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Deduction of Earning Manipulation in the Pakistani Equity Market

by

Jawairia Zahidi

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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

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by

Jawairia Zahidi

(MAF231009)

THESIS EXAMINING COMMITTEE

S. No.	Examiner	Name	Organization
(a)	External Examiner	Dr. Tahira Awan	IIU, Islamabad
(b)	Internal Examiner	Dr. Zeeshan Ahmed	CUST, Islamabad
(c)	Supervisor	Dr. Arshad Hassan	CUST, Islamabad

Dr. Arshad Hassan
Thesis Supervisor
April, 2025

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

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

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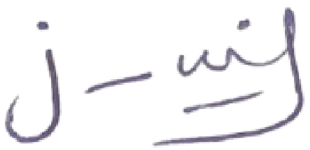

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Abstract

The purpose of the study is to provide insights into the non-financial sectors of Pakistan that are engaged in earning manipulation, and to assess the validity of Beneish M score model in the Pakistan Equity market. The sample size consists of 74 non-financial companies across 12 sectors from 2020 to 2023. The logistic analysis and discriminant analysis were used to determine the manipulators and non-manipulators based on the Beneish M-Score model and the proposed model. The results of the logistic analysis showed that 131 observations were found as manipulators and 91 observations were non-manipulators. The model achieved an overall accuracy of 90.54%. Discriminant analysis of the Beneish M-Score model showed an overall accuracy of 96.8%. Beneish model showed that the Days Sales in Receivable Index, Gross Margin Index, Sales Growth Index, Asset Quality Index and Total Assets to Total Accruals positively and significantly influence the earning manipulation while the Selling General and Administrative Expenses and Leverage Index negatively influence the earning manipulation.

The manipulators and non-manipulators for the proposed model based on the practitioner's warning signs are estimated by using Beneish Model and then tested through logit and discriminant analysis. The Proposed model J score showed an accuracy of 82.43%. The common variables Gross Margin Index, Sales Growth Index, and Total Assets to Total Accruals are significant and one additional variable FFA (Frequent Financing Activity) that was not the part of Beneish model is significant. The study concludes that the Beneish Model is more effective in identifying the manipulator and non-manipulator firms than the proposed model. However, Frequent Financing Activity should also be considered for examining the earnings manipulation.

Keywords: Earning Manipulation, Beneish M-Score Model, Proposed Model, Logistic Analysis, Discriminant Analysis

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Abbreviations

AQI	Asset Quality Index
DEPI	Depreciation Index
DMI	Debt Maturity Index
DSRI	Days' Sales in Receivable Index
FFA	Frequent Financing Activity
GMI	Gross Margin Index
INV	Inventory
LVGI	Leverage Index
NOESGR	Non-Operating Expense to Sale Growth Rate
OCF	Operating Cash Flow
SGAI	Selling and General Administration Expenses Index
SGI	Sales Growth Index
TATA	Total Accruals to Total Assets

Chapter 1

Introduction

1.1 Theoretical Background

Managers use Earnings manipulation to present a more favorable financial statement to achieve the predetermined financial targets and mislead investors (karimi, 2021). Beneish (1999) defined a "typical earnings manipulator" as a business that is growing rapidly as indicated by particularly high year over year sales, facing rapidly declining fundamentals by declining in asset quality, declining profit margin, and raising leverage and implementing aggressive accounting techniques such as growth in receivable higher than the sales, accruals that immensely inflate the earning and a reduction in depreciation expenses (Beneish, Lee, & Nichols, 2012). Earning manipulation is a questionable practice of managers in financial reporting aimed at securing personal benefits (Saleem, Shahzad, & Ahmed, 2024). Both small and large firms are involved in this practice.

Financial statement fraud is when management intentionally falsifies financial reports in a way that harms investors and creditors by providing misleading or inaccurate information (Elliott & Willingham, 1980). A crucial aspect of addressing earning manipulation is the identification of "red flags". Red flags include situational pressures like sudden drops in revenue, loss of market share, or unrealistic budget targets. These pressures significantly increase the likelihood of financial statement fraud (Koornhof & Du Plessis, 2000). Common examples of red flags include unusual accounting discrepancies, illogical financial relationships, unexplained or odd transactions, or changes in personal behavior (Elsayed, 2017).

Theoretical frameworks such as Agency theory and Signaling theory provide valuable insights into the motivations behind earning manipulation. Conflict of interest is discussed under the agency theory proposed by Jensen & Mackling in 1976. The first type of conflict of interest arises when the directors are not the right holder of the net asset of the company, while the other type of conflict of interest is among the stockholder and creditors because the creditors have a first right to the assets in case of bankruptcy (Talab, Flayyih, & Ali, 2017). According to Akileng (2014), managers have more information about the company's operation, and finances than the shareholders, they can change the earnings by delaying in recognition of expenses or inflating revenues to gain short-term goals and bonuses.

Michael Spence originally proposed the Signaling theory in 1973 in his seminal work on economic labor in which he incorporated information asymmetry into the financial decision model (Bergh, Connelly, Ketchen, & Shannon, 2014). The company information is revealed to the public through financial statements management has information or signals so there is no information asymmetry issue (Narsa, Afifa, & Wardhaningrum, 2023). Investor uses that information in the decision-making process, and when companies are involved in earning manipulation they send misleading signals such as overstated revenues or understated expenses. By maintaining a consistent pattern of growth and earning they communicate their future expectation, which can impact the stock prices (Yimenu & Surur, 2019).

Globally, earning manipulation has been the subject of extensive research. For instance, studies have shown that firms across various countries engage in earning manipulation to meet or exceed analysts' forecasts, which can lead to significant financial scandals and loss of investor confidence (Svabova, 2021). Earning manipulation has a significant impact on the entire market it not solely affect the individual firm. History highlights the global accounting scandals such as WorldCom, Enron, and Parmalat. These issues highlighted the need for corporate governance to protect the interests of investors (Ball, 2009). Saleem et al. (2024) study highlighted that approximately 46% of non-financial companies that are registered on the Pakistan Stock Exchange are involved in earning manipulation, indicating a serious risk to market reliability.

Additionally, the incidence of earning manipulation is further complicated by the unique characteristics of Pakistani companies; due to different motivations and behaviors regarding financial statements the family-owned business has a greater chance to be involved in earning manipulation compared to non-affiliated companies (Khan & Kamal, 2022).

Beneish M-score model is a widely recognized tool for detecting earning manipulation this study employs this model. In 1999, Beneish Messod proposed a mathematical model called Beneish M score model to detect the earning manipulations of companies (Valaskova & Fedorko, 2021). Beneish M score model is one of the most well-known frameworks for identifying earning manipulation it creates a systematic relationship between the specific accrual and the manipulation (Svabova, Kramarova, Chutka, & Strakova, 2020).

1.2 Gap Analysis

Due to conflict of interest managers tend to lean towards earning manipulation whether it is a small or large company. Therefore, the financial information that is reported through financial statements may not necessarily present a true picture of the business. Instead, it often reflects the image that managers want to present to the market. Various pressures such as meeting targets or staying aligned with industry competitors can compel managers to be involved in earning manipulation.

The Beneish Model is one of the models used for the detection of earning manipulation across the globe. The same model has been tested in Pakistan and found the affectivity of the model in finding manipulator and non-manipulator companies (Siddiqui & Ahmed, 2020). However, to measure earnings management we have several models such as the Jones, Dechow-Dichev model, Modified Jones Model, and Kothari's model (Talab et al., 2017). Currently, there is no specific model to detect earnings manipulation in Pakistan, nor can we confidently say how effective a particular model is. Globally, the Beneish model is effectively used to detect earning manipulation, but in Pakistan, it is not tailored to Pakistan's unique regulatory, economic, and corporate governance landscape potentially reducing the effectiveness of the model. Developing a country-specific model for earning manipulation detection in Pakistan could significantly enhance the effectiveness of identifying fraudulent financial reporting. In Pakistan no model is specifically designed or tested for the Pakistani market, leaving a gap in tools for the detection of earning manipulation effectively.

Only the Beneish model is used to identify the earning manipulation, but the robustness of the result has not been tested by using an alternative model; at the same time, this model has certain effects that are not covered. This study tests the Beneish M score and confirms the relation and robustness of the model. It examines the attributes that create red flags in the financial market using discriminant analysis and logit analysis.

Beneish M score model explores the 8 variables but ignores some important attributes this study will use that ignored variable and proposed a new model. The variables used in the proposed model are derived from the red flag in financial statements, they are; gross margin index, sales growth index, total accruals to total asset, inventory index, debt maturity index, negative operating cash flow, frequent financing activity, and non-operating expense to sales growth ratio.

1.3 Problem Statement

Earning manipulation remains a pervasive issue within the Pakistan Stock Exchange (PSX), significantly impacting the integration of financial reporting and investor confidence. The earning manipulation not only misleads investors but also undermines the overall stability of the financial market, leading to increased cost of capital and reduced foreign investment (Ilyas, Khan, & Khan, 2019). The primary focus of this study is to examine whether companies in the non-financial sector of Pakistan engage in earning manipulation when preparing their financial statements, utilizing the Beneish model as a diagnostic tool. Although the Beneish M score model is effective in detecting earning manipulation globally; it is less adopted by non-financial sector of Pakistan. Due to this, it creates significant challenges for investors who require reliable information regarding the investment market. The absence of a robust framework to identify the earning manipulation harms the transparency of financial reporting.

In this study, the Beneish M score model is used to find insights to help investors and decision-makers identify possible earnings manipulation. Therefore, the goal of this research is to develop a comprehensive model employing to currently used earnings manipulation indicators in Pakistan equity market for detecting earnings manipulation.

1.4 Research Question

1 Do non-financial sectors listed on the Pakistan stock exchange engage in earnings manipulation?

2 Do the Beneish M score model valid for detecting earnings manipulation in Pakistan's non-financial sectors?

3 Do predictive model have the potential to detect earnings manipulation in Pakistan's non-financial sectors effectively?

1.5 Purpose of the Study

1 To provide insight about the non-financial sector of Pakistan equity market engaged in earning manipulation.

2 To explore the validity of the Beneish M score model for detecting Pakistan's non-financial sector.

3 To propose an appropriate model for detecting earning manipulation in Pakistan.

1.6 Significance of Study

For several important stakeholders, including lenders, investors, administration, and legislators, this study is extremely important:

1.6.1 Investors

To make a prudent financial choice that minimizes possible risk and maximizes profits, investors need accurate and reliable information. According to the study, transparent financial reporting is essential for building investors' confidence. Investors can more accurately evaluate the accuracy of financial statements and spot any earning manipulation by applying the Beneish model, which will ultimately help them make more informed investment decisions.

1.6.2 Administration

Transparent financial reporting benefits company management by fostering stronger bonds with investors, fostering trust, and possibly increasing market value. The study recommends that management use the Beneish model as a tool to detect instances of earning manipulation in their companies. Management can improve internal control and corporate governance by recognizing and combating manipulative practices. This will help them avoid actions that might cause the stakeholders to lose faith in them.

1.6.3 Policymakers

Policymakers and regulatory agencies can use this study to prioritize audits and investigations, focusing resources on companies that pose a greater risk of manipulation. The Beneish model's proactive approach not only improves the effectiveness of regulatory oversight but also helps to create a more stable financial environment.

1.6.4 Lenders

Lenders rely on accurate financial information to determine a company's creditworthiness, and this study helps lenders mitigate credit risk by offering insights into potential earnings manipulation practices. By knowing how earning manipulation affects financial statements, lenders can make better lending decisions and lower the chance of default.

1.7 Plan of Study

This research is structured into five parts. Overview of the topic, Theoretical Background, Gap of the Research, Problem Statement, Research Questions, Purpose of the Study, and Importance of the study are covered in the first chapter. Literature reviews of all available empirical studies related to the topic of research to develop a hypothesis are included in the second chapter of the study. The third portion of this study consists of information on variables, data, and time-frequency of the study, and econometric models. The econometric models used in this study are Logistic analysis and Discriminant analysis. Chapter fourth discusses the results of econometric models. Chapter five of this research provides information on the conclusion of the results and recommendations.

Chapter 2

Literature Review

2.1 Literature

According to Mollah and Sakib (2020), accounting frauds has a great substantial impact on the financial reporting of the companies. This research explores the efficiency of the Beneish model in detecting earning manipulation in Pharmaceutical companies in Bangladesh. The conflict of interest between the managers and stockholders that leads to earning manipulation is defined under the agency theory. This study finds that the Bangladeshi pharmaceutical companies are involved in accounting fraud.

Hołda (2020) after the 2008 crisis of false representation of financial statements, the recipients paid more attention to details. Thus scientific research pays more attention to the models that are used to detect accounting frauds. This research determines the fundamentals of the Beneish model operation and its use to polish realities. He Pick up the 30 companies from the Warsaw stock exchange that are involved in earning manipulation and the same figure of companies that are not involved in the earning manipulation. The result showed the 100% accuracy of the Beneish M score and success in the identification of non-manipulated companies. Like other numerous authors of studies from various countries, this study's results showed the efficiency of the Beneish model in finding financial fraud.

