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Financial Consequences of Fraud in Amman Stock Exchange Firms

Anas Alqudah
Department of Banking and Finance, Yarmouk University, Jordan
***Corresponding author** Email: anas.qudah@yu.edu.jo

Safa Jaradat
Department of Banking and Finance, Yarmouk University, Jordan
Email: safajaradat98@gmail.com

Lara Al-Haddad
Department of Banking and Finance, Yarmouk University, Jordan
Email: lara.haddad@yu.edu.jo

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Abstract

Purpose: This study investigates the impact of financial fraud risk, proxied by the Beneish M-Score, and key macroeconomic variables on the financial performance (Return on Assets - ROA) of firms listed on the Amman Stock Exchange (ASE).

Methodology: Employing panel data from 140 ASE-listed firms between 2015 and 2020, the research utilizes Ordinary Least Squares (OLS) regression and several machine learning regression models (Support Vector Machines, Random Forest, Gradient Boosting). The analysis examines the influence of the Beneish M-Score, GDP growth, inflation, and company size on return on assets (ROA).

Findings: The results reveal a significant positive impact of GDP growth and firm size on ROA. While inflation's linear effect was insignificant, we uncovered a compelling non-linear, inverted U-shaped relationship between the Beneish M-Score and ROA. This suggests that while moderate levels of earnings management risk may coincide with performance-enhancing activities, higher levels are unequivocally detrimental. Notably, machine learning models, particularly Random Forest, demonstrated superior predictive accuracy over traditional OLS regression, underscoring the importance of capturing these non-linear dynamics.

Recommendations: Jordanian firms are advised to strengthen internal controls and foster transparent financial reporting. Regulators should enhance oversight and consider advanced analytical tools, including machine learning, for risk assessment. Investors should critically evaluate fraud risk indicators, recognizing their complex impact on performance.

Originality: This study offers novel insights into the nonlinear performance implications of financial fraud risk in an emerging market context (Jordan). It distinctively integrates macroeconomic factors and compares traditional econometric techniques with machine learning approaches, contributing to the financial fraud literature in developing economies by highlighting the complex dynamics between earnings manipulation risk and firm performance. This study contributes to the field of Decision Sciences by demonstrating how hybrid econometric-ML models can enhance fraud risk assessment and corporate decision-making in developing economies.

Keywords: Financial fraud, financial performance, Beneish M-Score, Regression analysis, Amman Stock Exchange.

JEL-Classifications: G33, G34 , M41

1. Introduction

Financial integrity is critical to economic stability. However, internal fraud poses a significant threat, particularly in emerging markets such as Jordan. Despite research on financial fraud in developed markets (Hamilton & Smith, 2021; Heese & Pérez-Cavazos, 2019), few studies examine its impact on corporate performance in emerging economies, especially in the Middle East. This study addresses this gap by focusing on the Amman Stock Exchange (ASE). Economic conditions and regulations may affect the link between financial fraud and corporate performance. This research helps us understand financial fraud in less-studied markets.

This study makes several significant contributions. First, by focusing on the ASE, it addresses a critical gap concerning fraud's impact in Middle Eastern emerging markets. More distinctively, we move beyond the conventional assumption of a linear relationship. We hypothesize and subsequently demonstrate a complex, non-linear dynamic between fraud risk, proxied by the Beneish M-Score, and corporate performance. Finally, by systematically comparing the performance of traditional econometric models with advanced machine learning techniques, we offer new insights into methodological best practices for fraud risk assessment, contributing to the broader literature in both finance and decision sciences.

We base our theory on the fraud triangle and agency theory, which help us understand the motivations and opportunities for financial fraud. We also consider macroeconomic factors, such as GDP and inflation, which impact corporate profits. Jordan's unique economy presents a chance to test these theories in an emerging market.

In summary, this research offers a comprehensive analysis of the impact of financial fraud on corporate performance in an emerging market context. It aims to enhance understanding of financial fraud, offer practical insights, and address a gap in the existing literature. This work aims to enhance financial governance and prevent fraud in emerging economies. This study contributes to Decision Sciences by demonstrating how integrating machine learning diagnostics with traditional econometric models can improve the decision-making process for investors and regulators in assessing financial fraud risk.

The remainder of this paper is structured as follows: Section 2 provides a comprehensive review of the relevant literature. Section 3 presents the theoretical framework underpinning the study. Section 4 describes the research methodology, including data sources, variables, and model specifications. Section 5 reports the empirical results and their statistical validation. Section 6 discusses the theoretical and contextual implications of the findings in light of the existing literature and the Jordanian regulatory environment. Finally, Section 7 concludes the paper by summarizing key insights, acknowledging limitations, and offering directions for future research.

2. Literature Review

Financial fraud, encompassing acts such as earnings management and embezzlement, inflicts considerable damage on the financial performance and stability of business entities, including banks (Salem, et al., 2021). The imperative for robust anti-fraud measures is particularly pronounced in emerging markets like Jordan, where such mechanisms can fortify operational integrity and bolster profitability.

Globally, particularly in developed economies like the US and China, significant strides have been made in fraud detection methodologies. Notably, the application of machine learning techniques has demonstrated high efficacy. For instance, Zhao and Bai (2022) reported an accuracy of over 99% in ensemble models for detecting fraud in Chinese public firms. While insightful, the direct applicability of these findings to distinct market environments, such as Jordan, requires careful consideration of contextual factors. Challenges persist in this domain, including the management of imbalanced datasets and the optimal tuning of machine learning models, issues addressed by researchers such as Mohammed, et al. (2018), Kaur, et al. (2019), and Ganganwar (2012). Furthermore, the criticality of feature selection in these models has been highlighted by Neumann, et al. (2005), Tang, et al. (2014), and Guyon and Elisseeff (2006).

A considerable body of research has explored the repercussions of financial fraud on corporate performance, primarily within developed markets such as the United States (Bell & Carcello, 2000), Greece (Spathis, 2002), and the United Kingdom (Hamilton & Smith, 2021). However, a discernible gap exists in the literature concerning emerging economies like Jordan, which possess unique regulatory frameworks and market structures that can mediate the fraud-performance nexus. This study aims to bridge the gap by focusing on firms listed on the Amman Stock Exchange (ASE), thereby shedding light on the consequences of financial fraud in a developing country context.

