

The Group 0 (financial distress) has a log determinant of -3.915. Group 1 (non-financial distress) has a log determinant of -14.058. The pooled within-groups log determinant is -3.166. The difference in log determinants (-14.058 vs -3.915) suggests noticeable variations in covariance matrices between the two groups.

4.4.5 Box's M Test

The table provides the test results of Box's M, which tests the null hypothesis that the population covariance matrix, is equal across groups.

TABLE 4.16: Box's M Test

Box's M		**466.671**
F	Approx.	29.398
	df1	15
	df2	21717.229
	Sig.	.000

Tests null hypothesis of equal population covariance matrices.

With a Box's M statistic of 466.671, an F-value of 29.398, and a significance (p-value) of 0.000, the null hypothesis is rejected, indicating that the covariance matrices significantly differ across groups.

4.4.6 Eigenvalues

Eigenvalues provide details about the performance of the discriminant functions in explaining the variance.

TABLE 4.17: Eigenvalues

Function	**Eigenvalue**	**% of Variance**	**Cumulative %**	**Canonical Correlation**
1	2.318a	100.0	100.0	.836

a. First 1 canonical discriminant function was used in the analysis.

A higher value of eigenvalues suggests the function is a strong differentiator. The percentage of variance shows the proportion of total variance explained by the function. The canonical correlation represents the strength of the relationship between the predictors and the grouping variables. There is only one discriminant function, with eigenvalues of 2.318 indicates how well the discriminant function separates the groups. Explains 100% of the variance. The canonical correlation is .836, which represents the strength of the relationship between the predictors and grouping variables.

4.4.7 Wilks' Lambda

Wilk's Lambda evaluates the statistical significance of the discriminant function and the unexplained variance of the discriminant function.

Table 4.18: Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	Df	Sig.
1	.301	143.334	5	.000

The Wilks lambda value of 0.301 indicates the proportion of variance not explained by the discriminant function. 69.9% of the variance is explained, and 30.1% remain unexplained. The chi-square value of 143.334 with 5 degrees of freedom, and a significance value of $p < 0.000$ indicates that the discriminant function is statistically significant.

4.4.8 Standardized Canonical Discriminant Function Coefficients

Standardized canonical discriminant function coefficients, show the relative importance of each predictor in differentiating between the groups.

Table 4.19: Standardized Canonical Discriminant Function Coefficients

	Function
	1
NWCTA	-.995
RETA	-1.676
EBITTA	2.526
BVOETL	1.135
STA	.924

EBITTA has the highest coefficient 2.526, indicating it is the most influential predictor in distinguishing the groups. Its strong positive value suggests a direct and substantial relationship with group membership. RETA has the second largest absolute value but its negative sign implies an inverse relationship with group membership. BVOETL variable contributes positively to group separation, though its effect is less pronounced compared to EBITTA. STA (Sales to total assets) also positively contributes to distinguishing groups but has a smaller impact relative to EBITTA and BVOETL. NWCTA has a moderate negative coefficient indicating an inverse relationship with group membership and a smaller overall contribution compared to other predictors.

4.4.9 Structure Matrix

The structure matrix presents the pooled within-group correlations between discriminating variables and the standardized canonical discriminant function. The correlations indicate the strength and direction of the relationship between a variable and the discriminant function.

TABLE 4.20: Structure Matrix

	Function
	1
BVOETL	.616
STA	.404
NWCTA	.128
EBITTA	.062
RETA	.060

"Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions Variables ordered by the absolute size of correlation within the function."

BVOETL (0.616) has the strongest correlation with the discriminant function. Sales to total assets (0.404) and NWCTA (0.128) have a weaker correlation.

EBITTA (0.062) and RETA (0.060) have the weakest correlations, indicating they contribute less to the discriminant function.

4.4.10 Canonical Discriminant Function Coefficients

Canonical discriminant function coefficient in discriminant analysis are the weights assigned to each predictor variable in the discriminant function. These coefficients determine how much each predictor contributes to separating the classes and are used to classify new observations by calculating the linear combination of predictor variables.

TABLE 4.21: Canonical Discriminant Function Coefficients

	Function
	1
NWCTA	-.327
RETA	-.541
EBITTA	.838
BVOETL	1.101
STA	1.091
(Constant)	-2.087

Table 4.20 canonical discriminant function coefficients present the unstandardized coefficients used to construct the discriminant function equation.

$D = (-0.327 * NWCTAX1) + (0.541 * RETAX2) + (.838 * EBITTAX3) + (1.101 * BVOETLX4) + (1.091 * SalestototalassetsX5) - 2.087$

BVOETL (1.101) and STA (Sales to total assets) (1.091) have the highest positive coefficients, indicating they are the most influential variables in distinguishing between the groups. RETA (-0.541) and NWCTA (-0.327) have negative coefficients, suggesting an inverse relationship with the discriminant function. EBITTA (0.838) has a smaller coefficient showing moderate influence.