Talab et al. (2017) state the quality of financial reporting among Iraqi-listed companies influenced by earning management. The earning manipulation behavior of companies is identified by using the Beneish model. The study used 23 banks for the year 2014-2015 and showed the extensive manipulation of profit. The study advises using international audit quality to reduce such practices. Overall the M score model is considered effective in reducing the earning manipulation and safeguarding the investor interest.

Financial statements are meant to present accurate financial information to stakeholders for better investment decisions. Recently professional fraud has increased that leads to financial statement manipulation. The research aims to use the Beneish model to identify the firms that are involved in earning manipulation. The study chooses the companies from Istanbul Bursa (BIST 50) that were regularly listed for the period 2015, 2016 and 2017. The results showed a positive correlation between the variables like Asset Quality index and the sales, General and Administrative expenses, and the probability of financial information manipulation (Erdoğan & Erdoğan, 2020).

Tarjo and Herawati (2015) the study examined the efficiency of the Beneish model in fraud detection using the data from businesses that the financial service authority's database indicates were deceptive between 2001 and 2014. The outcome shows that the overall Beneish model helps identify fraud. The strong indicators of fraud include the total accruals depreciation index, gross profit index, selling, and administrative index, while the leverage, sales index, and asset quality index did not show potential in fraud detection.

Narsa et al. (2023) the variable that can contribute to earning manipulation this paper combines the fraud triangle theory with a modified Beenish M score. Four new ratios are added with five original ones of Modified Beneish M score. The study used the sample size of 284 manufacturing companies that were registered on the Indonesia equity market in the period 2017 and 2019. The study explores that the logistic regression and t-test to prove that the total debt has a positive relation with earning manipulation while asset growth, change in receivable relative to sale, and auditor change have a negative relation with earning management. Meanwhile, there is no connection between earning management and return on assets. The study suggests that the businesses that engage in manipulation have fewer independent commissioners and face larger pressure from leverage.

Svabova et al. (2020) conducted a study in Slovakia the determination of the research is to create a discriminant model that will identify the firms that are involved in earning manipulation in Slovakia's economy. Using the real data of the firms that were involved in accounting fraud in connection to tax fraud from 2009 to 2018. Using the three-year consecutive data from 2016 to 2019 helped in identifying the trend in the company's tendency for opportunistic earning manipulation. The study concludes that 32.7% of companies are involved in earning manipulation and 38.4% are non-manipulators. A high probability of earning manipulation is implied when a company is consistently marked as fraudulent.

Due to recent real-world accounting scandals of large corporations, the term corporate governance is created to protect the investors' interest. Corporate governance plays a crucial role in detecting earning manipulation. The board of directors must protect the investors' interest and make decisions for the wealth maximization. Due to internal control and regular audits corporate governance aids fraud detection meanwhile, the research explores the link between the independent board and earning management by using the Beneish Model. The study used the 372 companies registered in the Malaysian Equity Market from 2010-2013. This study concludes that board independence has a negative and significant relationship with earnings manipulation, and finds that the higher number of independent board reduce the tendency of earning manipulation (Busirin, Azmi, & Zakaria, 2015).

The study conducted in Pakistan chose two groups one is manipulator companies and the other one is non-manipulator companies. He chooses the 10 samples of 100 companies registered in the Pakistan stock exchange PSX 100 and data collected from financial reports of the companies from 2014 to 2019. To determine the Beenish model, used the criteria -2.22 if the M score is greater than -2.22 companies are involved in manipulation and if the M score is less than -2.22 then the companies are not engaged in earning manipulation. The study concludes that 30% of firms are manipulators and the indicators are the asset quality index and gross margin index (Siddiqui & Ahmed, 2020).

Halilbegovic, Celebic, Cero, Buljubasic, and Mekic (2020) conducted this study in Bosnia and Herzegovina, to check the efficiency of the Beneish M score model at small and medium-size companies. The study used a representative part of the population of 4,580 small and medium-sized companies. The study finds the overall applicability and affectivity of the Beneish model on the market of FBiH.

Kamal, Salleh, and Ahmad (2016) states that the Beneish model is one tool to identify financial reporting fraud and earnings manipulation. Its effectiveness has been demonstrated by the discovery of 71% of significant frauds before public disclosure and 76% of companies engaged in earnings manipulation in the United States. This study evaluates the model's accuracy in detecting fraud in Malaysian publicly traded companies. The model correctly detected manipulation in 82% of cases when it was examined. The results validate the model's application by business management to identify anomalies before filing reports to Bursa Malaysia, thereby reducing the risk to the company's reputation.

This study was conducted in BRICS countries, determining the extent to which the financial reporting can be trusted by stakeholders. The financial statement tells the financial performance and position of the business, but how much can we trust it? This question revolves around the concept of earning quality, which encompasses two aspects: earning management and earning manipulation. In this study discretionary accruals are used as a measure for earning manipulation, while non-discretionary accruals as an alternative for earnings management. Secondary data from BRIC countries are used in this study. The Modified Jones Model is used to evaluate the earning management and earning manipulation for each country. The findings of the study provide strong evidence about those companies that are engaged in earnings management and earnings manipulation in BRICS nation. However, in the case of Russia, the model failed to detect significant earning manipulation. One possible reason behind this failure is the limited availability of the data from Russian companies, which do not adhere to IFRS or GAAP, but rather follow their GAAPs. This study is significant for auditors, financial statement users, and accounting standard-setting bodies like IASB and GAAP organizations, suggesting that they should minimize the role of discretionary accruals (Shahzad, 2016).

The paper discussed earnings management among Vietnamese companies registered on the Hochiminh Stock Exchange (HOSE) during the years 2013-2014, using the Beneish model to detect such behaviors. Earnings manipulation refers to the significant practice used by the management to present a favorable financial picture, achieve short-term goals, or mislead investors. This phenomenon has been widely studied in developed economies while its identification in growing companies like Vietnam has been less explored. The study aims to detect earning manipulation among the registered companies of Vietnam. By using the set ratios of the Beneish model researcher identifies that 84.4% of companies are involved in earning manipulation. The results demonstrate that in the Vietnam market, the Beneish model is effective in identifying the manipulator companies (Nguyen & Nguyen, 2016).

The study by Husnurrosyidah and Fatihah (2022) investigated how well the two fraud detection methods the Beneish model and F score identify the financial statement fraud in registered firms of Jakarta Islamic Index. The study is descriptive and quantitative, focusing on assessing the accuracy of these methods and their common error in fraud detection. The study found that the Beneish model is more effective in detecting fraud in selected companies. According to the research, the Beneish model is more reliable in fraud detection. The result emphasizes how well the fraud detection technique improves reporting integrity, which in turn, can protect investors and stakeholders from financial misstatements and fraudulent activities.

Wang, Ye, Wang, and Wang (2023) investigate the link among management earning manipulation and the similarity of management discussion and analysis. The study used the representative of 13,679 Chinese A-share registered companies over 12 years from 2008 to 2020 and demonstrated how earning manipulation can influence the content of management discussion and analysis in a company report. The study concludes that the management makes MD&A sections to manipulate the earnings. Managers may influence the profit to accomplish personal goals due to agency problems. This behavior can distort the affectivity of reliable information and it difficult for investors to make decisions. Ratmono, Darsono, and Cahyonowati (2020) a study conducted in Indonesia examines the score models in detecting financial statement fraud trends. It adds to the body of research on financial statement fraud. It provides practical evidence on factors that encourage fraud in financial reporting and highlights important insights into the mechanisms behind fraudulent behavior in companies. The analysis using the F-score and M-score models identified 284 firms out of 385 observation samples as potentially involved in fraudulent financial reporting; these models flagged a significant number of companies, indicating the need for additional investigation.

Irwandi, Ghozali, Faisal, and Pamungkas (2019) The study investigates the relationship between audit opinion, industry nature, financial stability, and fraudulent financial reporting with a moderating role of real earning management. The study conducted in Indonesia chose the manufacturing companies listed in the Indonesia Equity Market from the period 2013-2017 and found that financial stability has a significant impact on the likelihood of fraudulent financial reporting. By using SPSS path analysis research found that the industry plays a crucial role in earning manipulation. While the audit estimation has no significant impact on fraudulent financial reporting, meaning that companies may still engage in financial manipulation regardless of the auditor's opinion. The moderating impact of real earning management has a significant impact indicating that companies use real earning management to inflate the revenues.

Beneish (1999) study the main goal is to create a model that can identify earnings manipulation by analyzing a sample of businesses that participate in it. By concentrating on financial statement variables that either directly imply manipulation or otherwise, the model seeks to determine the distinctive features of these businesses. There are 1708 controls and 50 manipulators in the sample size.

The study discovered a consistent correlation between specific financial statement characteristics and the likelihood of earnings manipulation. This implies that accounting data can assist evaluate the accuracy of accounting earnings and offer insightful information about the possibility of manipulation.

Before such practices become publicly known, the algorithm can identify almost half of the companies engaged in earning manipulation, giving investing professionals a handy screening tool to look for potential red signals. Because the approach makes use of data that can be taken straight out of an organization's annual report, it is simple to deploy. Because the necessary data is easily accessible, it can be used by experts and investors with modest financial resources. Kumalasari and Puspaningsih (2024) uses the Beneish model to identify the manipulated financial statements that affect a company's worth. The study used the 171 manufacturing companies registered in the Indonesia equity market from 2016 to 2018. Regression analysis is used to explore the connection among fraudulent financial reporting, as identified through the Beneish model. The research found that 31% of manufacturing companies are involved in earning manipulation. Furthermore, it found that financial manipulation behavior hurts the company's market worth.

According to Svabova (2021), nowadays earning manipulation is a major topic in finance. Earning manipulation refers to the key tactics used by managers to influence the statements to achieve their personal goals, such as preventing losses or sustaining steady profit growth. The study investigates how combining several detection models improve the possibility of spotting possible earning manipulation and bolsters the validity of the results. In this paper, the three approaches M-score SVK, the Beneish model, and the propensity model of manipulation are used. The paper concludes that the likelihood of earning manipulation increases when all three models point to potential issues. These three methods strengthen the dependability of the analysis and enhance the ability to detect manipulation. By using these models investors know the accurate and reliable financial position of the companies. The study of Nyakarimi and Kariuki (2020) investigates whether Kenyan banks were manipulating their financial statements. Research was conducted on all registered banks in Kenya, aimed to determine whether any of these institutions had been involved in earning manipulation that distorted the financial reporting and misled the investors. For analysis, the study used the Beneish model and probit regression analysis. The study revealed that 21.1% banks of in Kenya are involved in manipulating earnings, while 78.8% of banks adhered to proper financial reporting. The study reports that the manipulation could undermine the confidence of investors in the accuracy and integrity of financial reporting.

To detect earning manipulation, this research examines the use of machine learning techniques, particularly the Bayesian Naive Classifier. The research compares the efficiency of mathematical models such as the Beneish model with conventional manual auditing techniques to improve decision-making processes in identifying earning manipulation. The aim of the study is to evaluate how well these methods can use financial statements to categorize businesses as manipulators or non-manipulators. 53 financial statements covering four years in a row were used in this study. The Beneish model achieved 84.84% classification accuracy, outperforming manual auditors. This suggests that the mathematical model outperforms manual auditing techniques in identifying earnings manipulation (Dbouk, 2017).

According to Abusharbeh and Zakarneh (2024), looks into the potential for manipulating earnings of non-financial companies registered on the Palestine equity market. Specifically, it evaluates the ability of the Beneish model to detect earning manipulation by using the panel regression analysis. The study used the data gathered from the business financial accounts. The study period consists of 7 years from 2016 to 2022. The fixed effect model and the two-step generalized technique of moments were utilized for the analysis. The Beneish model, which emphasizes overstated revenues, accruals, and leverage as important markers of Palestine-registered enterprises, was found to be useful in detecting earning manipulation. However, factors such as collection period, gross profit, asset consumption, operating expenses, and firm size were not significant in forecasting financial statement distortions.

This study investigates the relationship between family business groups (FBG) and earning manipulation, focusing on both affiliated and non-affiliated firms in Pakistan. Earnings manipulation refers to actions taken by companies to distort their financial statements, either by manipulating accounting practices (accrual-based earnings manipulation) or engaging in real activities that affect financial results. The study uses a representative of 323 firms registered on the Pakistan Stock Exchange for 6 years 2014-2019. The study used an Ordinary Least Square and panel data model for analysis. The study found a negative association between FBG affiliated organizations and accrual-based earning manipulation. The size of earning manipulation was higher in no-affiliated organizations related to those affiliated with FBG (Khan & Kamal, 2022).