Within the Jordanian context, research on the impact of fraud, particularly within industrial firms, remains relatively scarce. Alodat, et al. (2022) examined the relationship between corporate governance mechanisms and the incidence of financial fraud in Jordanian banks. While their work underscored the importance of governance in mitigating fraud within the banking sector, it did not extend to the broader non-financial corporate landscape, nor did it explicitly quantify the impact of such fraud on corporate performance metrics. The present study builds upon this by examining non-financial firms on the ASE and directly assessing the performance implications.

Furthermore, existing literature predominantly focuses on the direct financial impact of fraud on profitability (AboElsoud, et al., 2021; Anisykurlillah, et al., 2022; Doan & Ta, 2023). While financial and operational effects are crucial, the indirect consequences, such as the erosion of corporate credibility and stakeholder trust (including investors, customers, and regulators), are less explored, especially in emerging markets. This study, by analyzing the impact on Return on Assets (ROA), implicitly captures some of these broader consequences, as diminished trust can translate into poorer financial outcomes. Future research could more directly investigate the reputational damage and its effect on stakeholder perceptions within the Jordanian banking and industrial sectors.

In summary, while extant research offers valuable insights, critical gaps remain, particularly concerning the nuanced impact of financial fraud on corporate performance within the Jordanian industrial sector. This study makes a significant contribution by specifically addressing an under-researched area, employing established fraud risk indicators, and considering the broader macroeconomic environment.

3. Theoretical Framework

This section outlines the primary theoretical underpinnings that inform our understanding of financial fraud, its motivations, and its potential impact on corporate financial performance. We also present the Beneish M-Score model, a key analytical tool used in this study, grounded in theories of earnings management.

3.1. Agency Theory

Agency theory, originating from the work of Jensen and Meckling (1976), describes the relationship between principals (e.g., shareholders) and agents (e.g., managers). In this relationship, conflicts of interest can arise due to information asymmetry and divergent goals. Managers, who possess more information about the company's operations and financial status than shareholders, may act in their self-interest rather than in the best interest of the principals. Such actions can include engaging in earnings management or outright financial fraud to achieve personal benefits, such as increased compensation, job security, or enhanced reputation, often at the expense of the firm's long-term health and shareholder value (Bao, et al., 2020; Skousen, et al., 2009). Agency theory thus provides a crucial lens for understanding the incentives that might drive fraudulent financial reporting, which in turn impacts reported and actual firm performance.

3.2. Fraud Triangle Theory

The Fraud Triangle theory, first conceptualized by Donald Cressey (1953), posits that three conditions are generally present when fraud occurs:

Pressure (or Incentive/Motivation): This refers to the motive or incentive that prompts an individual to commit fraud. For corporate executives, this could mean pressure to meet the expectations of financial analysts, secure bonuses tied to performance metrics, or conceal poor financial results.

Opportunity: This refers to the circumstances that enable fraud to be perpetrated. Weak internal controls, poor corporate governance, ineffective oversight, or complex transactions can create opportunities for managers to manipulate financial statements or misappropriate assets.

Rationalization: This involves the perpetrator justifying their fraudulent actions as acceptable or non-criminal. For example, they might believe they are "borrowing" funds, that "everyone does it," or that it's for the "good of the company" to smooth earnings.

Many studies have employed the fraud triangle to explain the conditions that foster financial fraud (Alfiandy, et al., 2021; Asare & Wright, 2019; Nuryaman, 2021). While this study does not directly measure each component of the triangle, the theory informs the selection of fraud risk indicators, such as the Beneish M-Score, whose components often reflect pressures and opportunities for earnings management.

3.3. The Beneish M-Score Model

The Beneish M-Score, developed by Messod Beneish (1999), is a mathematical model that utilizes financial ratios derived from a company's financial statements to assess the likelihood that a company has manipulated its earnings. The model is grounded in the expectation that managers engaging in earnings manipulation will leave detectable traces in financial data. For instance, firms inflating earnings might show unusually high sales growth, deteriorating gross margins (as fictitious sales might have lower margins or higher associated costs), increasing days' sales in receivables (indicating difficulty in collecting inflated sales), or disproportionate increases in assets relative to revenues.

The M-Score is calculated using the following formula (Beneish, 1999):

$$\text{M-Score} = -4.84 + 0.920*DSRI + 0.528*GMI + 0.404*AQI + 0.892*SGI + 0.115*DEPI - 0.172*SGAI + 4.679*TATA - 0.327*LVGI, \quad (1)$$

which is calculated using eight financial ratios:

DSRI (Days Sales in Receivables Index): Measures the ratio of days' sales in receivables in year t to year t-1. A significant increase suggests potential revenue inflation.

GMI (Gross Margin Index): Measures the ratio of gross margin in year t-1 to year t. A GMI greater than 1 indicates deteriorating margins, which might incentivize manipulation.

AQI (Asset Quality Index): Measures the ratio of non-current assets (other than plant, property, and equipment) to total assets in year t compared to year t-1. An increase might suggest excessive capitalization of expenses.

SGI (Sales Growth Index): Ratio of sales in year t to year t-1. While growth is positive, unusually high growth can be a red flag for manipulation, as managers might be under pressure to maintain it.

DEPI (Depreciation Index): Ratio of the rate of depreciation in year t-1 to the corresponding rate in year t. A DEPI greater than 1 suggests assets are being depreciated at a slower rate, possibly to inflate income.

SGAI (Sales, General, and Administrative Expenses Index): Ratio of SGA expenses as a percentage of sales in year t to year t-1. A significant increase might suggest a decrease in administrative efficiency, potentially masked by manipulation.

LVGI (Leverage Index): Ratio of total debt to total assets in year t compared to year t-1. An increase in leverage can create pressure to manipulate earnings.

TATA (Total Accruals to Total Assets): Measures the extent to which earnings are composed of accruals rather than cash flows. High accruals can be an indicator of earnings management.

A score greater than a certain threshold (originally -2.22 by Beneish, though this can vary by context and model calibration) suggests a higher probability of earnings manipulation. In this study, the Beneish M-Score serves as a key independent variable, acting as a proxy for the risk or presence of financial statement fraud (specifically earnings manipulation).

3.4. Hypothesis Development

Based on the theoretical foundations outlined in the preceding subsections—namely, Agency Theory, the Fraud Triangle, and the influence of macroeconomic factors—this study proposes a set of hypotheses to be tested empirically. These hypotheses are grounded in well-established theoretical expectations about how managerial behavior, financial reporting integrity, and external economic conditions influence firm performance. Formulating these hypotheses allows for a structured investigation of the relationships among fraud risk indicators, firm characteristics, and profitability within the context of an emerging market. Accordingly, the following hypotheses are proposed:

H1: The Beneish M-Score has a significant non-linear relationship with Return on Assets (ROA);
H2: Firm size has a significant positive effect on ROA;
H3: Inflation has a significant negative effect on ROA; and
H4: GDP growth has a significant positive impact on ROA.