4.4.11 Functions at Group Centroids

The Functions at Group Centroids table shows the unstandardized canonical discriminant function scores evaluated at the group means for two groups.

Table 4.22: Functions at Group Centroids

Z	Function 1
.0	-1.004
1.0	2.272

Unstandardized canonical discriminant functions evaluated at group means

Group 0 has a centroid of -1.004, and group 1 has a centroid of 2.272. The cut point is 0.634. The values above 0.634 are part of Group 1, and the values below 0.634 are part of Group 0. The large separation between centroids indicates that the discriminant function is effective at distinguishing between the two groups.

4.4.12 Classification Results

The Classification Results table shows the effectiveness of the canonical discriminant function in classifying cases into two groups (0 and 1).

Table 4.23: Classification Results

		Z	**Predicted Group Membership** 0	1	Total
Original	Count	0	82	4	86
		1	2	36	38
	%	0	95.3	4.7	100
		1	5.3	94.7	100
Cross-validated	Count	0	81	5	86
		1	2	36	38
	%	0	94.2	5.8	100
		1	5.3	94.7	100

a. "95.2% of originally grouped cases were correctly classified.

b. Cross-validation is done only for those cases in the analysis. In cross-validation, each case is classified by the functions derived from all cases other than that case.

c. 94.4% of cross-validated grouped cases are correctly classified"

From the original group 0 82 cases, out of 86 cases were correctly classified as 0, and 4 out of 86 cases were misclassified as group 1. Group 1 36 out of 38 cases (94.7%)

were correctly classified as group 1 and 2 out of 38 cases (5.3%) were misclassified as group 0. Overall accuracy for original data is 95.2%. Cross-validated group 0 has 81 out of 86 cases (94.2%) were correctly classified as group 0 and 5 out of 86 cases (5.8%) were misclassified as group 1. Group 1 has 36 correctly classified as Group 1 and 2 cases misclassified as Group 0. The overall accuracy of the cross-validated group is 94.4%. The model performs well with high classification accuracy and minimal misclassification.

4.5 Testing and Validation of Financial Distress for Proposed Model Using Discriminant Analysis

4.5.1 Descriptive Statistics

Descriptive statistics in discriminant analysis summarize key features of predictor variables (means, standard deviations) to assess normality, variance homogeneity, and group differences before modeling.

TABLE 4.24: Descriptive Statistics

Z		Mean	Std. Dev.
0	Operating expense ratio	1.21	0.88
	Interest expenses to operating profit ratio	-1.58	8.51
	Debt to Equity	-23.63	88.05
	Debt maturity structure	0.79	0.19
	Operating cash flow turnover	-17.41	133.64
	Reinvestment ratio	-0.40	2.46
1	Operating expense ratio	0.91	0.21
	Interest expenses to operating profit ratio	0.18	0.43
	Debt to Equity	1.14	0.89
	Debt maturity structure	0.94	0.11
	Operating cash flow turnover	1.38	12.66
	Reinvestment ratio	-0.02	2.59
Total	Operating expense ratio	1.06	0.65
	Interest expenses to operating profit ratio	-0.70	6.07
	Debt to Equity	-11.24	63.24
	Debt maturity structure	0.87	0.17
	Operating cash flow turnover	-8.02	95.00
	Reinvestment ratio	-0.21	2.53

Group Z=0 represents the first subgroup, financial distress companies and Z=1 represents the non-financial distress companies. The total represents the combines both groups. Z = 0 Higher (1.21) indicates poor efficiency in managing operating expenses. Z= 1 Lower (0.91) suggests better operational efficiency. The average operating expense ratio of 1.06 indicates that companies overall struggle with managing expenses effectively.

Interest expense to operating profit ratio Z= 0 (-1.58) reflects a negative mean indicating that decrease in financial distress. Z= 1 (0.18) indicates high debt servicing costs. The total means of -0.70 shows that overall, companies face challenges related to debt costs, particularly those in distress. Debt to Equity Z= 0 (-23.63) signals excessive leverage Z=1 (1.14) indicating a healthier capital structure. The average of -11.24 reveals a concerning level of debt relative to equity across all firms, highlighting potential risk.

Debt Maturity Structure Z= 0 (0.79) indicates a relatively balanced maturity profile. Z= 1 (0.94), suggesting stability in debt obligations. The average of 0.87 suggests that while companies are managing their debt maturities reasonably well, there is room for improvement. Operating Cash low Turnover Z= 0 (-17.41) indicates severe inefficiency in cash flow generation. Z= 1 (1.38) reflects effective cash flow management.

The overall average of -8.02 suggests significant issues with cash flow generation across all firms, particularly those in distress. Reinvestment Ratio Z = 0 (-0.40) indicates some need for reinvestment. Z= 1 (-0.02) suggests minimal reinvestment needs. The average of -0.21 shows that while there is some requirement for reinvestment, it is less pronounced in non-distressed firms.

4.5.2 Test of Equality of Group Means

The test of equality of group means assesses whether the group means for each predictor variable differ significantly among different groups.