Saleem et al. (2024) consider earnings management (EM) has long been a significant issue in financial statements, with extensive documentation in accounting theory and practice. There is little research on earning manipulation in Pakistan even though several models have been employed to identify it in other economies. The paper aims to examine whether earning manipulation occurs in Pakistan's non-financial industries. Data gathered from seven significant industries the food, chemical, cement, textile, and sugar sectors that were registered on the Pakistan Equity Market among 2012 and 2019 were examined. Beneish (1999) M-score model was used in the study to identify instances of earning manipulation. The result showed that 46% of Pakistani non-financial registered enterprises manipulated their earnings. Research demonstrates the efficiency of the Beneish model in detecting earning manipulation in this particular situation. This finding helps investors, banks, and other interested parties identify earning manipulation and improve the caliber of financial reporting. These findings should also be taken into account by scholars and experts who study future profit forecasts.

According to Ayati and Mulya (2024), the Association of Certified Fraud Examiners reports that financial report fraud is a major problem in Indonesia, so it's crucial to identify the best model for detecting such fraud. The study examines the impact of the fraud hexagon on two popular models used for manipulation detection the M-score model and the Overall Manipulation Index. The fraud hexagon consists of capability, stimulus, and realization that are thought to influence fraudulent behavior in organizations. The study used a sample of 24 state-owned enterprises from 2017 to 2021. By using STATA 17 software the study uses the panel data regression and applies both approaches fixed effect model and the common effect model. The study revealed that the Beneish model did not show a significant influence when combined with the fraud hexagon in identifying financial reporting fraud. Overall Manipulation Index demonstrates a positive significant relationship with identifying financial reporting fraud. The study concludes that the Overall Manipulation Index is a more effective tool for detecting financial statement manipulation than the Beneish model.

This study explores the main cause of financial reporting fraud in Malaysian businesses. By analyzing enforcement action releases from the Securities Commission of Malaysia (SC) and Bursa Malaysia. It identifies 76 firms involved in fraud between 1996 and 2016). The fraud triangle framework, alongside the Malaysian International Standards on Auditing 240, is utilized to pinpoint these factors. A bivariate probit model is employed for analysis. Among various pressure proxies, the results show that aggressive tax reporting and financial difficulties heighten the probability of fraud. Regarding opportunity factors such as the presence of dedicated institutional investors, board independence, an effective audit committee, and a female board member contribute to active monitoring and reduce fraud occurrence. According to justification, the likelihood of fraud is increased by past infractions and frequent changes in external auditors. By identifying distinct elements that may encourage fraudulent intent in businesses, this study offers auditors, managers, and regulators important insights for preventing, identifying, and dealing with fraud (Ghafoor, Zainudin, & Mahdzan, 2022).

Adu-Gyamfi (2020) quantitative study examines the link between share price and earning manipulation focusing on which firm sizes are more likely to engage in creative accounting practices. The study analyzes the data from 22 companies out of 41 registered companies of the Ghana Equity Market, covering the period from 2011-2016. Using the M-score model, the study revealed that 26.2% of the sample engaged in creative accounting. It also revealed that 28.4% of smaller companies and 25.4% of larger companies manipulated earnings during the period. However, the Mann-Whitney U test showed no significant difference in earnings manipulation between small and large companies. Spearman's correlation analysis, conducted on both the full sample and separately for small and large companies, found no significant connection among earnings manipulation and equity price. This research highlights the extent of earnings management in Ghanaian public companies and underscores the need for stricter measures to prevent such practices, ensuring market stability and protecting investors.

Financial statement manipulation involves intentionally altering records to meet targets, often driven by motives like budget goals or rewarding senior managers, creating conflicts of interest. This has become more prevalent in Bangladesh. In response, the board seeks improved detection methods. This study examines data from 105 companies registered on the Dhaka Equity Market for the 2016-2017 periods.

The Beneish model identified manipulation risks, with scores ranging from 7.06 to -8.98. At a cut-off of -1.78, 25 companies were flagged, and 57 at -2.22. A logistic model further explored manipulation likelihood based on additional company variables. The findings assist in identifying at-risk companies and improving corporate governance in emerging economies like Bangladesh (Arman & Sharmin, 2019).

This study examines the connection between integrated thinking (IT), earnings manipulation, and value creation. It builds on the idea that integrated reporting (IR) promotes IT, which enhances both financial and non-financial value creation, while the fraud triangle theory suggests that earnings manipulation could impact value creation. Using a sample of 497 observations from Malaysia's top 100 publicly listed companies (PLCs) from 2014 to 2018, the study finds that IT is positively related to value creation. However, earnings manipulation, measured by Beneish's M-score, shows insignificant association with value creation, except for value creation as measured by Tobin's Q ratio (Mohammed, Sutainim, Islam, & Mohamed, 2021).

Account manipulation has been widely researched and debated in countries such as the USA, Canada, the UK, Australia, Finland, and France. This paper provides a comprehensive review of the literature and proposes a conceptual framework for account manipulation, focusing on wealth transfer between stakeholders. The manipulation typically targets earnings per share and the debt/equity ratio.

The paper also explores the roles of various actors involved along with their potential gains and losses. It examines different account manipulation techniques earnings management, income smoothing, big bath accounting, creative accounting, and window-dressing along with their definitions, motivations, and research methodologies. The study highlights both common elements and key differences among these techniques (Stolowy & Breton, 2004).

Another study examines the influence of earnings management on a firm's cost of capital, highlighting its role in stock valuation by investors and analysts. Using an agency model with correlated firm cash flows shows that earnings manipulation is more prevalent during economic expansions. This manipulation lowers the correlation betsween firms' cash flows, reducing the risk premium required by investors and influencing the firm's cost of capital, despite diversification (Strobl, 2013).

Bartov (1993) investigates whether managers manipulate earnings by timing the recognition of income from asset sales. Since asset sale timing allows managers to influence earnings under acquisition cost accounting, the study examines two hypotheses: earnings smoothing, which seeks to reduce earnings fluctuations, and the debt-equity hypothesis, which links a firm's debt-equity ratio to earnings manipulation. The findings show that managers time asset sales to smooth earnings and manage bond covenant restrictions. Both effects persist independently. Sensitivity analysis confirms the robustness of these results. The study suggests that while acquisition-cost accounting is reliable, it can be exploited for earnings manipulation, raising concerns about its effectiveness compared to current-cost accounting.

Aubert and Grudnitski (2012) explores whether the mandatory adoption of IFRS in the European Union led to a reduction in earnings manipulation, measured by the gap between reported earnings and analysts' ex-post earnings estimates. This research used a sample of 15,034 from 20 European countries, and the earning manipulation before and after the adoption of IFRS. The study found impressive results after the adoption of IFRS, suggesting the adoption of IFRS would result in a decrease in earning manipulation practices. This research contributes to the literature on IFRS adoption and provides useful insights for investors.

Yıldırım and Kovacevic (2022) consider the affiliation between sustainability and earnings manipulation. The idea of the study is that companies registered in sustainability indices are more trustworthy in reporting their earnings due to their commitment to environmental, social, and economic responsibility. To detect earning manipulation Beneish model is used, the study used 262 non-financial companies registered on the Borsa Istanbul in 2017 and 261 companies in 2018. The result revealed that half of the companies in both years were expected to employ in earning manipulation. 40% of the companies in the sustainability index were identified as manipulators. The research concludes that, contrary to the assumption that sustainability focused companies would be more ethical in their financial reporting, the sustainability index alone does not guarantee more accurate or reliable earning reporting.

The study investigates the relationship between the ethical attitude and earnings management, seeking to understand whether earning management is perceived as manipulation or strategic adoption. By incorporating the factors such as investor sentiment and corporate social responsibility, the research broadens the scope of ethical decision making in financial reporting. The study suggests that investor sentiments and CSR enhance the effective power of a conceptual framework that link ethical orientation with how earning management is viewed. It argues that a strong ethical orientation and the ability to manage stakeholder demands can help prevent earning manipulation (Baskaran et al., 2020).

Yolanda and Kholmi (2024) conducted a study to evaluate the reliability of financial reporting for stakeholders, focusing on the quality of profits in Indonesia non-financial companies. The study used the non-discretionary accrual as an indicator of earning management and discretionary accruals as an indicator of earning manipulation. To conduct their analysis used the secondary data of non-financial companies gathered from Indonesia Stock Exchange from 2020 to 2022. A modified Jones Model is applied to estimate earnings management and manipulation, with panel data regression for analysis. The study concluded that discretionary accruals significantly affect total accruals, while non-discretionary accruals do not. This study aims to aid auditors, financial report users, and standard-setting bodies in detecting fraudulent activities.

This study examines whether failing firms engage in more earnings manipulation and whether auditors detect such actions. It finds that as firms approach insolvency, their financial statements show significantly higher income-increasing accruals compared to non-failing firms, particularly in non-going-concern years. These firms display patterns similar to those of SEC-sanctioned fraud cases, including large increases in receivables, inventory, assets, sales, and working capital, along with greater discrepancies among net income and cash flows. Additionally, auditors appear to reverse these overstatements in going-concern years. The study analyzes 293 bankrupt organizations with 2,500 observations (Rosner, 2003).

Kalelkar and Nwaeze (2011) investigates the influence of the Sarbanes-Oxley Act (SOX) on the valuation weights of earnings and their modules, particularly focusing on discretionary accruals, which were considered most vulnerable to manipulation before SOX. The analysis finds significant increases in the valuation weights of earnings and their components after SOX was enacted. However, the study also reveals that for firms where institutional investors hold 15% or more of equity, the post-SOX shifts in valuation weights are statistically insignificant.

This study develops a refined measure of real earnings management, focusing on deviations from industry norms in operating and investing activities, which may reflect strategic decisions rather than manipulation. Using principal components analysis, the measure captures (i) deviations across multiple activities and (ii) additional manipulation signals. The approach is effective as manipulation is more likely when multiple abnormal income-increasing activities align with other manipulation indicators. The measure negatively correlates with future performance and earnings persistence, detects manipulation across firm life cycles, and outperforms traditional metrics, predicting lower future earnings and persistence in 82% of cases, compared to 36% and 46% for conventional methods. It requires no long time-series data or future outcomes, making it more broadly applicable (Christensen, Huffman, Lewis-Western, & Valentine, 2022).

This research aims to examine the link among fraud causes and false financial statements. It evaluates the applicability of Z-score and F-score in identifying fraudulent financial statements among Jordanian industrial firms from 2015 to 2019.

The dependent variable was false financial statements, and the independent fraud factors included financial security, external strain, financial priorities, and business nature. Using multiple regression analysis, the study found that while some fraud triangle variables were unrelated to fraudulent reporting, others showed a strong association with fraud. The results also validated the effectiveness of the fraud detection models used (Saleh, Aladwan, Alsinglawi, & Salem, 2021).

Zaki (2017) compares the effectiveness of the Fraud Triangle and Fraud Diamond models in evaluating the risk of fraudulent financial statements. It notes that managers motivated by personal gain, may engage in unethical behavior undermining financial reporting reliability. The study uses Logistic Regression to analyze data from 100 companies registered on the Egyptian Equity Market in 2012.

Fraud probability is assessed using the Z-Score, P-Score, and Beneish. The findings show that the Fraud Diamond Model is more relevant than the Fraud Triangle Model for predicting fraud, despite some factors in the Fraud Diamond Model not being statistically significant. Overall, the Fraud Diamond's factors provide a reliable tool for detecting fraud in Egypt.

Vladu, Amat, and Cuzdriorean (2016) paper addresses the issue of earning manipulation in financial reporting, a practice where preparers of accounting information alter financial statements to present a more favorable image of a company's financial situation. The study examines how earning manipulation can mislead investors by inflating revenues, understating expenses, or employing other deceptive methods. To address this issue research used the ratios; liquidity, profitability, and leverage ratios by analyzing key financial statement measures. Using a sample of publicly traded companies in Spain, the study found that the financial ratios derived from financial statements can serve as a powerful tool to identify potential earning fraud. The study concludes that financial ratios are an effective means for identifying fraudulent activities of financial statements.

This study addresses the challenges faced by investors in accurately identifying earning manipulation in financial statements. With the rise in financial reporting fraud, investors' mistrust in the capital has increased, highlighting the need for effective tools to detect such practices. The study uses a sample of 81 non-financial companies registered on the Tehran Equity Market from 2012-2018. To analyze the data, the study develops a model and employs the Beneish model, along with Multi-Layer perception techniques, to evaluate the probability of earnings manipulation. To improve the forecast accuracy of identifying earning manipulation, the researcher created a new model. This model builds upon the Beneish model but incorporates additional corporate governance variables that can provide more insights into the likelihood of earning manipulation. These variables include; audit committee structure, legal inspector and independent auditor, board of directors' structure, and corporate ownership structure. The study found that the proposed model performs better than the Beneish model in terms of predictive accuracy. By integrating governance variables, the new model is better equipped to detect manipulation in financial statements. The study concludes that it is indeed possible to detect earning manipulation in financial statements using the Beneish model and a new, developed model that incorporates additional corporate governance variables (Maleki Nia, tehrani, Tabriz Akbar, & Fallah shams, 2021).

This study analyzed auditors' views on risk management, audit fees, and earnings manipulation, using data from 155 Tehran Stock Exchange-listed companies

(1860 firm-year observations) between 2007 and 2019. The results showed that weak internal controls significantly increase earnings manipulation opportunities, while economic indicators affect audit fees. Auditor switches and prior audit reports had no significant impact on audit fees or earnings manipulation (Sabralipor, Pakmaram, Rezaei, & Bahri Sales, 2025).