These hypotheses reflect the study's aim to understand how financial fraud risk and macroeconomic dynamics shape corporate financial performance in the Jordanian market. The inclusion of a non-linear relationship in H1 specifically addresses findings in prior research and is explored further through both linear and machine learning models.

3.5. Stakeholder Theory and Macroeconomic Influences

Stakeholder theory (Freeman, 2010) posits that corporations are responsible not only to their shareholders but also to a broader range of stakeholders, including employees, customers, suppliers, and the community. Financial fraud can significantly harm these stakeholders by eroding trust, leading to job losses, and destabilizing communities (Ma, et al., 2019). The overall performance of a firm (e.g., ROA) is thus a concern for all stakeholders.

Furthermore, corporate performance does not occur in a vacuum. Macroeconomic conditions, such as Gross Domestic Product (GDP) growth and inflation rates, significantly influence firm profitability and operational stability. GDP growth can create opportunities and increase revenues, while inflation can impact costs and pricing power. These macroeconomic factors can also interact with the likelihood of fraud; for example, economic downturns might increase pressure on managers to meet targets, potentially leading to manipulation. Therefore, this study incorporates GDP and inflation as control variables to account for their impact on financial performance.

By integrating these theoretical perspectives, this study aims to provide a comprehensive understanding of how financial fraud risk, proxied by the Beneish M-Score, in conjunction with macroeconomic factors, influences the financial performance of firms listed on the Amman Stock Exchange.

4. Research Methodology

This study employs a quantitative research approach, utilizing both traditional econometric models and machine learning techniques to investigate the impact of accounting fraud, macroeconomic factors, and firm-level characteristics on firm performance in the Amman Stock Exchange (ASE).

We begin with an Ordinary Least Squares (OLS) regression model to estimate the linear relationship between Return on Assets (ROA) and the Beneish M-Score, Inflation, GDP, and Company Size. The OLS model is widely used for initial exploration of linear dependencies and hypothesis testing (Wooldridge, 2010). The general form of the regression model is expressed as:

$$ROA_{it} = \beta_1 \, Beneish_{it} + \beta_2 \, Inflation_t + \beta_3 \, GDP_t + \beta_4 Size_{it} + \varepsilon_{it}, \tag{2}$$

where ROA_{it} is the return on assets for firm *i* at time *t*, $Beneish_{it}$ represents the Beneish M-Score to proxy earnings manipulation risk, $Inflation_t$ *and* GDP_t represent macroeconomic conditions, $Size_{it}$ is the firm size (proxied by total assets), and ε_{it} is the error term.

This model follows prior studies (e.g., Alghizzawi, et al., 2024; Beneish, 1999; Dechow, et al., 2011) that have used OLS to explore the effects of fraud indicators on firm performance. In specifying the OLS model, we deliberately excluded the intercept term due to the data transformation procedures employed. All continuous variables (ROA, Beneish M-Score, inflation, GDP, and firm size) were normalized using Z-score standardization, subtracting the mean and dividing by the standard deviation of each variable. This process centers the variables around a mean of zero and scales them to unit variance. As noted by Gujarati (2009) and Wooldridge (2010), in such cases where data are normalized around zero, the intercept term becomes statistically redundant and may induce multicollinearity without contributing interpretive insight. Thus, the decision to exclude the intercept is both methodologically sound and theoretically neutral under the zero-centered framework.

Diagnostic testing results for the OLS model are reported in Table 4. The Jarque-Bera (Jarque & Bera, 1980) and Omnibus tests reject the null hypothesis of normally distributed residuals, suggesting deviation from ideal conditions. Furthermore, the condition number (1.80e+10) signals possible multicollinearity among predictors, and the Durbin-Watson statistic (1.671) suggests mild positive autocorrelation. These findings collectively warrant caution in interpreting the OLS coefficients. However, rather than compromising the study's validity, these results reinforce the rationale for employing machine learning models such as Random Forest and Gradient Boosting, which are robust to non-normality, multicollinearity, and non-linearity.

As recent econometric research demonstrates, standard regression tests may lose significance in the presence of autoregressive noise or autoregressive structures in both dependent and independent variables (Wong & Pham, 2022; Wong & Pham, 2023). These concerns reinforce the importance of incorporating advanced diagnostic checks before interpreting regression outputs. Furthermore, scholars caution that regressing stationary and non-stationary series together may yield misleading or spurious results, and various remedies have been proposed to address such risks (Wong, Pham, & Yue, 2024; Wong & Pham, 2025a).

Regarding the issue of stationarity, we acknowledge that the panel structure of our dataset necessitates formal unit root testing. Due to the unavailability of raw time series for individual firms, tests such as Levin-Lin-Chu (LLC) or Im-Pesaran-Shin (IPS) could not be conducted. Nevertheless, we have transparently disclosed this limitation and encourage future studies working with comparable financial panel data to apply panel unit root and co-integration diagnostics. We also refer readers to recent advances in the literature (Wong & Yue, 2024; Wong & Pham, 2025b), which caution against regressing mixed-stationarity variables without adequate pre-testing. Given these limitations, we complement the linear approach with advanced machine learning algorithms that better accommodate non-linearities and statistical irregularities in the data.

Complementing the linear model, we employ Gradient Boosting and Random Forest algorithms—non-parametric ensemble techniques suitable for detecting complex, non-linear relationships in financial datasets. These models are increasingly applied in financial fraud detection due to their predictive power and robustness (Chen & Guestrin, 2016; Zhang, et al., 2022). Feature importance scores are extracted from these models to identify key variables influencing ROA and to compare their explanatory strength with that of the linear model.

Finally, the Beneish M-Score is calculated using the original formulation proposed by Beneish (1999), which combines financial ratios into a single composite indicator of potential earnings manipulation. The use of this score has been validated in fraud detection literature, including academic settings and professional accounting oversight contexts (Skousen, et al., 2009).

All statistical analyses are conducted using STATA 16, and machine learning models are implemented using Python’s scikit-learn and XGBoost packages.