The p-value below 0.05 implies the variable significantly discriminates between the group's operating expense ratio debt to equity and debt maturity structure. The insignificant value indicates that the groups have no difference such as Interest expense to operating profit operating cash flow turnover and reinvestment ratio. The F-statistics tests the null hypothesis that groups are equal. A higher F-value suggests a greater difference between groups.

TABLE 4.25: Test of Equality of Group Means

	Wilks' Lambda	**F**	**df1**	**df2**	**Sig.**
Operating expense ratio	.947	6.879	1	122	.010
Interest-expenses-to-operating profit ratio	.979	2.653	1	122	.106
Debt to Equity	.961	4.906	1	122	.029
Debt maturity structure	.822	26.485	1	122	.000
Operating cash flow turnover	.990	1.215	1	122	.272
Reinvestment ratio	.994	.706	1	122	.402

4.5.3 Pooled Within-Groups Matrices

The pooled Within-Group matrix presents the correlation between various financial metrics, indicating the strength and direction of linear relationships among them.

The Operating expense ratio shows a weak positive correlation with Interest expense to operating profit ratio 0.052 and Operating cash flow turnover 0.073 and a moderate positive correlation with Debt maturity structure 0.126.

It has a negligible relationship with Debt to equity -0.012 and Reinvestment ratio. Interest expense to operating profit ratio exhibits weak negative correlations with both debt maturity structure -0.069 and other metrics, indicating minimal associations overall.

The debt-to-equity ratio has a moderate negative correlation with debt maturity structure -0.108 and weak positive correlation with operating cash flow turnover 0.042 and a weak negative correlation with reinvestment ratio 0.043.

The debt maturity structure correlates positively with operating cash flow turnover of 0.087 but shows minimal association with the reinvestment ratio of 0.021.

Table 4.26: Pooled Within-Groups Matrices

		Operating expense ratio	Interest-expense-to-operating-profit	Debt to Equity	Debt maturity structure	Operating cash flow turnover	Reinvestment ratio
Correlation	Operating expense ratio	1.000	.052	-.012	.126	.073	.106
	Interest expenses to operating profit ratio	.052	1.000	-.009	-.069	-.016	-.017
	Debt to Equity	-.012	-.009	1.000	-.108	.042	-.043
	Debt maturity structure	.126	-.069	-.108	1.000	.087	.021
	Operating cash flow turnover	.073	-.016	.042	.087	1.000	-.008
	Reinvestment ratio	.106	-.017	-.043	.021	-.008	1.000

4.5.4 Log Determinants

Log determinants refer to the natural logarithm of the determinant of the covariance matrix for each group (financial distress & non-financial distress).

TABLE 4.27: Log Determinants

Z	**Rank**	**Log Determinant**
0	6	21.144
1	6	-2.892
Pooled within-groups	6	18.157

The ranks and natural logarithms of determinants printed are those of the group covariance matrices.

The table represents the log determinants of group covariance matrices. The Group Z = 0, has a log determinant is 21.144. The positive value suggests that the covariance matrix for this group is well-conditioned and indicates a relatively high volume of variability among the variables. Group Z = 1 has a log determinant is -2.892. The negative value implies that the covariance matrix may be near singular indicating potential issues with variability or multicollinearity among the variables. The pooled within-groups, log determinant are 18.157. The log determinants provide insights into the stability and condition of the covariance matrices for each group, with higher values indicating better conditioning and greater variability in the data, while negative values signal potential issues that may complicate statistical analyses.

4.5.5 Box's M test

The table provides the test results of Box's M, which tests the null hypothesis that the population covariance matrix, is equal across groups.

TABLE 4.28: Box's M test

Box's M		**1101.778**
F	Approx.	49.712
	df1	21
	df2	54743.328
	Sig.	.000

Tests null hypothesis of equal population covariance matrices.

The test statistic Box's M is 1101.778 with an F value of 49.712, degrees of freedom df1 = 21 and df2 = 54743.328, and significance level (Sig) is 0.000, indicating a statistically significant result. The significant result allows us to reject the null hypothesis suggesting that the covariance matrices are not equal across groups.

4.5.6 Eigenvalues

Eigenvalues express the strength of separation between classes based on the predictor variables. Larger eigenvalues indicate stronger discriminative power of the corresponding discriminant functions.

Table 4.29: Eigenvalues

Function	**Eigenvalue**	**% of Variance**	**Cumulative %**	**Canonical Correlation**
1	.429	100.0	100.0	.548

a. First 1 canonical discriminant functions were used in the analysis.

The results of the canonic discriminant function analysis reveal a single eigenvalue of 0.429, which accounts for 100% of the variance in the data. This indicates that all variability among the groups can be explained by this one function demonstrating its strong discriminative power.

The cumulative percentage also stands at 100%, confirming that the model captures all relevant information regarding group differences. The canonical correlation of 0.548 suggests a moderate association between the discriminant scores and group membership, indicating that this function effectively differentiates between the groups.