Khan and Kamal (2022) investigates the link between earnings manipulation and corporate governance in family business groups, focusing on how ownership structure, board composition, and auditors influence earning manipulation behavior. The study uses a representative of 327 non-financial firms registered on the Pakistan Equity Market for 10 years from 2010 to 2019, including 187 FBG firms and 140 non-affiliated firms. The findings show that a FBG affiliation reduces earning manipulation under discretionary accruals but not under real activity manipulation. Corporate governance and network auditors also help reduce earning manipulation in FBG affiliated firms, although corporate governance and network auditors have an inverse effect on real activity manipulation. The study finds that block and institutional ownership are negatively related to earning manipulation. It also reveals that family business group affiliated firms have lower payout dividend ratios compared to stand-alone firms. This research contributes to the literature by offering country-specific evidence on corporate governance regulations and their impact on earning manipulation in Pakistan, providing valuable insights for policymakers, regulators, and business managers.

Maniatis (2021) study aims to detect earning manipulation among the listed on the Athens Equity Market General Index for 2017-2018. By using the Beneish model, which assesses the likelihood of financial reporting fraud, the study analyzes 40 companies. The findings show that 82.5% of the sample 33 companies are not engaged in earning manipulation while 17.5% of companies are involved in earning manipulation. The results provide valuable perceptions for auditors, supervisory bodies, and researchers on financial fraud in Greece.

Selem and Elkholy (2025) explores the effect of adopting IFRS on earning management in Saudi Arabian commercial banks, focusing on accrual earning management and real earnings management. The study aims to investigate how IFRS adoption helps in detecting earning manipulation and promotes transparency in financial reporting. Data from 10 banks between 2015 and 2023 was analyzed using SPSS. The results shows that the standards help reduce earning manipulation. The influence of control variable like bank size and profitability on earning management decreases. The conclusions highlight the role of IFRS in detecting earnings manipulation and promoting transparency in Saudi Arabian banks.

Falana, Igbekoyi, and Oluwagbade (2025) conducted this study in Nigeria to investigate how company attributes effect financial reporting among multinational corporations. 46 firms data from 2011-2023 were used and analyzed through regression analysis. Results revealed that companies leverage has a negative influence on reporting quality and firm size and innovation positively affect reporting quality. The research suggests that the firms prioritize quality reporting with large assets and manage leverage with strong financial control.

Chapter 3

Data Description

3.1 Population and Sample of the Study

The quantitative data used in this research is collected from the annual reports of companies and relevant websites of companies. The target population consists 74 companies across 12 non-financial sectors including Auto assembler, auto parts and accessories, oil and gas marketing companies, oil and gas exploration companies, chemical, cable and electrical goods, cement, technology, sugar, engineering, glass and ceramics, and fertilizer. The data spans from 2020 to 2023.

3.2 Econometric Model

The research used the Beneish model developed by Messod Beneish in 1999. Beneish model used eight variables to examine whether the companies are involved in earning manipulation are not. These eight financial ratios are derived from the financial statements. These eight variables are;

$$M - score = -4.84 + 0.920 * DSRI + 0.528 * GMI + 0.404 * AQI + 0.892 * SGI + 0.115 * DEPI - 0.172 * SGAI + 4.679 * TATA - 0.327 * LVGI \tag{3.1}$$

The robustness of the model will also be confirmed by using logistic regression;

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

Whereas,

Z = $\beta_0 + \beta_1$DSRI + β_2GMI + β_3AQI + β_4SGI + β_5DEPI + β_6SGAI + β_7LVGI + β_8TATA + ϵ

Where;

DSRI =Days sales in receivable index

GMI =Gross margin index

AQI =Asset quality index

SGI =Sales growth index

DEPI =Depreciation index

SGAI =Selling, general, and administrative expenses index

LEVI =Leverage index

TATA=Total accrual to total assets

To determine the Beenish M score model -2.22 criteria is used if the M score is greater than -2.22 companies are involved in manipulation and if the M score is less than -2.22 then the companies are non-manipulators.

3.3 Variable description of Beneish Model

Based on the existing literature the study will use the eight variables of the Beneish model to identify the companies that are engaged in earning manipulation; these eight variables are;

3.3.1 Days Sale in Receivables Index

The day's sale in the receivable index is the ratio of days sales in receivable in the current year compared to the previous year (Beneish, 1999) if there is any mismatch between receivables and sales growth means the receivables increase disproportionately compared to sales. A high day sales in the receivable index is considered a red flag for earning manipulation. Companies use this technique to make their financial statement more favorable by a change in credit policy or by minimizing expenses.

Mostly the day sales in receivable rise the earning manipulation increase so there is a positive relationship between the day sale in receivables and earning manipulation. Day's sale in the receivable index is measured through;

$$DSRI = (\textbf{net receivable}_t/\textbf{sales}_t)/(\textbf{net receivable}_{t-1}/\textbf{sales}_{t-1})$$

3.3.2 Gross Margin Index

Gross margin is the difference between sales and cost of goods sold. The gross margin index is a ratio that compares a company's gross profit in one year to its gross profit in the previous year (Kamal et al., 2016) gross margin index shows how a company's profit from its core business has changed over time.

Deterioration in the gross profit sends a negative signal about a company's prospects. Deterioration in gross margin increases the possibility of earning manipulation, there is a positive relationship between the gross margin index and earning manipulation. Gross margin index calculated through;

$$\text{GMI} = \left(\text{sales}_{t-1} - \text{cost of goods sold}_{t-1}\right)/(\text{sales}_t - \text{cost of goods sold}_t) \qquad (3.2)$$

3.3.3 Asset Quality Index

Asset quality index measures the changes accruing at the risk of recognition of assets (Nyakarimi, 2022) an increase in long-term assets other than PPE indicates that a company engages in deferral cost to boost its profit.

AQI is the ratio of asset quality in the current year to asset quality in t-1. It is calculated as;

$$\begin{aligned}\textbf{AQI} &= (1 - (\textbf{Current Assets}_t + \textbf{PPT}_t)/\textbf{Total Assets}_t)/ \\ &\quad (1 - \textbf{Current Assets}_{t-1} + \textbf{PPT}_{t-1})/\textbf{Total Assets}_{t-1})\end{aligned} \qquad (3.3)$$

3.3.4 Sales Growth Index

A ratio comparing sales from the current year to the previous year does not exactly involve earning manipulation but the growth of the firm may be more likely to engage in earning manipulation due to its financial position and capital need (Siddiqui & Ahmed, 2020).

It indicates that there is a positive relationship between sales growth and earning manipulation. The sales growth index is measured as;

$$SGI = \frac{sales_t}{sales_{t-1}}$$

3.3.5 Depreciation Index

The depreciation index is the ratio of depreciation in two consecutive years. Kamal et al. (2016) state that if the depreciation index is less than 1 indicates that the company slowed down its depreciation rate raising the likelihood that the company has revised the assets estimate life and adopted a new method to inflate the revenues thus expecting a positive relation between the depreciation index and earning manipulation.

It is measured as;

$$\begin{aligned}\mathbf{DEPI} = [&\mathbf{Depreciation}_{t-1}/\mathbf{Depreciation}_{t-1} + \mathbf{PP\&E}_{t-1}] \\ &/[\mathbf{Depreciation}_t/\mathbf{Depreciation}_t + \mathbf{PP\&E}_t]\end{aligned} \tag{3.4}$$

3.3.6 Selling, General and Administrative Expenses

Selling, general, and administrative expenses are measured by the current year's SGAI ratio to the sale of the previous year's SGAI ratio of sales. Beneish (1999) if there is a disproportionate increase in SGAI means there is earning manipulation. It indicates that there is a positive relationship between the SGAI and earning manipulation. It is calculated as;

$$SGAI = \left(\frac{\text{SGA expenses}_t}{\text{sales}_t}\right) \Big/ \left(\frac{\text{SGA expenses}_{t-1}}{\text{sales}_{t-1}}\right) \tag{3.5}$$

3.3.7 Leverage Index

Beneish (1999) the leverage index is calculated by the total assets to total liabilities ratio of the current year compared to the total asset to total liability ratio in the previous year. If it is greater than 1 indicate that there is a rise in leverage to buy more assets. The leverage index is calculated through the;

$$LEVI = [LTD_t + \text{current liabilities}_t/\text{total assets}_t]/[LTD_{t-1} + \text{current liabilities}_{t-1}/\text{total assets}_{t-1}] \tag{3.6}$$

3.3.8 Total Accruals and Total Assets

Total accrual to total asset index measures the proportion of non-cash items in a company's statements. A high increase in non-cash working capital is interpreted as indicating a possible financial profit manipulation (Siddiqui & Ahmed, 2020). It is measured by;

$$TATA = (\text{income from operations}_t - \text{cash flow from operation}_t)/\text{total assets}_t \tag{3.7}$$

3.3.9 Proposed Model

Beneish M score was proposed to detect earning manipulation and tested worldwide. Pakistan is an emerging economy and there are historical issues of corporate governance and transparency of information.

The proposed model is designed to detect earning manipulation in Pakistan and check the effectiveness of the model. The proposed model is the J score, derived from the red flag in financial statements and the variables used are;

$$\text{J-score} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \epsilon \tag{3.8}$$

Whereas;

X_1= Gross Margin Index

X_2= Sales Growth Index

X_3= Total Accruals to Total Assets

X_4=Debt Maturity index

X_5= Frequent Financing Activity

X_6= Inventory Index

X_7= Operating Cash Flow

X_8= non-operating expense to sales growth ratio

3.4 Proposed Model Variable Description

3.4.1 Gross Margin Index

The gross profit index compares the gross profit of a company in a current year to its gross profit in the previous year (Arman & Sharmin, 2019).

There is a positive relationship between the gross margin index and earning manipulation It is measured as;

$$GMI = (\textbf{sales}_{t-1} - \textbf{cost of goods sold}_{t-1})/(\textbf{sales}_{t} - \textbf{cost of goods sold}_{t}) \quad (3.9)$$

3.4.2 Sales Growth Index

The sales growth index is a financial instrument used to measure the rate at which a company's sales are growing over a specific period. It is often used whether a company's sales growth is sustainable and to detect potential red flags.

An increase in the sales growth index leads to an increase in the chance of earning manipulation (Ayati and Mulya, 2024). It is measured as;

$$SGI = \frac{sales_t}{sales_{t-1}} \quad (3.10)$$

3.4.3 Total Accrual to Total Assets

Accrual represents the difference between accounting earnings and cash flows. A high ratio of accruals means that a large portion of a company's earnings is non-cash, an indication of earning manipulation (Alareeni & Aljuaidi, 2014).

It is measured as;

$$TATA = (\textbf{Income from operations}_t - \textbf{cash flow from operations}_t) \\ /(\textbf{Total Assets}_t) \tag{3.11}$$

3.4.4 Debt Maturity Index

The debt maturity index measures the portion of debt that is due in the near term from its total debt. This index helps the company to assess the company's ability to pay the upcoming debt obligations (Welch, 2011).

It is measured as;

$$\text{Debt maturity index} = STD/STD + LTD \tag{3.12}$$

3.4.5 Frequent Financing Activity

Frequent financing activity refers to the efforts of companies to raise capital through issuing new shares, taking debt, or selling off assets (Taggart, 1977). Operating cash flow turnover measures how efficiently a company converts its cash flow into revenue. It is calculated as a change in equity or a change in debt.

3.4.6 Inventory Index

Inventory index measures the changes in a company's inventory levels over time. The inventory index is a ratio that measures changes in a company's inventory over time. Significant changes in inventory could signal issues like overproduction or aggressive accounting practices like overstating inventory to overstate the profit (Fridson & Alvarez, 2011).

The inventory index is calculated as;

$$\text{Inventory index} = (Inv_t/CGS_t)/(Inv_{t-1}/CGS_{t-1}) \tag{3.13}$$

3.4.7 Negative Operating Cash Flow Index

Negative operating cash flow is a situation in which a company's cash outflows exceed its cash inflows. Negative operating cash flows indicate that the company's core operations are not generating enough cash to cover the operating expenses (Lee, Ingram, & Howard, 1999). It is calculated as;

Operating cash flow turnover= EBIT/OCF

If OCF is negative then = 1 otherwise 0

3.4.8 Non-Operating Expenses to Sales Growth Ratio Index

It compares non-operating expenses relative to sales over two years. It shows the percentage change in the proportion of non-operating expenses to sales from t-1 to t period (Mohanram, Saiy, & Vyas, 2017). It is measured as;

$$\text{NOE to sales growth ratio index} = (NOE_t/sales_t/)/(NOE_{t-1}/sales_{t-1}) \tag{3.14}$$

3.5 Data Analysis

3.5.1 Logit Analysis

Logit analysis is a statistical method used for modeling dummy variable outcomes. This technique estimates the probability of a particular event occurring based on one or more independent variables (Hilbe, 2009). The logit model is particularly useful in social sciences for its ability to handle dichotomous outcomes where the explanatory variable can take on two possible values, often coded as 0 and 1 (Vladu et al., 2016). In this case, the non-manipulator firms are denoted with 0 and the manipulator firms are denoted with 1. The manipulator and non-manipulator are estimated by using the Beneish M score model and then the Beneish M score model and proposed model are tested by using the Logistic regression.