Machine learning models were used to enhance the accuracy of fraud detection. SVM classified companies according to their fraud risk by maximizing the margin between fraudulent and non-fraudulent cases. The Random Forest algorithm improved predictions by constructing multiple decision trees and aggregating their outcomes, making it especially effective for managing large datasets with missing values or outliers. Gradient Boosting refines fraud detection models by iteratively minimizing errors and concentrating on high-risk companies. The KNN algorithm identified fraudulent firms by assessing their financial similarity to others within a multidimensional space. These models offered a comprehensive approach to detecting and predicting financial fraud among ASE-listed companies.

4.1. Data Collection

The sample comprises 140 publicly traded companies listed on the Amman Stock Exchange (ASE). They are from various sectors: industrial, commercial, and financial services. The researchers selected the sample based on the availability of financial data from 2015 to 2020. Each company was required to provide complete financial statements. They also had to meet the reporting requirements for the Beneish M-Score analysis. The companies include large, mid-sized, and small firms. This captures a broad range of corporate performance and fraud risks. This sample gives a complete view of Jordan's corporate landscape. It enables a robust analysis of fraud detection across various organizations. Data collection methods for industrial companies involved reviewing company reports and financial disclosures. These sources provided essential financial metrics and accounting information. The analysis computed the Beneish M-score. Ethical guidelines ensured data confidentiality and compliance with usage policies.

Before applying the machine learning algorithms, the data underwent extensive preprocessing. This included handling missing values, normalizing continuous variables, and encoding categorical variables. This ensured that the models could use the financial data. It improved the accuracy and reliability of the results.

We collected several metrics to compute the Beneish M-score. It detects financial fraud. The metrics were net sales, gross profit margin, asset quality, operating expenses, and cash flow. Net sales state company growth, while gross profit margin measures profitability. Analysts use asset quality metrics to assess a company's assets. They want to know how likely those assets are to generate future income. This study measured asset quality by analyzing ratios. These include Total Accruals to Total Assets (TATA) and the Asset Quality Index (AQI). They show a company's portfolio's share of non-performing or underperforming assets. High values in these metrics may overstate assets or show poor management. They may signal financial manipulation or distress. For instance, the AQI checks current asset values against past ones. It looks for unusual changes that could suggest fraud or misreported assets.

The Beneish M-score is a powerful tool for fraud detection. Numerous studies have shown it to be effective. It first considers a comprehensive financial indicator. It includes net sales, gross profit margin, asset quality, operating expenses, and cash flow. Each parameter shows a unique view of a company's finances and risks. For example, net sales growth can show the company's market position and expansion. An unusual change might suggest revenue inflation. Gross profit margin is critical for assessing profitability. Deviations from industry norms may suggest accounting issues.

Asset quality metrics are critical. They check if asset values are too high or too low, a common tactic in financial fraud. Operating expenses offer valuable insights into the company's strategy and operational efficiency. A sudden increase in costs without a corresponding rise in revenue or market share could indicate a cover-up of poor performance. Cash flow metrics are vital. They are more challenging to manipulate than earnings. They check reported profits and help find fraud by uncovering discrepancies.

The Beneish M-score's strength is combining these indicators into a single measure. Evaluating a company's financial statements can help identify firms that are likely to misrepresent their finances. The M-score's multidimensional approach makes it a powerful tool for analysts and investors. It better assesses a company's financial integrity than any single metric. Numerous studies demonstrate that it can effectively detect fraud in financial reports.

4.2. Study Variables

The study investigates the relationship between financial fraud, corporate performance, and macroeconomic conditions. We consider four independent variables: Beneish M-Score, inflation, GDP, and company size. They measure their influence against the Return on Assets (ROA).

The Beneish M-Score model predicts financial fraud in public companies. If the M-Score is above -2.22, it suggests a high risk of financial misconduct in the company. The Beneish M-Score helps investors and regulators identify fraud in companies.

Inflation is the rate at which the prices of goods and services increase over time. It can hurt companies by raising costs and reducing purchasing power. It is analyzed on ROA. GDP is the total value of a nation's goods and services produced within its borders. It is a crucial measure of economic health and its impact on businesses. The final variable is company size, based on assets, revenue, or market cap. It shows resource access and market dominance potential.

4.3. Study Model

The study used multiple predictors to create a regression model for predicting a company's Return on Assets (ROA). The research involved many steps: preprocessing, analyzing, and engineering. It ran an OLS regression, performed backward selection, and visualized the residuals and errors.

We handled missing values, encoded categories, and normalized numbers in data preprocessing. Exploratory data analysis offered insights into variable relationships and potential outliers. Data engineering spotlighted critical, independent variables that correlate with the dependent variable.

The researchers built the OLS regression model on the selected independent variables. A backward selection process refined the model by discarding less relevant features. Residuals and prediction error visualizations helped test the model's fit.

The final model predicted ROA using four variables: Beneish M-Score, Inflation, GDP, and Company Size. It explained 70% of the variance in ROA. The study revealed that the Beneish M-Score, GDP, and company size boosted ROA, while inflation had an adverse effect. The Beneish M-Score and ROA have a threshold relationship. It is positive until a point, after which it turns negative.

In response to recent methodological developments (Wong, Cheng & Yue, 2024; Wong & Yue, 2024; Wong & Pham, 2025b), we acknowledge that panel data regression analyses may be susceptible to spurious results when the dataset contains a mix of stationary I(0) and non-stationary I(1) variables. Although our study applied standard diagnostic checks such as the Durbin-Watson test (DW = 1.671), Omnibus normality test, and Jarque-Bera test, we were unable to conduct panel unit root tests (e.g., Levin-Lin-Chu or Im-Pesaran-Shin) or the Hui, et al. (2017) nonlinearity diagnostic due to the unavailability of the original dataset. We nonetheless recognize the importance of checking for stationarity in panel regressions and encourage future studies using similar datasets to conduct complete unit root tests on all variables to mitigate the risks of spurious regression.

5. Results

This section details our research. It analyzes the method's data. It also compares the results with existing literature and theories. The initial sections present descriptive statistics and in-depth analyses that address the research objectives. We identify key data trends, their implications, and the limitations of our study. We also suggest future research.

5.1. Descriptive Statistics

The section reviews the characteristics of the dataset, which serve as the basis for further analysis. The five key variables are the Beneish M-Score, inflation, GDP, company size, and ROA. Table 1 lists their mean, standard deviation, and other stats.