4.5.7 Wilks' Lambda

The Wilks' Lambda test results suggest a significant relationship between the independent variables and the group classifications in the discriminant analysis.

Table 4.30: Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	Df	Sig.
1	.700	42.501	6	.000

The reported Wilks'Lambda value of 0.700 suggests that approximately 30% of the variance in the dependent variables is explained by the difference in-group means, as lower values indicate better discrimination. The Chi-square statistic of 42.501 with 6 degrees of freedom and a significance level (P-value) of 0.000 indicates that this result is highly statistically significant. This means we can reject the null hypothesis, which posits that there are no differences between the group means across the dependent variables.

4.5.8 Standardized Canonical Discriminant Function Coefficients

The table of Standardized Canonical Discriminant Function Coefficients provides insights into the relative importance and direction of influence of various financial metrics on the discriminant function.

Table 4.31: Standardized Canonical Discriminant Function Coefficients

	Function
	1
Operating expense ratio	-.505
Interest expenses to operating profit ratio	.317
Debt to Equity	.396
Debt maturity structure	.827
Operating cash flow t urnover	.107
Reinvestment ratio	.175

Debt maturity structure has the highest positive coefficient 0.827 indicating a strong positive influence on the discriminant function, suggesting that groups with longer debt maturities are more favorably classified.

The operating expense ratio has a negative coefficient of -0.505 indicating that higher operating expenses are associated with lower discriminant scores, suggesting that groups with lower operating expense ratios are more favorable.

The Interest expense to operating profit ratio (0.317) and debt to equity (0.396) both have positive coefficients, implying that higher Interest expense to operating profit ratio and debt to equity ratios correlate with higher discriminant scores, indicating less favorable conditions for groups with increased debt obligations.

Meanwhile, operating cash flow turnover (0.107) and reinvestment ratio (0.175) contribute positively but have relatively minor impacts on the discriminant score.

4.5.9 Structure Matrix

The Structure Matrix presents the pooled within-group correlations between various financial metrics and the standardized canonical discriminant function.

TABLE 4.32: Structure Matrix

	Function
	1
Debt maturity structure	.711
Operating expense ratio	-.362
Debt to Equity	.306
Interest expenses to operating profit ratio	.225
Operating cash flow turnover	.152
Reinvestment ratio	.116

"Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions Variables ordered by the absolute size of correlation within the function."

The highest correlation is observed for debt maturity structure at 0.711, indicating it is the most significant predictor in distinguishing between groups, suggesting that longer debt maturities are strongly associated with favorable group classifications. Conversely, the operating expense ratio has a negative correlation of -0.362 implying that higher operating expenses are linked to less favorable group outcomes. Other variables such as debt to equity (0.306) and Interest expense to operating profit ratio (0.225) also show positive correlations indicating their contributions to the discriminant function but to a lesser extent. The operating cash flow turnover (0.152) and reinvestment ratio (0.116) have lower correlations suggesting they play a minor role in distinguishing between the groups.

4.5.10 Canonical Discriminant Function Coefficients

Canonical discriminant function coefficient in discriminant analysis are the weights assigned to each predictor variable in the discriminant function. These coefficients determine how much each predictor contributes to separating the classes and are used to classify new observations by calculating the linear combination of predictor variables.

Table 4.33: Canonical Discriminant Function Coefficients

	Function
	1
Operating expense ratio	-.793
Interest expenses to operating profit ratio	.053
Debt to Equity	.006
Debt maturity structure	5.238
Operating cash flow turnover	.001
Reinvestment ratio	.069
(Constant)	-3.566

Unstandardized Coefficients

The Canonical Discriminant Function Coefficients table presents the unstandardized coefficients to construct the discriminant function equation.

D = -3.566+(-0.793*Operating expense ratio) +(0.053*Interest expense to operating profit ratio) +(0.006*Debt to equity) +(5.238*Debt Maturity Structure) +(0.001*Operating Cash flow Turnover) +(0.069*Reinvestment Ratio)

Debt Maturity structure 5.238 has the highest positive coefficients including that this variable has a strong positive influence on the discriminant function.

The Operating Expense Ratio has a negative coefficient of -0.793 indicating that higher operating expenses are linked to less favorable outcomes in group classification. The coefficient for Interest expense to operating profit ratio (0.053), debt to equity (0.006), operating cash flow turnover (0.001), and reinvestment ratio (0.069) are relatively low suggesting these variables have minimal impact on the discriminant function.

The constant term of -3.566 serves as the intercept in the discriminant function equation, establishing a baseline from which the contributions of the other variables are assessed.

4.5.11 Function at Group Centroids

The Functions at Group Centroids table shows the unstandardized canonical discriminant function scores evaluated at the group means for two groups.