Logit analysis of the Beenish M score model and proposed model performed through the Eviews. The binary logit analysis is performed to detect the role of the various variables in the detection of the earning manipulation. Then the Expectation-Prediction Evaluation for Binary Specification is performed that classify the performance of the Binary logistic model for detecting the earning manipulation, comparing it to the baseline constant probability model. After that the Goodness of fit evaluation for binary specification was performed that represents the quantiles of risk, assessed through a Hosmer-Lemeshow (H-L) test.

3.5.2 Discriminant Analysis

Discriminant Analysis is a statistical technique used to differentiate between groups based on case attributes, identifying which variables contribute most to group separation. It generates canonical discriminant functions, which are linear combinations of predictor variables that maximize group differentiation (McLachlan, 2005). In predictive DA, the goal is to assign new cases to predefined groups by using scores on the predictor variables. DA seeks the most parsimonious model for distinguishing between groups and classifying cases accurately. Statistical significance is tested using chi-square tests to assess how well the discriminant function separates the groups, while also evaluating the accuracy of classifications against theoretical predictions (Agresti, 2006).

Discriminant analysis was performed through the SPSS software. The Beneish M score model and the proposed model were tested through the discriminant analysis. In discriminant analyses following tests were performed;

a. Descriptive statistics

Descriptive statistics of discriminant analysis try to forecast the group membership and whether the independent variables of each group are significantly different in each group.

b. Tests for Equality of Group Mean

Test for equality of group mean is a statistical method used to determine if there are any statistically significant differences between the independent group means.

c. Pooled Within-Group Matrices

A pooled within-group matrix shows the correlation between the variables within groups

d. Log Determinants

Log Determinants of a covariance matrix reflect the overall variance or spread of the data in multiple dimensions. Lower log determinants suggest less variability and greater group homogeneity. A higher log determinant indicates high variability.

e. Box M Test

Test result or box's m test assesses whether the covariance matrices of different groups (manipulators and non-manipulators) are equal.

f. Eigenvalues

Eigenvalues in discriminant analysis indicate the importance of different combinations of variables in distinguishing the classes. Large eigenvalues indicate more important directions for classification.

g. Wilks Lambda

Wilks Lambda evaluates the effectiveness of the discriminant analysis to evaluate the effectiveness of the discriminant function in distinguishing between the group classes. It is the measure of how well the groups are separated by the discriminant function. h. Standardized Canonical Discriminant function coefficient This test indicates the coefficients of the relative contribution of each variable to the discriminant function, standardized to remove the effects of different measurement scales.

i. Structure Matrix

The structure matrix provides a way to assess the association between the original predictor variables and the discriminant functions. The structure matrix helps to understand which variables are most influential in separating the groups.

j. Canonical Discriminant function coefficients

Canonical discriminant function coefficients are used to create the discriminant function, which is a linear combination of the predictor variables that maximizes the separation between the groups. These coefficients are part of the discriminant function that assigns a score to each observation, which is then used to classify the data into one of the subgroups.

k. Function at group centroids

Function at group centroids provides the cutoff point of the discriminant function in classifying the groups.

l. Classification Results

The classification results from discriminant analysis summarize how well the model classifies observations into predefined classes.

Chapter 4

Results and Discussion

Testing of Beneish M-score model using logit analysis. The Beneish M-score model is used to discriminate the manipulators and non-manipulators and the same classification is used to check the validity of model using binary logit analysis and discriminant analysis.

4.1 Testing of Beneish M Score Model and its Validation Using Logit Analysis

4.1.1 Descriptive Statistics

Descriptive statistics describes the basic behavior and main feature of the data of study. Table 4.1 depicts the descriptive statistics for financial ratios used in earning manipulation detection.

Descriptive statistics play a crucial role in detecting earnings manipulation by identifying suspicious financial patterns. By analyzing various indices such as Days Sales in Receivable Index (DSRI),Gross Margin Index (GMI),Sales Growth Index (SGI),Asset Quality Index (AQI), Selling, General, and Administrative Expenses Index (SGAI). Descriptive statistics can help summarize complex data into easily understandable figures, revealing potential red flags for fraudulent activities, such as unusual increases or inconsistencies in these indices.

Table 4.1: Descriptive Statistics

	DSRI	**GMI**	**SGI**	**AQI**	**DEPI**	**SGAI**	**TATA**	**LVGI**
Mean	1.0218	0.8217	1.2973	1.0805	1.0195	0.9868	0.0533	1.022
Mdn	0.9545	0.774	1.2574	0.9715	1.0053	0.9382	0.0442	1.0216
Max.	4.0547	4.6544	3.4703	5.5093	2.5024	1.9864	0.4491	1.8421
Mini.	0	-2.4885	0.5403	-0.7568	0.138	0.197	-0.7558	0.1731
STD	0.5147	0.716	0.3969	0.6477	0.2889	0.2766	0.1334	0.2277
Skew	2.1423	1.4508	1.8153	3.3403	1.3788	0.7972	-0.768	-0.2585
Ku	11.6635	13.2387	10.6054	19.8374	8.9418	4.4125	8.8787	6.2701

This table displays the descriptive statistics of the variables where SGI = Sales Growth Index, AQI = Asset Quality Index, DEPI = Depreciation Index, DSRI = Day's sales in Receivables Index, SGAI = Selling and General Administrative expenses Index, TATA = Total Accruals to Total Assets, GMI = Gross Margin Index and LVGI = Leverage Index.

The mean of DSRI is 1.0218 which indicates an increase in day's sales in receivables, which suggest that the companies are inflating their revenues or changing in credit policy. SGI mean is 1.2973 suggesting the aggressive revenue growth, which motivate the management to manipulate earnings to sustain or exceed the market expectations. AQI has a mean of 1.2973 indicating that the companies have a greater proportion of non-current assets. LVGI also have a mean greater than indicating that the companies are in financial risk. GMI, TATA and SGAI have a mean less than 1 indicating that these variables could not signal potential earning manipulation.

For DSRI maximum and minimum values are 0.0000 and 4.0547. GMI has an extreme minimum value of -2.4885, indicating outliers. A large range of GMI and SGI suggests high variability. Skewness indicates the asymmetry of the data distribution DSRI and GMI show positive skewness, meaning longer tails on the right. A skewness value greater than 1 indicates significant asymmetry, often caused by outliers. Kurtosis reflects the "peakedness" of the distribution. DSRI and GMI have very high kurtosis, indicating sharp peaks and heavy tails (presence of outliers). SGAI and LVGI have moderately high kurtosis, suggesting less extreme outliers.

4.1.2 Earning Manipulation Using Binary Logit Analysis

The Binary Logit analysis is performed to detect the role of various variables in the detection of earning manipulation. Table 4.2 represents the binary logistic regression, which predicts a binary dependent variable (0, 1).

Table 4.2: Binary Logit

Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
DSRI	5.850431	1.044542	5.600955	0.0000
GMI	4.023757	0.805652	4.994409	0.0000
SGI	2.089973	0.709948	2.943839	0.0032
AQI	2.180245	0.666654	3.270431	0.0011
DEPI	-0.575611	0.858338	-0.670611	0.5025
SGAI	-6.669691	1.476911	-4.515973	0.0000
TATA	39.48183	6.478045	6.094714	0.0000
LVGI	-7.480072	1.628718	-4.592614	0.0000
Mean dependent var	0.590090	S.D. dependent var		0.492928
S.E. of regression	0.278053	Akaike info criterion		0.540023
Sum squared resid	16.54504	Schwarz criterion		0.662642
Log-likelihood	-51.94254	Hannan-Quinn criteria.		0.589529
Deviance	103.8851	Restr. Deviance		300.5106
Avg. log-likelihood	-0.233975			
Obs with Dep=0	91	Total obs		222
Obs with Dep=1	131			

Table 4.2 Binary logit analysis depicts that the DSRI has a p-value of 0.0000 positively and statistically significant, suggesting that a higher DSRI increases the likelihood of earning manipulation. GMI probability value of 0.0000 is positive and significant, indicating a higher likelihood of manipulation as GMI increases.

SGI has a probability value of 0.0032 positive and significant impacts, indicating a higher likelihood of manipulation as SGI increases. AQI has a probability value of 0.0011 positive and significant, meaning higher AQI values correlate with a higher risk of manipulation. DEPI the p-value is greater than the common significance level indicating that the depreciation is not statistically significant in predicting the outcome in this model. It suggests that DEPI does not have a strong or consistent impact on the likelihood of earnings manipulation within this model, despite its high coefficient. The SGAI coefficient is negative and significant, suggesting that higher SGAI decreases the likelihood of manipulation. TATA has a probability of 0.0446 positive and significant, indicating that higher TATA is associated with a higher likelihood of earning manipulation. LVGI negative and significant implies that higher leverage decreases manipulation risk. The Akaike Information Criterion is 0.540023 value helps in assessing model fit, with a lower value typically indicating a better fit. Out of 222 observations, 91 have a dependent =0, and 131 have a dependent =1, meaning 131 cases are classified with earning manipulation.

4.1.3 Expectation-Prediction Evaluation for Binary Specification

This table evaluates the classification performance of the binary logistic model for detecting earning manipulation, comparing it to the baseline "constant probability" model. Table 4.3 assesses the model's classification performance. Estimated equation correctly classified observations.

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	79	9	88	0	0	0
P(Dep=1)>C	12	122	134	91	131	222
Total	91	131	222	91	131	222
Correct	79	122	201	0	131	131
% Correct	86.81	93.13	90.54	0	100	59.01
% Incorrect	13.19	6.87	9.46	100	0	40.99

Estimated equation performance Dep = 0 (non-manipulation) and Dep =1 (manipulation). 79 cases are correctly classified as 0 out of 91 and 122 cases are correctly classified as 1 out of 131 observations. Non-manipulator cases are correctly classified with 86.81% and manipulator cases are correctly classified as 93.13%.

The overall accuracy is 90.54% indicating a strong classification performance.

4.1.4 Goodness-of-Fit Evaluation for Binary Specification

This table represents the goodness-of-fit evaluation for a binary logistic regression model based on quantiles of risk, assessed through a Hosmer-Lemeshow (H-L) test and Andrews'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	2.E-12	0.0017	22	21.9914	0	0.00862	22	0.00862
2	0.0027	0.0578	21	21.3086	1	0.69142	22	0.14219
3	0.0580	0.2350	19	19.4090	3	2.59095	22	0.07320
4	0.2404	0.4836	17	14.2356	5	7.76444	22	1.52109
5	0.5060	0.7945	8	7.43513	15	15.5649	23	0.06341
6	0.7947	0.9124	3	3.06937	19	18.9306	22	0.00182
7	0.9182	0.9883	1	0.95746	21	21.0425	22	0.00198
8	0.9885	0.9987	0	0.10853	22	21.8915	22	0.10907
9	0.9989	1.0000	0	0.00926	22	21.9907	22	0.00926
10	1.0000	1.0000	0	0.00018	23	22.9998	23	0.00018
		Total	91	88.5245	131	133.476	222	1.93081
H-L Statistic			1.9308		Prob. Chi-Sq(8)		0.9831	

The data is divided into 10 quantiles, each with expected and actual frequencies for Dep = 0 and Dep = 1. The H-L statistics is 1.9308 with a p-value of 0.9831, which is above 0.05. This high p-value suggests the model fits the data well, as there is no significant difference between observed and expected values. The Andrews statistics is 129.7347 with a p-value of 0.0000, indicating significance and potential misfit.

4.1.5 Marginal Effect

The marginal effect indicates how much a one-unit change is in each independent variable, providing insights into the practical implications of change in these predictors.

Table 4.5: Marginal Effect

Variables	**X**	β	**L= X***β	βP	**Marginal Effect**
DSRI	1.0218	5.850431	5.97797	4.902032	0.7947
GMI	0.8217	4.023757	3.306321	3.371476	0.5465
SGI	1.2973	2.089973	2.711322	1.751173	0.2839
AQI	1.0805	2.180245	2.355755	1.826811	0.2961
DEPI	1.0195	-0.57561	-0.58684	-0.4823	-0.0782
SGAI	0.9868	-6.66969	-6.58165	-5.58848	-0.9059
TATA	0.0533	39.48183	2.104382	33.08153	5.3628
LVGI	1.022	-7.48007	-7.64463	-6.2675	-1.0160
		L	1.64263		
		P	0.837892		

The column Variable represents a different variable that is included in the Logit model. X shows the mean values of variables extracted from descriptive statistics of the proposed model. Beta shows the coefficients extracted from Binary Logit analysis represents the estimated impact of each variable on the dependent variable. L shows the linear prediction for each variable. DSRI 0.7947, GMI 0.5465, SGI 0.2839, and AQI 0.2961 indicate that increasing by one unit raises the expected outcomes by 0.7947, 0.5465, 0.2839 and 0.2981. TATA 5.3628 high marginal effect indicating that TATA has a substantial influence; increasing TATA by one unit raises the expected outcome by over 5 units. The DEPI -0.0782, SGAI -0.9059, and LVGI -1.0160 show a negative impact indicating that increasing by one unit decreases the expected outcome.