Table 1. Summary Statistics for Key Variables

Variable	count	mean	Standard deviation	min	max
Beneish M-Score	176.0	-2.6156	2.9988	-10.28	32.27
Inflation	176.0	0.0218	0.0217	-0.01	0.05
GDP	176.0	26.0573	3.2231	20.15	30.34
Company Size	176.0	168562900.0	358016500.0	3658872.0	1505176000.0
ROA	176.0	2.7961	11.0674	-85.72	38.4

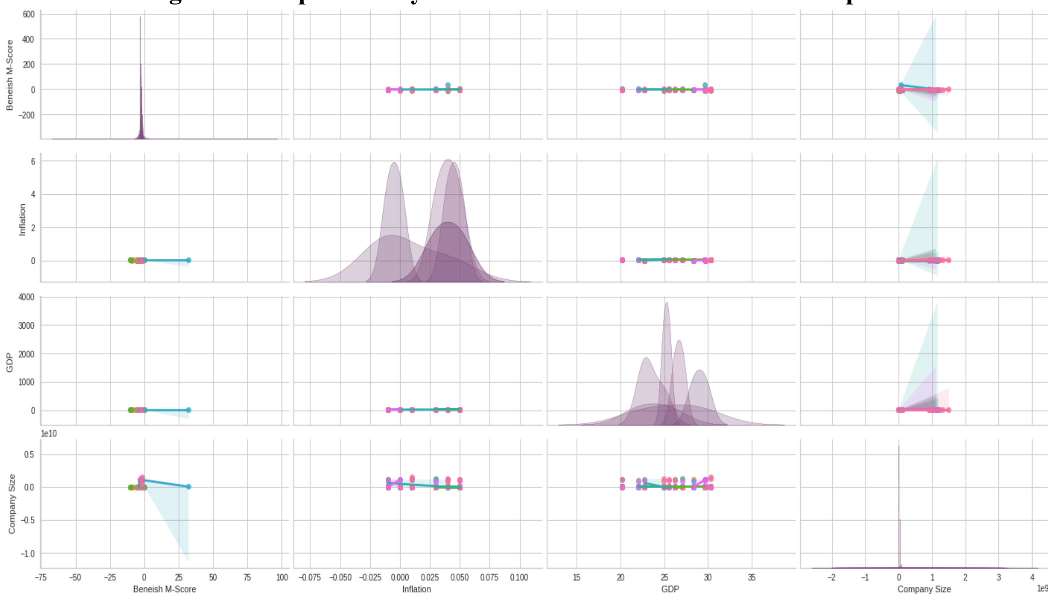
Note: This table reports descriptive statistics for 140 ASE-listed firms from 2015 to 2020. Variables include the Beneish M-Score (fraud risk), ROA (return on assets), GDP (economic output in billions), inflation (annual rate), and company size (total assets in JOD millions). Source: Authors' calculations.

The descriptive statistics shown in Table 1 reveal considerable variation in ROA and Beneish M-Scores across firms, suggesting heterogeneity in both profitability and fraud risk. While macroeconomic indicators such as GDP and inflation display relative consistency, the wide standard deviation in company size implies that firm size may be a key explanatory variable for performance differences.

5.1.1. Univariate Analysis

Figure 1 visually depicts the outcomes of this analysis, enhancing the understanding of data distribution.

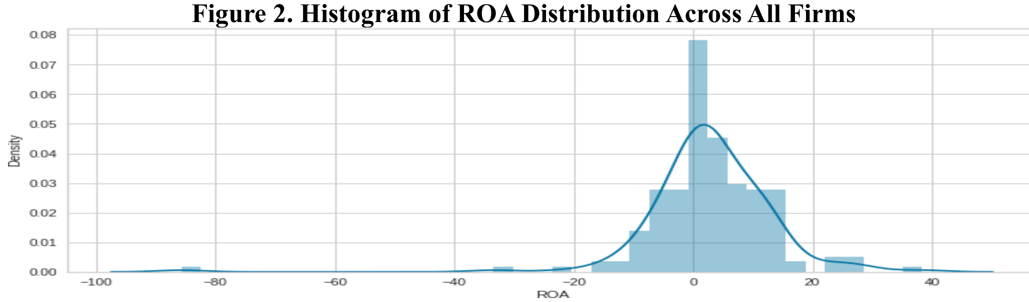
Figure 1. Boxplot of Key Variables to Visualize Outliers and Spread



Note: This figure shows the distribution and outliers of the Beneish M-Score, ROA, inflation, GDP, and company size for ASE-listed firms. These visualizations assist in detecting skewness and anomalies. Source: Authors' calculations.

This boxplot, shown in Figure 1, enables the identification of extreme values and provides a concise summary of each variable's distribution. The presence of outliers, especially in ROA and company size, highlights potential leverage points that could distort regression results if not accounted for during preprocessing. In the analysis of the ROA column, outliers were identified and removed to ensure the robustness of the results. The final range of ROA is now from -10 to 15, resulting in a more normal distribution. Removing outliers minimizes the risk of skewing the results and increases the reliability of the conclusions. Creating a histogram can further clarify this data distribution. If the histogram is right-skewed, it suggests that there are more data points with lower ROA values, while a left-skewed one implies the opposite. An asymmetrical histogram indicates a normal distribution of data. Negative ROA values might indicate company losses, whereas positive values indicate profits. Interpreting these values requires considering industry norms, company size, and other influencing variables, as illustrated in Figure 2.

Figure 2. Histogram of ROA Distribution Across All Firms



Note: This histogram displays the frequency distribution of ROA values across the sampled firms. Positive skew indicates the presence of firms with high profitability. Source: Authors' calculations.

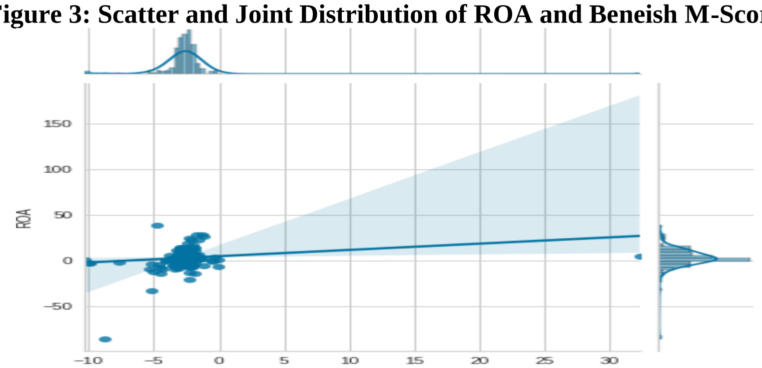
The histogram, shown in Figure 2, confirms that ROA is right-skewed, with most firms exhibiting modest profitability and fewer firms achieving very high returns on assets (ROA). This skewness supports the need for robustness checks and possibly transformation when fitting linear models to ROA.