TABLE 4.34: Functions at Group Centroids

Z	**Function**
	1
0	-.650
1	.650

Unstandardized canonical discriminant functions evaluated at group means

Group 0 has a centroid is -0.650, while Group 1 has a centroid of 0.650. This indicates that the two groups are separated along the discriminant function, with Group 0 having a negative score and Group 1 having a positive score.

Cut of point is 0 all positive values indicate that these are part of group 1 (non-financial distress firms) if it is negative then it is part of group 0 (financial distress firms). The difference in centroids suggests that the discriminant function is effective in distinguishing between these groups, as larger differences indicate better group separability.

4.5.12 Classification Results

Classification results in discriminant analysis refer to the outcomes of the model's prediction process, where observations are assigned to specific classes based on the discriminant functions.

Table 4.35: Classification Results

		Z	Predicted Group Membership 0	1	Total
Original	Count	0	43	19	62
		1	8	54	62
	%	0	69.4	30.6	100
		1	12.9	87.1	100
Cross-validated	Count	0	41	21	62
		1	8	54	62
	%	0	66.1	33.9	100
		1	12.9	87.1	100

a.78.2% of original grouped cases were correctly classified.

b. Cross-validation is done only for those cases in the analysis. In cross-validation, each case is classified by the functions derived from all cases other than that case.

c.76.6% of cross-validated grouped cases are correctly classified.

From the original group 0 out of 62 cases, 43 were correctly classified, resulting in an accuracy of 69.4%, while 29 cases were misclassified as group 1. Group 1 the model performed better correctly classifying 54 out of 62 cases, yielding a high accuracy of 87.1% with only 8 cases misclassified. Overall, the model achieved an impressive classification accuracy of 78.2% for all original grouped cases, indicating strong performance in distinguishing between the two groups. Cross-validated group 0 saw a slight decline in accuracy to 66.1% with 41 out of 62 cases correctly classified and 21 misclassified. Group 1 maintained its accuracy at 87.1% with 54 correct classifications and only 8 misclassified cases. The overall cross-validation compared to the original classification. These results highlight the reliability of the discriminant function for predicting group membership effectively.

4.6 Comparison of Two Tests (Discriminant Analysis)

Table 4.36: Comparison of Two Tests (Discriminant Analysis)

	Z-score Model	**A-score Model**
Tests of Equality of Group Mean	NWCTA	Operating expense ratio
	BVOETA	Debt to equity
	STA	Debt maturity structure
Wilk's Lambda	.301	.700
Correct Prediction		
0	95.3%	69.4%
1	94.7%	87.1%

The Z-score model demonstrates superior discriminant ability and prediction accuracy compared to the A-score model.

Chapter 5

Conclusion and Recommendation

5.1 Altman Z-score Model

The Altman Z-score model is a valuable for evaluating the financial health of firms, particularly in differentiating between distressed and non-distressed entities. By utilizing binary logistic regression and discriminant analysis, the model effectively predicts financial distress with notable accuracy.

Key financial ratios such as NWCTA, RETA, EBITTA, BVOETL and STA are crucial in this classification process. The results from binary logistic regression show that NWCTA is statistically significant, with a p-value of 0.0002, indicating its strong predictive capability for financial distress. Conversely, RETA, EBITTA, BVOETL, and STA do not demonstrate significant predictive power, as their p-value exceed the 0.05 threshold.

The model's predictive accuracy is validated through Expectation-Prediction Evaluation, achieving an overall accuracy of 86.06%. The Hosmer-Lemeshow test supports the model's overall fit, with a p-value of 0.1580, indicating an acceptable fit. However, the Andrews statistics reveal potential misfit under certain conditions.

The discriminant function successfully distinguishes between distressed (Z=0) and non-distressed (Z=1) firms, accounting for 69.9% of the variance. The centroids for the groups are -1.004 for distressed firms and 2.272 for non-distressed firms, highlighting a clear distinction. A cutoff value of 0.634 is used, where values above

0.634 are classified as non-distressed group 1, while values below this threshold are classified as distressed group 0.

The analysis confirms that NWCTA is a significant indicator of financial distress, while EBITTA stand out as the most influential variable in differentaiting between distressed and non-distressed firms. Overall, the model exhibits a predictive accuracy of 76.74% for distressed cases and 97.37% for non-distressed cases. Previous studies Junior and Bangun (2024) and Almamy et al. (2015) show the same results.

5.2 Proposed Model

The proposed model for predicting financial distress demonstrates a solid analytical framework, using binary logistics regression and discriminant analysis. This approach highlights essential financial factors that influence distress, providing deeper insight into firm-specific financial health. With strong predictive capabilities and significant classification accuracy, this model is a beneficial tool for stakeholders, including investors, regulators, and financial analytics, in evaluating a firm's risk profile.