4.2 Testing of Beneish M-Score Model and Its Validation Using Discriminant Analysis

4.2.1 Descriptive Statistics of Manipulator and Non-Manipulator

Table 4.6 displays group-level descriptive statistics for variables used in discriminant analysis.

The data is divided into two groups M=0 and M= 1. M=0 likely represents non-manipulated firms and M=1 likely represents manipulated firms.

TABLE 4.6: Descriptive Statistics of Manipulators and Non- Manipulators

M		**Mean**	**Std. Deviation**
0	DSRI	0.79	0.37
	GMI	0.65	0.62
	SGI	1.21	0.29
	AQI	0.98	0.39
	DEPI	1.02	0.21
	SGAI	0.99	0.27
	TATA	-0.03	0.12
	LVGI	1.02	0.24
1	DSRI	1.18	0.54
	GMI	0.94	0.76
	SGI	1.36	0.45
	AQI	1.15	0.77
	DEPI	1.02	0.33
	SGAI	0.99	0.28
	TATA	0.11	0.11
	LVGI	1.02	0.22
Total	DSRI	1.02	0.51
	GMI	0.82	0.72
	SGI	1.3	0.4
	AQI	1.08	0.65
	DEPI	1.02	0.29
	SGAI	0.99	0.28
	TATA	0.05	0.13
	LVGI	1.02	0.23

Descriptive statistics are reported separately for each group, as well as combined. Difference in the means between groups suggests potential discriminating power.

Standard deviation measures the spread of values around the mean. A larger standard deviation indicates the variability within the group. The number of observations in each group is consistent (91 for M=0 and 131 for M=1).

DSRI mean for non-manipulators is 0.79 and for manipulators is 1.18. Manipulated firms (M=1) tend to have higher DSRI, suggesting potential revenue recognition manipulation.

The standard deviation is slightly higher for M=1 (0.54), indicating greater variability among manipulated firms. GMI mean for non-manipulated firms are 0.65 and for the manipulator is 0.94, manipulated firms have a higher GMI, indicating possible deterioration in gross margin.

The standard deviation of manipulator firms suggests more diverse manipulation tactics. SGI means for non-manipulator is 1.21 and for non-manipulator is 1.36. Manipulated firms exhibit higher sales growth, potentially indicating aggressive revenue growth strategies.

The AQI mean for non-manipulator are 0.98 and for manipulator are 1.15. The mean of manipulated firms has a higher AQI, pointing to possible high differenced cost to current assets. The DEPI mean for non-manipulators is 1.02 and for manipulators is 1.02, similar means for both groups suggest this variable may have less discriminating power.

SGAI mean for the manipulator is 0.99 and for the non-manipulator is 0.99, no difference indicates this variable is not a good discriminator. TATA has a mean for non-manipulators is -0.03and for manipulators is 0.11. Manipulator firms exhibit higher TATA, consistent with earnings manipulation involving accruals. LVGI mean for non-manipulator firms is 1.02 and for manipulator firms 1.02, similar means for both groups, suggesting less discriminating power.

DSRI, GMI, SGI, AQI, and TATA clear mean differences between groups, indicating their potential as strong predictors for discriminant analysis. DEPI, SGAI, and LVGI have no mean differences and low variability, suggesting the limited ability to separate groups. Manipulated firms M=1 tend to exhibit higher variability for most of the variables (e.g. DSRI, GMI), suggesting more diverse manipulation practices.

4.2.2 Tests of Equality of Group Means

Table 4.7 depicts the test for equality of group means. This table tests whether each independent variable significantly differs across groups. The significance value indicates whether difference in the group means statistically significant.

TABLE 4.7: Tests of Equality of Group Means

	Wilks' Lambda	**F**	**df1**	**df2**	**Sig.**
DSRI	0.857	36.727	1	220	0
GMI	0.958	9.561	1	220	0.002
SGI	0.963	8.547	1	220	0.004
AQI	0.982	4.139	1	220	0.043
DEPI	1	0.015	1	220	0.902
SGAI	1	0.006	1	220	0.938
TATA	0.748	74.21	1	220	0
LVGI	1	0.027	1	220	0.87

The p-value below 0.05 implies the variable significantly discriminates between groups such as DSRI, GMI, SGI, AQI, and TATA. The insignificant value indicates that the groups have no differences such as DEPI, SGAI, and LVGI. The F-statistics tests the null hypothesis that groups are equal. A higher value indicates greater group differences.

4.2.3 Pooled within-Groups Matrices

Table 4.8 pooled within-groups matrices represent the correlations between the independent variables. Diagonal values are always equal to 1 because these represent the correlation of a variable with itself. Off-diagonal values indicate the degree of linear relationship between pairs of variables within groups.

Table 4.8: Pooled Within-Groups Matrices

	DSRI	GMI	SGI	AQI	DEPI	SGAI	TATA	LVGI
DSRI	1	-0.06	-0.251	-0.137	0.042	0.098	-0.034	0.113
GMI	-0.06	1	-0.356	-0.027	-0.013	0.4	-0.252	-0.002
SGI	-0.251	-0.356	1	-0.054	-0.273	-0.637	0.026	0.123
AQI	-0.137	-0.027	-0.054	1	-0.182	0.085	-0.143	-0.093
DEPI	0.042	-0.013	-0.273	-0.182	1	0.1	0.009	0.042
SGAI	0.098	0.4	-0.637	0.085	0.1	1	-0.023	-0.123
TATA	-0.034	-0.252	0.026	-0.143	0.009	-0.023	1	0.13
LVGI	0.113	-0.002	0.123	-0.093	0.042	-0.123	0.13	1

Values closer to 1 or -1 indicate strong positive or negative correlations, 0.5 moderate correlations while values closer to 0 indicate weak correlations. There is a moderate negative correlation between DSRI and SGI (-0.251). GMI and SGI show a moderate positive correlation (0.356). The correlation among DEPI, SGAI, and other variables is generally low, suggesting minimal relationships within the groups.

4.2.4 Log Determinants

This table provides information on the determinant of the pooled within-group covariance matrix. Log determinant values reflect the variability within groups. Lower log determinants suggest less variability within groups. Ranks indicate the dimensionality of the covariance matrix.

Table 4.9: Log Determinants

M	Rank	Log Determinant
0	8	-21.548
1	8	-17.427
Pooled within-groups	8	-18.464

The ranks and natural logarithms of determinants printed are those of the group covariance matrices. The pooled within-group determinants are lower (-18.464) compared to the determinants of individual groups, which aligns with the assumption of the homogeneity of covariance.

4.2.5 Tests Results (Box's M test)

Box's tests the null hypothesis that the covariance matrices of the groups are equal. The F-statistic associated with Box's M indicates whether the covariance matrices differ significantly.

Table 4.10: Test Results (Box's M Test)

Box's M		142.911
F	Approx.	3.810
	df1	36
	df2	126649.253
	Sig.	.000

Tests null hypothesis of equal population covariance matrices. Table 4.2.5 Box's M value is 142.911. The P-value is less than 0.05, the null hypothesis of equal population covariance matrix is accepted.

4.2.6 Eigenvalues

The table represents the proportion of variance explained by the discriminant function. Larger eigenvalues indicate strong discriminant power. The percentage of variance is explained by each discriminant function. Cumulative percentage variance is explained up to the current function. The canonical correlation represents the correlation between the discriminant scores and the groups. Values closer to 1 indicate stronger relationships.

Table 4.11: Eigenvalues

Function	**Eigenvalue**	**% of Variance**	**Cumulative %**	**Canonical Correlation**
1	1.190a	100.0	100.0	.737

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

There is only 1 discriminant function, with an eigenvalue of 1.190, explaining 100% of the variance. The canonical correlation is 0.737, indicating a strong relationship between the discriminant function and group membership.

4.2.7 Wilks' Lambda

Wilks, Lambda tests the significance of the discriminant function. Lower values indicate better discrimination. Chi-square tests the null hypothesis that the discriminant function does not explain group differences. The P-value indicates whether the discriminant function is statistically significant.

TABLE 4.12: Wilk,s Lambda

Test of Function(s)	**Wilks' Lambda**	**Chi-square**	**df**	**Sig.**
1	.457	169.337	8	.000

Wilks, Lambda is 0.457 and the associated p-value is 0.000 indicating that the discriminant function significantly differentiates between the groups.

4.2.8 Standardized Canonical Discriminant Coefficients

This table depicts the standardized canonical discriminant function coefficients. These coefficients indicate the relative contribution of each variable to the discriminant function, standardized to remove the effects of different measurement scales.

TABLE 4.13: Standardized Canonical Discriminant Function Coefficients

	Function
	1
DSRI	.694
GMI	.690
SGI	.729
AQI	.414
DEPI	.259
SGAI	.045
TATA	.798
LVGI	-.228

TATA has the highest coefficient, making it the most influential variable in discriminating between groups. DSRI 0.694 and GMI 0.690 are also strong contributors. Variables like SGAI 0. 045and LVGI 0.228 have minimal contributors to the discriminant function.

4.2.9 Structure Matrix

Structure Matrix displays pooled within-group correlations between the variables and the discriminant function. These values represent the strength of the relationship between each variable and the discriminant function.

TABLE 4.14: Structure Matrix

	Function
	1
TATA	.532
DSRI	.375
GMI	.191
SGI	.181
AQI	.126
LVGI	.010
DEPI	.008
SGAI	-.005

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

TATA 0.532 has the strongest correlation with the discriminant function, followed by DSRI 0.375 and GMI 0.191. Variables such as DEPI 0.010 and SGAI -0.005 have the weakest correlations, indicating they contribute minimally to group discrimination. The structure matrix helps to understand which variables are more aligned with the discriminant function.

4.2.10 Canonical Discriminant Function Coefficient

The Canonical Discriminant Function Coefficient indicates the unstandardized coefficients for each variable in the discriminant function.

Table 4.15: Canonical Discriminant Function Coefficients

	Function
	1
DSRI	1.453
GMI	.982
SGI	1.868
AQI	.644
DEPI	.896
SGAI	.162
TATA	6.907
LVGI	-.998
(Constant)	-5.833

Unstandardized coefficients

Discriminant function equation;

$$D = (-5.833) + 1.453 * \mathrm{DSRI} + 0.982 * \mathrm{GMI} + 1.868 * \mathrm{SGI} + 0.644 * \mathrm{AQI} + 0.896 * \mathrm{DEPI} + 0.162 * \mathrm{SGAI} + 6.907 * \mathrm{TATA} + (-0.998) * \mathrm{LVGI} \tag{4.1}$$

TATA 6.907 has the highest coefficient, confirming it has the strongest influence on the discriminant function. GMI 1.868 and DSRI 1.453 also have significant contributions. LVGI -0.998 has a negative impact on group discrimination, while SGAI 0.162 has minimal influence.

4.2.11 Functions at Group Centroids

Functions at group centroids represent the mean discriminant score for each group on the discriminant function.

Table 4.16: Functions at Group Centroids

M	Function
	1
0	-1.303
1	.905

Unstandardized canonical discriminant functions evaluated at group means.

Group 0 has a centroid of -1.303, and group 1 has a centroid of 0.905. These centroids indicate how the discriminant function separates the two groups. A large difference between centroids signifies better group separation. The cutoff point is -0.389 the companies which have a score less than -0.389 are classified as non-manipulators and companies that have a score greater than -0.389 are classified as manipulators.

4.2.12 Classification Results

Classification results represent the classification results of two predicted groups 0 and 1.

Table 4.17: Classification Results

		M	Predicted Group Membership 0	Predicted Group Membership 1	Total
Original	Count	0	88	3	91
		1	4	127	131
	%	0	96.7	3.3	100.0
		1	3.1	96.9	100.0
Cross-validated	Count	0	87	4	91
		1	6	125	131
	%	0	95.6	4.4	100.0
		1	4.6	95.4	100.0

a. 96.8% 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. 95.5% of cross-validated grouped cases are correctly classified. From the original group 0 88 cases were correctly classified as 0 and 3 cases were misclassified as 1. Accuracy for this group is 96.7%. Groups 1 from the original 127 cases were correctly classified as 1 and 4 cases were misclassified as 0. The accuracy for this group is 96.9%. Overall accuracy for original data is 96.8%. Cross-validation is a technique to assess the model's performance by partitioning data into subsets. Group 0 has 87 cases that were correctly classified and 4 cases were misclassified as 1. The accuracy for this group is 95.6%. Group 1 has 125 cases were classified correctly and 6 cases were misclassified as 0. Accuracy for this group is 95.4%. Overall accuracy for this group is 95.5%.