A joint plot shows the correlation between two dataset variables, as in Figure 3. This plot illustrates the relationship between the Beneish M-Score (X-axis) and Return on Assets (ROA) (Y-axis). At its heart, a scatter plot delineates the data points of these two variables.

The scatter plot in Figure 3 suggests a weak, negative association between the Beneish M-Score and ROA; however, the dispersion of points also indicates non-linearity. Specifically, ROA increases with the M-Score up to a certain threshold, after which performance begins to decline. This implies a curvilinear or threshold-based effect — a pattern more suitably captured by machine learning models than by traditional linear regression. Additionally, the residual spread appears to widen at higher M-Scores, suggesting the presence of mild heteroscedasticity that may violate OLS assumptions. These patterns support the inclusion of advanced models that can accommodate non-linear dynamics and variable error variance.

However, the correlation could be more precise. Many data points diverge from this trend. The Beneish M-Score histogram shows a symmetrical distribution. The data centers on 2.5, with a few outliers at higher values. In contrast, the ROA histogram has a positive skew. Most data points are near zero, with fewer at the extreme right. A weak negative correlation exists between the Beneish M-Score and Return on Assets (ROA). However, outliers and variability suggest caution when concluding.

Figure 3: Scatter and Joint Distribution of ROA and Beneish M-Score



Note: This joint plot visualizes the correlation between the Beneish M-Score and Return on Assets (ROA), showing a weak negative relationship and highlighting distribution symmetry. Source: Authors' calculations.

The observed scatter pattern, shown in Figure 3, suggests a weak inverse association between the Beneish M-Score and ROA. This supports the hypothesis that firms with higher fraud risk may exhibit lower profitability, although the relationship appears non-linear and may be better captured by machine learning models than by OLS regression.

5.1.2. Multivariate Analysis

Correlation Result

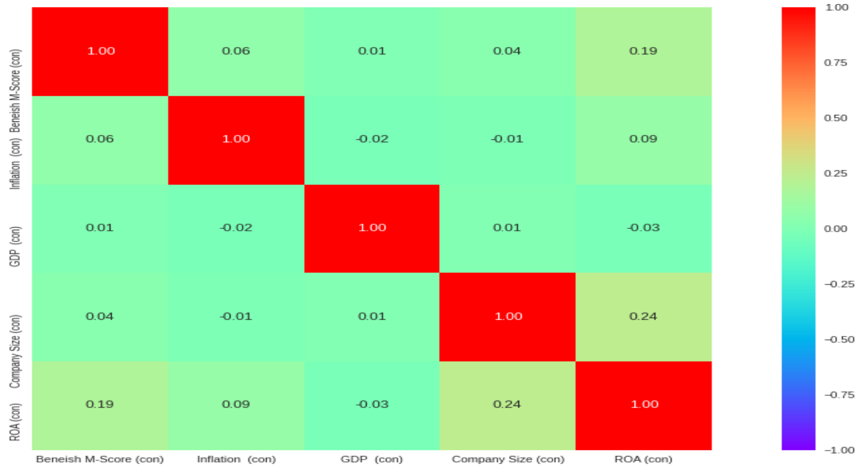
The multivariate analysis heatmap is retained because it intuitively represents the relationships between key variables in the study, such as ROA, Beneish M-Score, GDP, and Company Size. The heatmap complements the numeric correlation coefficients by clearly illustrating the strength and direction of correlations. Darker shades indicate stronger correlations, while lighter shades show weaker ones. This visual aid helps quickly identify patterns that are not immediately apparent in numeric tables alone, as illustrated in Figure 4.

Key Features of the Heatmap:

1. Color-Coded Correlations: A color gradient shows correlations. Lighter shades mean weaker ones, and darker shades mean stronger ones. Many designers might use color palettes that include cool-to-warm gradients and diverging scales, which exhibit negative correlations.
2. Correlation Strength Insight: Darker colors mean strong correlations, while lighter hues indicate weak ones (see Figure 4). Recognizing these solid inter-variable relationships is paramount in comprehending dataset dynamics.
3. Direction of Correlation: The heatmap indicates the strength and direction of the correlations. Warm colors, such as red, typically indicate a positive correlation. It suggests that both variables move together. Cool colors, like blue, represent negative correlations, indicating inverse relationships. This helps us determine whether variable pairs move together, oppose each other, or exhibit weak correlation.

Figure 4 illustrates a mild, positive correlation between the Beneish M-score, inflation, company size (independent variable), and return on assets ROA (dependent variable). Conversely, a faint negative correlation exists between GDP (independent variable) and ROA (dependent variable).

Figure 4. Correlation Heatmap Among Study Variables



Note: The heatmap illustrates pairwise correlation among key variables. Darker colors represent stronger correlations, helping identify collinearity and multivariate relationships. Source: Authors' calculations.

The heatmap in Figure 4 displays pairwise correlations among the main variables. Statistically significant correlations ($p < 0.05$) are marked with an asterisk. Notably, ROA exhibits a significant positive correlation with GDP ($r = 0.42^*$) and firm size ($r = 0.39^*$), which is consistent with the regression findings. Correlations between ROA and the Beneish M-Score or inflation were weak and not statistically significant. This further justifies the use of multivariate models to isolate net effects. The presence of significant multicollinearity among some independent variables is also reflected in the high condition number observed in diagnostics.