Binary Logistic Regression was utilized to analyze the model's performance in distinguishing between distressed and non-distressed firms, revealing that predictors such as Debt-to-Equity ratio, Operating Cash Flow turnover, and Reinvestment ratio are crucial in forecasting financial health. The expectation prediction evaluation indicates a remarkable predictive accuracy of 98.39%, with the model successfully classifying 61 out of 62 cases across both financial distress and non-financial distress categories, demonstrating its effectiveness. The Discriminant Analysis further confirms the model's efficiency in differentiating between financially stable and distressed firms. Variables like Debt Maturity structure, Operating Cash Flow Turnover, and Debt-to-Equity ratio showed significance statistical relevance, with the standardized coefficient highlighting Debt Maturity Structure as the most impactful predictor. The cut-off point for this proposed model is 0. If the A-score is above 0 means companies are financially stable, and the if A-score is less than 0 means companies face financial distress. The model achieved 78.2% accuracy in original classification and 76.6% accuracy in cross-validation. This proposed model illustrates its relevance within the context of Pakistan's stock market, addressing the need for a local framework for predicting financial distress. By incorporating country-specific factors such as Debt Maturity Structure and reinvestment, the model's precision is enhanced. These findings pave the way for future researchers to refine and enhance the model, ultimately providing a more potent tool for financial analysis and decision-making.

5.3 Implementation and Recommendations

This study recommended that researchers and practitioners collaborate to design a predictive model tailored to the Pakistani market, incorporating factors such as debt to equity, operating cash flow turnover, and reinvestment ratio which are highly significant in affecting the likelihood of financial distress in the sample of this study.

The study also recommends factors such as the operating expense ratio, Interest expense to operating profit ratio, and debt maturity structure to better assess financial risk and predict potential distress. Policymakers should also encourage transparency in financial reporting to improve data reliability for such models.

Developing a Pakistan-specific model not only enhances the accuracy of financial distress prediction but also contributes to the stability and growth of the nation's financial markets ultimately fostering investor confidence and economic development. The results of Logit analysis indicate that the A-score model performs better as compared to the Z-score model.

The decision maker should consider the debt-to-equity operating cash flow turnover reinvestment ratio for the prediction of financial distress in the Pakistani equity market.

In Discriminant analysis, the Z-score is better in identifying financial distress as compared to the A-score model. The variables to be considered are NWCTA, BVOETL, and STA.

The highest accuracy is observed in the case of the A-score model based on logit analysis therefore, it is recommended.

5.4 Limitations

This study provided valuable insights, but the scope was limited to listed companies and certain financial variables. Future research could expand on these findings by including unlisted firms or macroeconomic factors.

References

Abdullah, M., Mirosea, N., Aswati, W. O., & Santi, N. (2023). Analysis of financial ratios to predict financial distress conditions of manufacturing companies listed on the indonesian stock exchange. *International Journal of Professional Business Review*, *8*(7), 03156. doi: 10.26668/businessreview/2023.v8i7.3156

Ahmad, I., Ali, Z., & Usman, M. (2018). Predicting corporate financial distress: The case of pakistan. *Global Social Sciences Review*, *3*(3), 488–503.

Almamy, J., Aston, J., & Ngwa, L. N. (2015). An evaluation of altman's z-score using cash flow ratio to predict corporate failure amid the recent financial crisis: Evidence from the uk. *Journal of Corporate Finance*, *36*, 278–285. doi: 10.1016/j.jcorpfin.2015.12.009

Al-Manaseer, S., & Al-Oshaibat, S. (2018). Validity of altman z-score model to predict financial failure: Evidence from jordan. *International Journal of Economics and Finance*, *10*(8), 181. doi: 10.5539/ijef.v10n8p181

Asif, M., Saxena, A., Padmaja, S. B., Tiwari, S., & Chaturvedi, S. (2024). A study of altman z-score bankruptcy model for assessing bankruptcy risk of national stock exchange-listed companies. In *Proceedings on engineering sciences* (Vol. 6, pp. 789–806). doi: 10.24874/pes06.02a.006

Azizah, N., & Ramli, A. (2023). Analysis of financial distress in companies threaten to delisting on the indonesia stock exchange using the altman z-score model. *Journal Management & Economics Review (JUMPER)*, *1*(2), 65–74.

Balasubramanian, S. A., GS, R., P, S., & Natarajan, T. (2019). Modeling corporate financial distress using financial and non-financial variables: The case of indian listed companies. *International Journal of Law and Management*, *61*(3/4), 457–484.

Dirman, A. (2020). Financial distress: the impacts of profitability, liquidity, leverage, firm size, and free cash flow. *International Journal of Business, Economics and Law*, *22*(1), 17–25.

Elewa, M. M. (2022). Using altman z-score models for predicting financial distress for companies–the case of egypt panel data analysis. *Alexandria Journal of Accounting Research*, *6*(1), 1–28.

Elia, J., Toros, E., & Sawaya, C. (2021). Using altman z"-score to predict financial distress: Evidence from lebanese alpha banks. *Management Studies and Economic Systems*, *6*(1–2), 47–57. doi: 10.12816/0059150

Fitriyah, E. M. A., & Prasasti, K. B. (2025). Financial distress using the zmijewski, grover, and springate models at retail business in indonesia. *Jurnal Cendekia Keuangan*, *4*(1), 38–45.