4.3 Testing and Validation of Proposed Model

Testing and validation of proposed model using logit analysis. The manipulator and the non-manipulators are estimated by using the Beneish M-score model and then the proposed model is tested using Logit analysis and discriminant analysis.

4.3.1 Descriptive Statistics

The descriptive analysis describes basic behavior and the main feature of the data of the study. Table 4.3.1 provides a summary of key measures for each variable.

TABLE 4.18: Descriptive statistics

	GMI	**SGI**	**TATA**	**DMI**	**FFA**	**INV**	**OCF**	**NOE_SGR**
Mean	0.8172	1.2973	0.0533	0.6133	0.991	1.1312	0.2838	1.1945
Median	0.7723	1.2574	0.0442	0.6528	1	1.0499	0	1.0615
Maxi.	4.6544	3.4703	0.4491	1	1	6.0599	1	5.4501
Mini.	-2.4885	0.5403	-0.7558	0.0195	0	0	0	-0.0275
STD	0.7181	0.3969	0.1334	0.2854	0.0947	0.6654	0.4519	0.7527
Skew	1.4504	1.8153	-0.768	-0.3776	-10.393	3.2832	0.9592	2.1711
Ku	13.1337	10.6054	8.8787	1.9672	109.009	20.888	1.92	10.8185

GMI = Gross Margin Index, SGI = Sales Growth Index, TATA = Total Accruals to Total Assets, DMI = Debt Maturity Structure, FFA = Frequent Financing Activity, INV Inventory Index, OCF = Operating Cash Index, and NOE_SGR = Non-Operating Expenses to Sales Growth Index.

GMI represents the mean value of 0.8172 means that GMI could not signal potential earning manipulation. SGI's mean value of 1.2973 indicates aggressive revenue growth. INV shows a mean greater than 1 indicating that the inventory is accumulated and NOE_SGR also has a mean value of greater than reflecting the manipulation in non-operating expenses.

The middle value when data is sorted, it gives a sense of central tendency without being affected by outliers. OCF median = 0.0000 indicating a higher number of zero observations. For inventory the maximum value is 6.0599, indicating some companies have very high inventory-related measures.

The minimum values for most variables (e.g., TATA = -0.7558) reflect the existence of extremely low values in the dataset. Standard deviation indicates the variability or dispersion around the mean. GMI standard deviation is 0.7181 showing moderate variations in gross margin index. INV standard deviation = 0.6654, showing moderate variability in inventory.

Skewness measures asymmetry in the distribution. GMI and SGI have positive skewness indicating longer right tails and higher extreme values. TATA has negative skewness, suggesting the distribution has a longer left tail. Kurtosis measures the tailedness of the distribution. Variables like GMI (13.1337), SGI (10.6054), and INV (20.8884) have high kurtosis, indicating the presence of extreme outliers or heavy tails.

4.3.2 Earning Manipulation using Binary Logit Analysis

The Binary Logit analysis is performed to detect the role of various variables in the detection of earning manipulation. Table 4.19 represents the binary logistic regression, which predicts a binary dependent variable (0, 1).

TABLE 4.19: Binary Logit

Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
GMI	2.442423	0.649235	3.762000	0.0002
SGI	2.071955	0.682596	3.035407	0.0024
TATA	18.89620	3.285529	5.751341	0.0000
DMI	-0.359620	0.687474	-0.523104	0.6009
FFA	-4.528653	1.466188	-3.088726	0.0020
INV	-0.385547	0.359345	-1.072917	0.2833
OCF	0.435404	0.555756	0.783445	0.4334
NOE_SGR	0.047427	0.247928	0.191295	0.8483
Mean dependent var	0.590090	S.D. dependent var		0.492928
S.E. of regression	0.367051	Akaike info criterion		0.871595
Sum squared resid	28.83143	Schwarz criterion		0.994214
Log-likelihood	-88.74703	Hannan-Quinn criteria.		0.921101
Deviance	177.4941	Restr. Deviance		300.5106
Avg. log-likelihood	-0.399761			
Obs with Dep=0	91	Total obs		222
Obs with Dep=1	131			

GMI has a coefficient of 2.442423 suggesting a positive and significant effect on the dependent variable ($P - value = 0.0002$). SGI and TATA have a coefficient of 2.071955, 18.89620 also significant (p-value = 0.0024 and 0.0000), indicating a strong positive relationship. DMI and INV have a negative and insignificant effect on the dependent variable. FFA has a negative significant effect on the dependent variable. OCF and NOE_SGR have a positive insignificant effect on the dependent variable.

Standard errors measure the variability of the coefficients. Lower standard errors imply more reliable estimates. Z-statistics and P-values are used to test whether the coefficients are statistically significant. Variables with a $P - value < 0.05$ (GMI, SGI, TATA, and OCF) significantly influence the dependent variable. Akaike info criterion 0.871595 lower values suggest better models.

4.3.3 Expectation-Prediction Evaluation for Binary Specification

This table evaluates the classification performance of the binary logistic model for detecting earning manipulation, comparing it to the baseline "constant probability" model. Table 4.20 assesses the model's classification performance. Estimated equation correctly classified observations.

TABLE 4.20: Expectation-Prediction Evaluation for Binary Specification

	Estimated Equation			**Constant Probability**		
	Dep=0	**Dep=1s**	**Total**	**Dep=0**	**Dep=1**	**Total**
P(Dep=1)<=C	70	18	88	0	0	0
P(Dep=1)>C	21	113	134	91	131	222
Total	91	131	222	91	131	222
Correct	70	113	183	0	131	131
% Correct	76.92	86.26	82.43	0	100	59.01
% Incorrect	23.08	13.74	17.57	100	0	40.99

For non-manipulators Dep=0 the model correctly classified 70 out of 91 observations. For manipulator = 1 the model correctly classified 113 out of 131 observations. Overall, 82.43% of observations are correctly classified. Constant probability is a baseline model that assumes the probability of Dep =1 equals the observed proportion. The constant probability model achieves an accuracy of

59.01%, meaning the binary logit model (82.43) outperforms this baseline significantly. The binary logistic regression model performs well in predicting the binary outcome, with an accuracy of 82.43%.

4.3.4 Goodness-of-Fit Evaluation for Binary Specification

The table represents the goodness-of-fit evaluation for a binary logistic regression model based on quantiles of risk, assessed through a Hosmer-Lemeshow (H-L).

TABLE 4.21: 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	3.E-07	0.0730	21	21.5652	1	0.43479	22	0.74956
2	0.0750	0.2481	17	18.7120	5	3.28795	22	1.04811
3	0.2689	0.3785	18	14.8663	4	7.13373	22	2.03716
4	0.3792	0.4849	14	12.6961	8	9.30393	22	0.31666
5	0.5044	0.6576	10	9.61071	13	13.3893	23	0.02709
6	0.6613	0.7691	4	6.08996	18	15.9100	22	0.99177
7	0.7736	0.8634	3	3.66865	19	18.3314	22	0.14626
8	0.8667	0.9333	4	2.13545	18	19.8645	22	1.80302
9	0.9350	0.9853	0	0.74754	22	21.2525	22	0.77383
10	0.9868	0.9999	0	0.08743	23	22.9126	23	0.08776
		Total	91	90.1793	131	131.821	222	7.98123
H-L Statistic			7.9812		Prob. Chi-Sq(8)		0.4353	

The test divides the dataset into deciles of predicted probabilities and compares the observed and expected frequencies of outcomes (Dep = 0 and Dep = 1). A lower H-L statistics indicates a better fit, as it suggests smaller differences between observed and expected values. The total observed and expected counts for Dep =0 (91 vs 90.1793) and Dep = 1 (131 vs 131.821) align closely, suggesting the model predicts both categories well on aggregate. Small differences in individual quantiles (decile 2, decile 8) suggest the model slightly under or overestimates outcomes in certain probability ranges but not critically. The high p-value for the H-L test indicates the model fits well.

4.3.5 Marginal Effect

The marginal effect is the partial derivative of the response variable with respect to a dependent variable, holding all other variables constant. Marginal effect indicates how much a one-unit change in each independent variable, providing insights into the practical implications of change in these predictors.

Table 4.22: Marginal Effect

Variables	**X**	β	**L= X***β	**Bp**	**Marginal Effect**
GMI	0.8172	2.442423	1.995948	1.646391	0.5366
SGI	1.2973	2.071955	2.687947	1.396665	0.4552
TATA	0.0533	18.8962	1.007167	12.73757	4.1514
DMI	0.6133	-0.35962	-0.22055	-0.24241	-0.0790
FFA	0.991	-4.52865	-4.4879	-3.05268	-0.9949
INV	1.1312	-0.38555	-0.43613	-0.25989	-0.0847
OCF	0.2838	0.435404	0.123568	0.293498	0.0957
NOE_SGR	1.1945	0.047427	0.056652	0.03197	0.0104
		L	0.726701		
		P	0.674081		

The column Variable represents a different variable that is included in Logit model. X shows the mean values of variables extracted from descriptive statistics of proposed model. Beta shows the coefficients extracted from Binary Logit analysis represents the estimated impact of each variable on the dependent variable. L shows the linear prediction for each variable. GMI 0.5366 indicates that increasing by one unit raises the expected outcomes by 0.53366. TATA 4.1514 high marginal effect indicating that TATA has a substantial influence; increasing TATA by one unit raises the expected outcome by over 4 units. OCF 0.0957 and NOESGR 0.0104 indicate a small relative increase. The DMI -0.0790, FFA 0.9949 and INV -0.0847 shows a negative impact indicate that increasing by one unit decrease the expected outcome.

4.4 Testing and Validation of Proposed Model

Testing and validation of proposed model using discriminant analysis.

4.4.1 Descriptive Statistics of Manipulator and Non-Manipulator

The descriptive statistics of the manipulator and manipulator are given in Table 4.23. Table provides group statistics, breaking down the mean and standard deviation of various variables across two groups (M=0 and M=1), as well as their combined values.

TABLE 4.23: Group Statistics

M		**Mean**	**Std. Deviation**
0	GMI	0.64	0.62
	SGI	1.21	0.29
	TATA	-0.03	0.12
	DMI	0.59	0.29
	FFA	0.99	0.10
	INV	1.14	0.76
	OCF	0.12	0.33
	NOESGR	1.15	0.74
1	GMI	0.94	0.76
	SGI	1.36	0.45
	TATA	0.11	0.11
	DMI	0.63	0.28
	FFA	0.99	0.09
	INV	1.12	0.59
	OCF	0.40	0.49
	NOESGR	1.22	0.76
Total	GMI	0.82	0.72
	SGI	1.30	0.40
	TATA	0.05	0.13
	DMI	0.61	0.29
	FFA	0.99	0.09
	INV	1.13	0.67
	OCF	0.28	0.45
	NOESGR	1.19	0.75

Group M = 0 represents the first subgroup, non-manipulators companies, and M = 1 represents the manipulators companies. The total represents the combines both groups. The mean values for each group highlight differences in the variables between the two groups.

GMI for M = 0 0.64 and M = 1 0.94. Companies in group M =1 have higher gross margins on average, which could indicate manipulation signals. The standard deviation of GMI is slightly higher in manipulator M=1 0.76 indicating great variability in the manipulated companies.

TATA mean of non-manipulator companies is -0.03 and for manipulators, 0.11 suggests more aggressive earning manipulation. SGI is higher in manipulator companies M = 1 1.36 compared to M = 0 (1.21), reflecting possible growth manipulation. The variability is also greater for manipulated firms. INV is slightly higher for M = 0 than M = 1, indicating potential differences in inventory practices. Non- manipulator companies show much higher variability in the inventory index.

OCF is significantly higher in M = 1, which might reflect operational performance manipulation. Variability is also higher for manipulated firms. DMI is slightly higher in M = 1, which indicates the manipulation. NOESGR is higher in M = 1 1.22 and M=0 1.15 reflects that manipulation in non-operating expenses.

GMI, SGI, TATA, OCF. And NOESGR have higher means for manipulated companies indicating these variables could play a role in distinguishing manipulated from non-manipulated. For most variables, group = 1 has a higher standard deviation, indicating greater variability in earnings-related measures for companies in this group. OCF M = 0 standard deviation = 0.33 and M = 1 standard deviation = 0.4911 suggests more erratic cash flow patterns among group M = 1.

4.4.2 Tests of Equality of Group Means

The table 4.24 depicts the test for equality of group means. This table tests whether each independent variable significantly differs across groups. The significance value indicates whether difference in the group means statistically significant.

Table 4.24: Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
GMI	.955	10.250	1	220	.002
SGI	.963	8.547	1	220	.004
TATA	.748	74.210	1	220	.000
DMI	.996	.856	1	220	.356
FFA	1.000	.067	1	220	.796
INV	1.000	.065	1	220	.800
OCF	.909	21.944	1	220	.000
NOESGR	.998	.481	1	220	.489

The p-value bellows than the 0.05 implies the variable significantly discriminates between the groups GMI, SGI, TATA and OCF. While the insignificant value indicates that the groups have no difference such as DMI, FFA, INV and NOESGR. The F-statistics tests the null hypotheses that group are equal. Higher value indicates greater group difference.