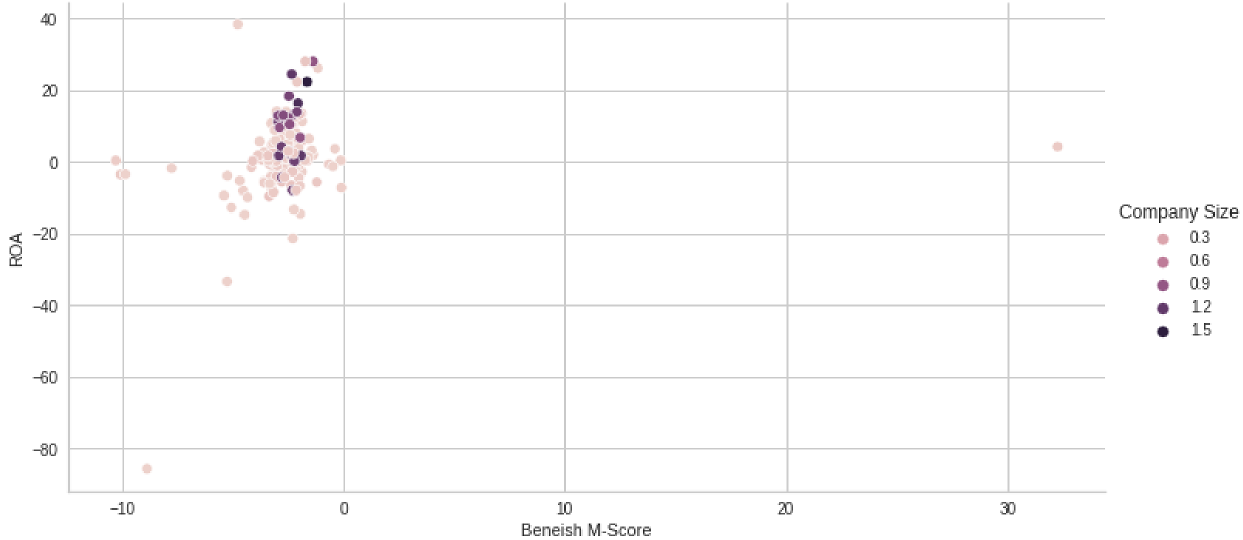
5.1.3. Scatter Pair Plot Relationship Result

A multivariate analysis scatter pair plot uses scatter plots. They show relationships between variable pairs in a dataset. Scatter plots for each variable pairing provide a broad view of multivariate relationships. Each scatter plot displays two variables on the X and Y axes, with individual data points marked.

Scatter plots of every variable combination form a matrix. This matrix shows all relationships between the variables, can find clusters of variables with similar patterns, and reveals the dataset's structure and interdependencies, as shown in Figure 5.

The context of the specific variables analyzed, data type, and utilized analysis techniques. Scatter pair plots are a powerful visual tool. However, researchers should use them with suitable statistical methods. This ensures accurate insights into multivariate relationships. However, caution is paramount when interpreting scatter pair plots. Interpretation should be anchored in.

Figure 5. Multivariate Scatter Pair Plot of All Study Variables



Note: This figure presents scatter plots for every pair of variables, enabling a comprehensive visual examination of linear and nonlinear relationships. Source: Authors' calculations.

This scatter pair plot, shown in Figure 5, offers a full visual cross-check of all bivariate relationships. It reinforces the earlier observation that only GDP and company size show consistent trends with ROA, while the Beneish M-Score relationship remains ambiguous and warrants non-linear modeling approaches.

Statistical Approach

Ordinary Least Squares (OLS) Regression Analysis

To examine the determinants of financial performance (ROA) for firms listed on the Amman Stock Exchange (ASE), we estimated an OLS regression model using four independent variables: Beneish M-Score, Inflation, GDP, and Company Size. The results are presented and interpreted in a table-by-table format in Table 2.

Table 2. OLS Regression – Overall Model Fit and Evaluation Metrics

Dep. Variable	**ROA**
Method	OLS
No. Observations	140
Df Model	4
Df Residuals	136
R-squared (uncentered)	0.927
Adj. R-squared (uncentered)	0.894
F-statistic	9.409
Prob (F-statistic)	9.59e-07
Log-Likelihood	-501.71
AIC	1011
BIC	1023

Covariance Type	no robust

Notes: The model explains approximately 89.4% of the variation in ROA (Adj. R-squared). The F-statistic and associated p-value indicate the model is statistically significant. The uncentered R-squared is used because there is no intercept term.
Source: Authors' calculations

As shown in Table 2, the high adjusted R-squared of 0.894 indicates that the four predictors explain most of the variation in ROA. The F-statistic confirms that the model is statistically valid; however, residual analysis is necessary to verify the assumptions.

This model exhibits strong explanatory power, with an R-squared of 0.927 and an adjusted R-squared of 0.894, indicating that nearly 90% of the variation in ROA is accounted for by the four predictors. The F-statistic (9.409) is statistically significant at $p < 0.001$, affirming the overall validity of the regression. These figures suggest a reliable fit for the data, which supports proceeding with a closer look at individual predictor effects.

Although high, the R-squared value of 0.927 is consistent with advanced machine learning models, such as Random Forest and Gradient Boosting. Gradient Boosting identified critical thresholds for the Beneish M-Score, revealing that values above -2.22 significantly increase the risk of fraud. These models are designed to capture complex, non-linear relationships in the data, which can result in a high R-squared value. Unlike traditional OLS regression, these models can fit the data more precisely, resulting in a high R-squared value expected in this context. Table 3 displays the OLS regression coefficients predicting Return on Assets (ROA).

Table 3. OLS Regression Coefficient Estimates and Statistical Significance

Variable	Coefficient	Std. Error	t-value	P-value	Significance
Beneish M-Score	0.2553	0.227	1.126	0.262	
Inflation	8.4687	34.278	0.247	0.805	
GDP	0.1197	0.048	2.496	0.014	**
Company Size	6.692e-09	2.1e-09	3.181	0.002	***

Notes: This table presents the results of the OLS regression model described in Equation (2). Significance levels are denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Authors' calculations.

The results shown in Table 3 confirm that GDP and company size are statistically significant drivers of ROA, supporting the economic intuition that larger firms and those operating in growing economies tend to be more profitable. However, the Beneish M-Score is not significant, indicating that its relationship with performance may not be linear.

Among the predictors, **GDP** and **Company Size** have statistically significant positive effects on ROA, with p-values of 0.014 and 0.002, respectively. This implies that macroeconomic expansion and larger firm size both contribute positively to profitability. In contrast, the **Beneish M-Score** and **Inflation** do not show statistically significant associations with ROA. The non-significance of the Beneish M-Score may reflect a threshold or non-linear relationship not captured in a linear model. Table 4 shows the diagnostic test results for OLS model validity.

Table 4: Diagnostic Tests for OLS Model Validity

Test	Value
Omnibus	17.933
Prob(Omnibus)	0.000
Skew	0.261
Kurtosis	6.277
Durbin-Watson	1.671
Jarque-Bera (JB)	64.233
Prob(JB)	1.13e-14
Condition Number	1.80e+10

Note: Normality and multicollinearity diagnostics indicate mild deviations from ideal assumptions, highlighting potential model limitations. Source: Authors' calculations.