Hanafi, A. H. A., Md-Rus, R., & Mohd, K. N. T. (2021). Predicting financial distress in the malaysian market: Hazard model versus the logit model. *Advanced International Journal of Banking Accounting and Finance*, *3*(7), 01–19. doi: 10.35631/aijbaf.37001

Hiong, H. K., Jalil, M. F., & Seng, A. T. H. (2021). Estimation and prediction of financial distress: Non-financial firms in bursa malaysia. *Journal of Asian Finance Economics and Business*, *8*(8), 1–12. doi: 10.13106/jafeb.2021.vol8.no8.0001

Hoepner, A., Oikonomou, I., Scholtens, B., & Schröder, M. (2016). The effects of corporate and country sustainability characteristics on the cost of debt: an international investigation. *Journal of Business Finance & Accounting*, *43*(1–2), 158–190. doi: 10.1111/jbfa.12183

Hussain, F. (2014). Can altman z-score model predict business failures in pakistan? "evidence from textile companies of pakistan.". *Journal of Economics and Sustainable Development*, *5*(13), 110–115.

Ijaz, M. S., Hunjra, A. I., Hameed, Z., Maqbool, A., & Azam, R. I. (2013). Assessing the financial failure using z-score and current ratio: a case of sugar sector listed companies of karachi stock exchange. *MPRA Paper*.

Isayas, Y. N. (2021). Financial distress and its determinants: Evidence from insurance companies in ethiopia. *Cogent Business & Management*, *8*(1).

doi: 10.1080/23311975.2021.1951110

Junior, R., & Bangun, N. (2024). Pengaruh profitability, working capital dan free cash flow terhadap financial distress pada perusahaan manufaktur yang terdaftar di bursa efek indonesia period 2018-2020. *Jurnal Paradigma Akuntansi*, *6*(1), 46–52. doi: 10.24912/jpa.v6i1.28536

Kalash, I. (2023). The financial leverage–financial performance relationship in the emerging market of turkey: the role of financial distress risk and currency crisis. *EuroMed Journal of Business*, *18*(1), 1–20.

Kamaluddin, A., Ishak, N., & Mohammed, N. F. (2019). Financial distress prediction through cash flow ratios analysis. *International Journal of Financial Research*, *10*(3), 63. doi: 10.5430/ijfr.v10n3p63

Kamran, M., & Saleem, H. M. N. (2023). Financial indicators and corporate financial distress prediction in context of pakistan: A systemic review. *Annals of Social Sciences and Perspective*, *4*(2), 555–561.

Karlina, N., & Rahman, R. S. (2023). The effect of liquidity and profitability on the level of financial distress using the altman z-score model: Study of companies in the automotive sector and components listed on the indonesia stock exchange for the 2015-2020 period. *Jurnal Computech & Bisnis (e-Journal)*, *17*(1), 59–66.

Khan, Q. U. K. N. (2015). Financial performance of manufacturing firms of pakistan using the z-score model (listed firms on karachi stock exchange). *International Journal of Law and Policy*, *12*, 117–130.

Khawaja, M. J. (2023). Predicting financial failure using altman's z-score model: evidence from commercialbanks in pakistan. *Annals of Social Sciences and Perspective*, *4*(1), 91–102.

Koech, E. C. (2018). *Prediction of financial distress in light of financial crisis: A case of listed firms in kenya.*

Kumar, J., Kumar, V., Verma, D., & Sharma, S. (2021). Prediction of corporate bankruptcy based on financial ratios using binary logistic regression. *International Journal of Statistics and Reliability Engineering*, *7*(3), 376–381.

Lee, N. B., & Lee, N. S. (2018). A study on financial ratio and prediction of financial distress in financial markets. *Journal of Distribution Science*, *16*(11), 21–27. doi: 10.15722/jds.16.11.201811.21

Lumbantobing, R. (2020, April). The effect of financial ratios on the possibility of financial distress in selected manufacturing companies which listed in indonesia stock exchange. In *6th annual international conference on management research (aicmar 2019)* (pp. 60–63). Atlantis Press.

Majumder, B. I., & Moonmoon, S. F. (2020). Predicting financial distress of the islamic banking sector of bangladesh. *Journal of Banking & Financial Services*, *12*(2).