4.4.3 Pooled Within-Groups Matrices

A pooled within-groups matrix shows the correlation between the variables within the groups. The diagonal element represents a value of 1.000, as each variable is perfectly correlated with itself. Off-diagonal elements show the strength and direction of relationships between variables.

Table 4.25: Pooled Within-Groups Matrices (Correlations)

	GMI	SGI	TATA	DMI	FFA	INV	OCF	NOESGR
GMI	1.000	-.351	-.254	.016	.064	-.025	-.058	.099
SGI	-.351	1.000	.026	-.138	.022	-.276	-.085	-.180
TATA	-.254	.026	1.000	.128	-.024	.164	.385	.029
DMI	.016	-.138	.128	1.000	.154	.068	.140	.030
FFA	.064	.022	-.024	.154	1.000	-.044	.057	-.068
INV	-.025	-.276	.164	.068	-.044	1.000	.088	.021
OCF	-.058	-.085	.385	.140	.057	.088	1.000	-.053
NOESGR	.099	-.180	.029	.030	-.068	.021	-.053	1.000

The correlation between GMI and SGI is -0.351. This negative value suggests an inverse relationship between these variables. The correlation between the OCF and INV is 0.088, indicating a weak positive relationship. Most correlations are weak, indicating the variables are relatively independent and contribute uniquely to the discriminant function.

4.4.4 Log Determinants

This table provides the determinant values for each group and the pooled covariance matrix. Log determinant values reflect the variability within the groups. Lower log determinants suggest less variability and greater group homogeneity. Ranks indicate the dimensionality of the covariance matrix.

Table 4.26: Log Determinants

M	**Rank**	**Log Determinant**
0	8	-18.740
1	8	-17.876
Pooled within-groups	8	-17.801

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

The pooled within-group determinant (-17.801) summarizes the overall variation.

4.4.5 Test Results (Box's M test)

This table checks the assumption of equality of covariance matrices between groups.

Table 4.27: Test Results

Box's M		94.362
F	Approx.	2.516
	df1	36
	df2	126649.253
	Sig.	.000

Tests null hypothesis of equal population covariance matrices.

Box's M value is 94.362. Since the p-value is less than 0.05, the null hypothesis of equal population covariance matrices is rejected.

4.4.6 Eigenvalues

The table represents the proportion of variance explained by the discriminant function. Larger eigenvalues indicate strong discriminant power. The percentage of variance is explained by each discriminant function. Cumulative percentage variance is explained up to the current function. The canonical correlation represents the correlation between the discriminant scores and the groups. Values closer to 1 indicate stronger relationships.

Table 4.28: Eigenvalue

Function	**Eigenvalue**	**% of Variance**	**Cumulative %**	**Canonical Correlation**
1	.609a	100.0	100.0	.615

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

There is only 1 discriminant function with an eigenvalue of .609, explaining 100% of the variance. The canonical correlation is 0.615, indicating a strong relationship between the discriminant function and group membership

4.4.7 Wilks' Lambda

Wilks' Lambda tests the significance of the discriminant function. Lower values indicate better discrimination. Chi-square tests the null hypothesis that the discriminant function does not explain group differences.

Table 4.29: Wilk,s Lambda

Test of Function(s)	**Wilks' Lambda**	**Chi-square**	**df**	**Sig.**
1	.621	102.796	8	.000

Wilks Lambda is 0.621 and the associated P-value is 0.000 indicating that the discriminant function significantly differentiates between the groups.

4.4.8 Standardized Canonical Discriminant Coefficients

This table depicts the standardized canonical discriminant function coefficients. These coefficients indicate the relative contribution of each variable to the discriminant function, standardized to remove the effects of different measurement scales.

TABLE 4.30: Standardized Canonical Discriminant Function Coefficients

	Function
	1
GMI	.663
SGI	.483
TATA	.836
DMI	.008
FFA	-.019
INV	-.026
OCF	.168
NOESGR	.065

TATA has the highest coefficient 0.836, making it the most influential variable in discriminating between the groups. GMI 0.663 and SGI 0.483 are also strong contributors. Variables like FFA, DMI, INV, OCF, and NOESGR have minimal contribution to the discriminant function.

4.4.9 Structure Matrix

Structure Matrix displays pooled within-group correlations between the variables and the discriminant function. These values represent the strength of the relationship between each variable and the discriminant function.

TABLE 4.31: Structure Matrix

	Function
	1
TATA	.744
OCF	.405
GMI	.276
SGI	.252
DMI	.080
NOESGR	.060
FFA	.022
INV	-.022

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions

Variables are ordered by the absolute size of correlation within the function.

TATA 0.744 has the strongest correlation with the discriminant function, followed by OCF, GMI, and SGI. Variables such as DMI, NOESGR, FFA, and INV have the weakest correlations, indicating they contribute minimally to group discrimination.

4.4.10 Canonical Discriminant Function Coefficient

The Canonical Discriminant Function Coefficient indicates the unstandardized coefficients for each variable in the discriminant function.

Table 4.32: Canonical Discriminant Function Coefficients

	Function
	1
GMI	.942
SGI	1.238
TATA	7.232
DMI	.029
FFA	-.197
INV	-.040
OCF	.389
NOESGR	.086
(Constant)	-2.753

Unstandardized coefficients

Table 4.32 depicts the coefficients from the equation of the discriminant function.

Discriminant function equation;

$$\begin{aligned} D = (-2.753) + 0.942 * GMI + 1.238 * SGI + 7.232 * TATA + 0.029 * DMI \\ (-.197) * FFA + (-.040) * INV + 0.389 * OCF + 0.086 * NOESGR \end{aligned} \tag{4.2}$$

TATA 7.232 has the highest coefficient, confirming it has the strongest influence on the discriminant function.

4.4.11 Functions at Group Centroids

Functions at group centroids represent the mean discriminant score for each group on the discriminant function.

Table 4.33: Functions at Group Centroids

M	Function
	1
0	-.932
1	.648

Unstandardized canonical discriminant functions evaluated at group means

Group 0 has a centroid of -0.932, and Group 1 has a centroid of 0.648.

To determine the J-score model use the criteria -0.284 if the J-score is greater than -0.284 companies are involved in earning manipulation and if the J-score is less than -0.284 then the companies are not involved in earning manipulation.

4.4.12 Classification Results

Classification results represent the classification results of two predicted groups 0 and 1.

Table 4.34: Classification Results[a,c]

		M	Predicted Group Membership		Total
			0	1	
Original	Count	0	70	21	91
		1	17	114	131
	%	0	76.9	23.1	100.0
		1	13.0	87.0	100.0
Cross-validatedb	Count	0	64	27	91
		1	17	114	131
	%	0	70.3	29.7	100.0
		1	13.0	87.0	100.0

a. 82.9% of originally grouped cases 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. 80.2% of cross-validated grouped cases correctly classified. Table 4.4.12 depicts the classification results. From original group 0 70 cases are correctly classified as 0 and 21 are misclassified as 1. Accuracy for this group is 76.9

%. Groups 1 from original 114 cases are correctly classified and 17 are misclassified as 0. Accuracy for group 1 is 87%. Overall accuracy for original data is 82.9%. Cross validation is a technique to assess the model's performance by partitioning the data onto subsets. Group 0 has 64 cases are correctly classified and 27 are misclassified as 1. The accuracy for cross validation for group 0 is 70.3%. On the other hand group 1 has a 114 cases are correctly classified and 17 cases are misclassified as 0. The accuracy for group 1 is 87.0%. The overall accuracy for cross validation group is 80.2%.

4.5 Comparison of Two Tests using Logit Analysis

TABLE 4.35: Comparison Table of Two Tests using Logit Analysis

	Beneish M score	**J score**
Significant Variables	Day's Sales in Receivables Index	Sales Growth Index
	Gross Margin Index	Gross Margin Index
	Sales Growth Index	Total Accruals to Total Assets
	Total Accruals to Total Assets	Frequent Financing Activity
	Asset Quality Index	
	Selling and General Administrative expenses Index	
	Leverage Index	
Overall Accuracy	90.54%	82.43%

The Beneish model is more effective in identifying the manipulators and non-manipulators then the J score.

4.6 Comparison of Two Tests using Discriminant Analysis

Table 4.36: Comparison Table of Two Tests using Discriminant Analysis

	Beneish M score	**J score**
Significant Variables	Day's Sales in Receivables Index	Sales Growth Index
	Gross Margin Index	Gross Margin Index
	Sales Growth Index	Operating Cash Flow
	Total Accruals to Total Assets	Total Accruals to Total Assets
	Asset Quality Index	
Accuracy 0	96.7%	76.9%
1	96.9%	87.0%

The Beneish model has greater accuracy then the J score.

Chapter 5

Conclusion and Recommendation

5.1 Beneish M Score Model

The Beneish model proves to be a valuable tool for detecting earnings manipulation through its application of both binary logistic regression and discriminant analysis. While certain financial ratios are strong indicators of potential manipulation risks, others may not provide significant insights. The manipulators and non-manipulators were calculated using the Beneish model, which classifies the companies then, it was confirmed through the logistic analysis and discriminant analysis. The analysis of the Beneish M-score model, through the application of binary logistic regression, demonstrates its effectiveness in detecting earnings manipulation among firms. The findings indicate that specific financial ratios, such as the Days Sales in Receivables Index (DSRI), Gross Margin Index (GMI), Sales Growth Index (SGI), Asset Quality Index (AQI), Selling and General Administrative expense Index (SGAI), Total Accruals to Total Assets (TATA) and Leverage Index (LVGI) are significant predictors of potential manipulation. The Akaike Information Criteria showed the Binary Logit analysis model is a fit. The expectation prediction model for binary specification correctly predicts 79 companies out of 91 as non-manipulators and 122 companies out of 131 as manipulators. The binary logistic regression model achieved an impressive overall accuracy of 90.54%.

Discriminant analysis corroborates the findings from binary logistic regression by highlighting the differences in means for key financial ratios between manipulated and non-manipulated firms.

The strong discriminative power of variables such as TATA (Total Accruals to Total Assets), DSRI (Days Sales in Receivables Index), GMI (Gross Margin Index), SGI (Sales Growth Index), and AQI (Asset Quality Index) indicates their utility in identifying firms at risk of earnings manipulation. The significant Wilks' Lambda value further confirms that the discriminant function effectively differentiates between groups.

The cutoff point of function at group centroid is -0.398 the companies that have a score greater than -0.398 are classified as manipulators and companies that have a score less than -0.398 are classified as non-manipulators.

Based on the discriminant analysis cutoff point the classification results achieved an overall accuracy of 96.8% and 95.5% of cross-validation grouped cases are correctly classified.

5.2 Proposed Model

By using both Binary Logit analysis and Discriminant analysis to distinguish between manipulative and non-manipulative companies, the proposed model for identifying earning manipulation exhibits a strong analytical framework. The suggested approach offers insights into the financial behavior connected to earning manipulation in addition to successfully identifying such practices.

Given its high prediction ability and notable categorization accuracy, this model may prove to be a useful resource for investors evaluating a company's financial integrity. To further increase detection skills, future studies could examine ways to improve this model by adding more factors or honing current measurements.

Binary logistic regression is used in the analysis of the proposed model to show how well it can identify firm-to-firm earnings manipulation. The results show that some financial ratios are important indicators of possible manipulation, including the Frequent Financing Activity (FFA), Total Accruals to Total Assets (TATA), Sales Growth Index (SGI), and Gross Margin Index (GMI). According to the binary specification's expectation prediction evaluation, 113 out of 131 companies are appropriately classed as manipulators and 70 out of 91 as non-manipulators.

The binary logistic regression model achieved an impressive overall accuracy of 82.43%. The discriminant analysis of the proposed model significantly discriminates between the groups such as Margin Index (GMI), Sales Growth Index (SGI), Total Accruals to Total Assets (TATA), and OCF.

The statistical significance of these variables, as evidenced by their low p-values, reinforces their importance in predicting earnings manipulation.

The cut-off point for the proposed model is -0.284. If the J-score is greater than -0.284 companies are involved in manipulation and if the J-score is less than -0.284 means that the companies are not involved in earning manipulation.

Based on this criterion the model achieved 82.9% of the original groups being correctly classified and 82.2% of cross-validation groups being correctly classified.

5.3 Recommendations

1. Beneish M-score model is good for detecting earning manipulation in the Pakistan Equity market.

2. Variables of Beneish Model Asset Quality Index, Sales Growth Index, Selling and General Administrative expenses, Day's Sales in Receivable Index, Total Accruals to Total Assets, Gross Margin Index, and Leverage Index significantly influence to earning manipulation.

The Logistic analysis finds that 131 companies are involved in earning manipulation and 91 companies are non-manipulators.

3. The new variable FFA (Frequent Financing Activity) significantly influences the tendency to manipulate or not. It should be considered.

4. The common variables of the Beneish Model and the Propose model are GMI, SGI, and TATA, which significantly influence earning manipulation in both models.

5.4 Limitation

This study provides important insights into earning manipulation in Pakistan; its findings should be cautious when considering their applicability to other countries or sectors.

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