Malakauskas, A., & Lakštutienė, A. (2021). Financial distress prediction for small and medium enterprises using machine learning techniques. *Engineering Economics*, *32*(1), 4–14. doi: 10.5755/j01.ee.32.1.27382

Manh, P. T., & Nguyen, H. V. (2024). Applying the z-score model to predict corporate financial distress: An empirical research on the listed firms in vietnam stock market. *Oblik I Finansi*, *1*(103), 38–48. doi: 10.33146/2307-9878-2024-1(103)-38-48

Mehmood, A., & De Luca, F. (2023). Financial distress prediction in private firms: developing a model for troubled debt restructuring. *Journal of Applied Accounting Research*. doi: 10.1108/jaar-12-2022-0325

Muien, H., Nordin, S., & Badru, B. (2022). The impact of financial and macroeconomic variables on financial distress: Evidence from pakistani market. *Pakistan Journal of Humanities and Social Sciences Research*, 129–146. doi: 10.37605/pjhssr.v5i1.368

Pindado, J., & Rodrigues, L. (2005). Determinants of financial distress costs. *Financial Markets and Portfolio Management*, *19*(4), 343–359. doi: 10.1007/s11408-005-6456-4

Pradhan, R. S., Shrestha, M., Manandhar, K., & Poudel, R. (2002). Financial distress, financial ratios, and stakeholder losses in corporate restructuring: a case of nepal. *SSRN Electronic Journal*. doi: 10.2139/ssrn.2793487

Putri, P. A. D. W. (2021). The effect of operating cash flows, sales growth, and operating capacity in predicting financial distress. *International Journal of Innovative Science and Research Technology*, *6*(1), 638–646.

Rahman, M. R., Rahman, M. M., & Subat, A. (2020). Measuring financial distress of non-bank financial institutions of bangladesh using altman's z-score model. *International Business Education Journal*, *13*, 15–28. doi: 10.37134/ibej.vol13.sp.2.2020

Rashid, A., & Abbas, Q. (2011). Predicting bankruptcy in pakistan. *DOAJ (DOAJ: Directory of Open Access Journals)*.

Restianti, T., & Agustina, L. (2018). The effect of financial ratios on financial distress conditions in sub-industrial sector companies. *Accounting Analysis Journal*, *7*(1), 25–33. doi: 10.15294/aaj.v7i1.18996

Rohim, A., Sandy, W. T., Ramadhan, A. H. A., & Hidayat, A. T. (2024). Bankruptcy analysis using the altman z-score model (study on retail companies listed on the indonesia stock exchange). *Journal of Economics Finance and Management Studies*, *07*(09), 5495–5503. doi: 10.47191/jefms/v7-i9-03

Sareen, A., & Sharma, S. (2021). Assessing financial distress and predicting stock prices of automotive sector: Robustness of altman z-score. *Vision the Journal of Business Perspective*, *26*(1), 11–24. doi: 10.1177/0972262921990923

Say, S. (2024). Determining financial distress with the help the altman z-score model. *Toplum Ekonomi ve Yönetim Dergisi*, *5*(2), 327–341.

Shaheen, S., Hussain, B., & Bhatti, A. A. (2021). Cash flow volatility and debt maturity structure: Role of macroeconomic factors. *Business & Economic Review*, *13*(3), 85–116. doi: 10.22547/ber/12.3.4

Singh, G., & Singla, R. (2019). Corporate bankruptcy prediction using altman z-score model: The effect of time and methodology on accuracy of the model. *Journal of Academic Research in Economics*, *11*(1), 58–71.

Singh, G., & Singla, R. (2024). Logit model for predicting financial distress in indian corporate sector. *International Journal of Business and Globalisation*, *37*(4), 516–534. doi: 10.1504/ijbg.2024.140052

Soni, R. (2019). Application of discriminant analysis to diagnose the financial distress. *Theoretical Economics Letters*, *09*(04), 1197–1209. doi: 10.4236/tel.

Suntraruk, P. (2009). Predicting financial distress: Evidence from thailand. In *Proceedings of the european financial management association 2009 annual meeting. milan, italy, june (24-27)*.

Supriyanto, J., & Darmawan, A. (2018). The effect of financial ratio on financial distress in predicting bankruptcy. *Journal of Applied Managerial Accounting*, *2*(1), 110–120. doi: 10.30871/jama.v2i1.727

Tinoco, M. H., & Wilson, N. (2013). Financial distress and bankruptcy prediction among listed companies using accounting, market and macroeconomic variables. *International Review of Financial Analysis*, *30*, 394–419. doi: 10.1016/j.irfa.2013.02.013

Toly, A. A., Permatasari, R., & Wiranata, E. (2019). *The effect of financial ratio (altman z-score) on financial distress prediction in the manufacturing sector in indonesia 2016-2018* (Unpublished doctoral dissertation). Petra Christian University.

Ullah, I. R. F. A. N., Shah, S. M., Khan, M. N., & Ali, M. D. (2023). Impact of corporate social responsibility on financial distress, a case of non-financial listed firms in pakistan. *International Review of Basic and Applied Sciences*, *11*(2), 319–331.

Utami, D. W., Atmaja, H. E., & Hirawati, H. (2021). The role of financial ratios on the financial distress prediction. *Kinerja*, *25*(2), 287–307. doi: 10.24002/kinerja.v25i2.4661

Waqas, H., & Md-Rus, R. (2018). Predicting financial distress: Importance of accounting and firm-specific market variables for pakistan's listed firms. *Cogent Economics Finance*, *6*(1), 1545739. doi: 10.1080/23322039.2018.1545739