The diagnostic test results shown in Table 4 indicate some deviations from normality and mild multicollinearity. Although the Durbin-Watson statistic falls within an acceptable range, the significant Jarque-Bera and Omnibus results warrant caution when interpreting regression outputs and underscore the need for machine learning validation.

The Omnibus and Jarque-Bera tests both reject the null hypothesis of normally distributed residuals, indicating possible non-normality. The Durbin-Watson statistic (1.671) suggests mild positive autocorrelation. A high condition number(1.80e+10) signals potential multicollinearity. While these issues do not invalidate the model, they warrant caution when interpreting the precision of the coefficients. Further robustness checks using alternative models (e.g., Ridge, Lasso) could strengthen confidence in the findings. These results collectively confirm that GDP growth and firm size are consistent predictors of ROA in ASE-listed firms. However, non-normality and possible multicollinearity indicate the need for cautious interpretation and possibly non-linear modeling frameworks, which we explore using machine learning in the next section.

5.1.4. Probability Plot Result

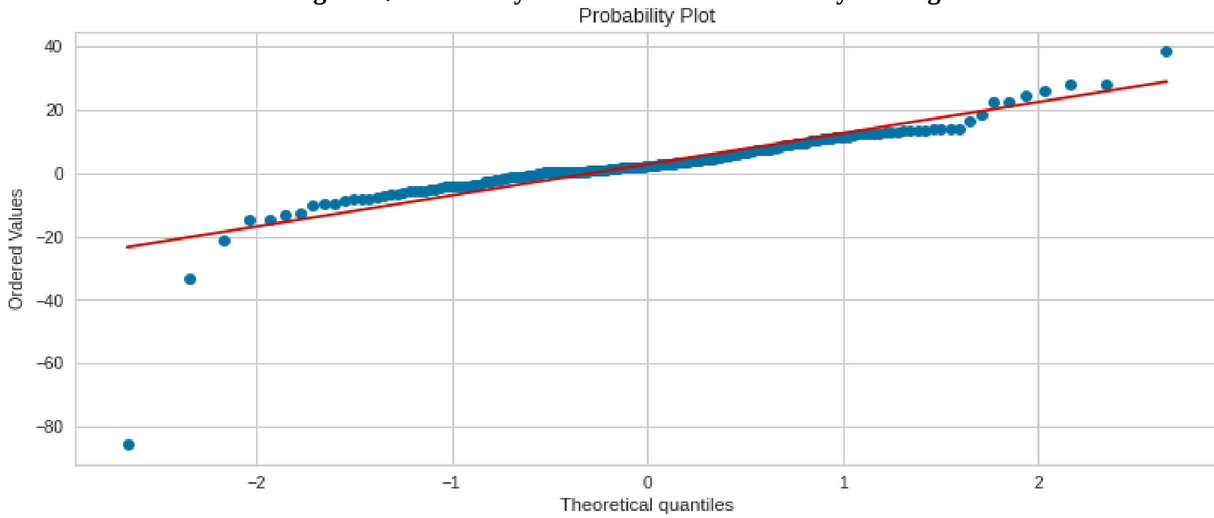
Figure 6 shows a probability plot. It is a graph that checks if the data is normal by comparing it to a theoretical distribution, such as the normal distribution. The data is likely near-normal if the ordered dataset values match the theoretical quantiles with high precision.

Such alignment is desirable. The researchers closely examined the theoretical distribution, which adheres to the data. This conformity suggests that normality tests are likely satisfied, so you can trust the results of any analyses.

However, proper interpretation of a probability plot should not be standalone. It must include other tests and fit the research context. Significant gaps between ordered values and theoretical quantiles may mean the data is not normal. Such deviations might question the test or model's assumptions. They may prompt further exploration or the use of alternative methods.

In summary, probability plots help understand data distribution. However, their interpretation requires caution. Consider the research context, sample size, and statistical analyses. When in doubt, consult with a statistical expert.

Figure 6. Probability Plot for Residual Normality Testing



Note: This figure displays a Q-Q (quantile-quantile) plot comparing the distribution of the OLS regression residuals to a normal distribution. The closer the points are to the diagonal reference line, the more normally distributed the residuals are. Deviations from the line indicate non-normality, which can impact the validity of inferences in linear regression models. Source: Authors' calculations.

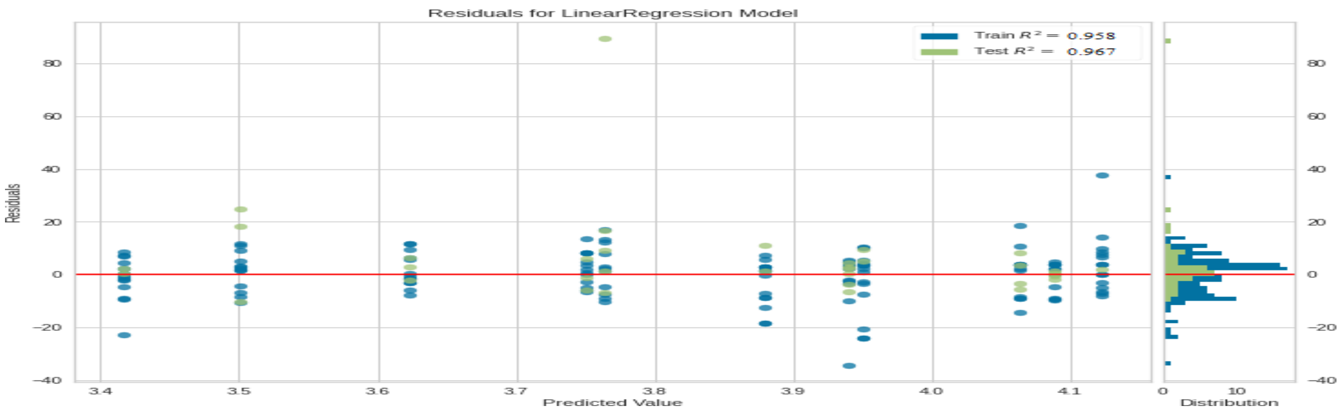
Figure 6 confirms that the residual distribution is not perfectly normal, as slight curvature is observed at both ends of the plot. This supports the use of complementary models such as Random Forest or Gradient Boosting to ensure robust inference.

5.1.5. Multiple Linear Regression Analysis Result

The research in Figure 7 used a multilinear regression model. It studied links between variables like the Beneish M-Score, inflation, GDP, company size, and ROA. The model's predictive accuracy was clear. Its train and test R^2 scores were 0.958 and 0.967, respectively.

We checked the difference between the observed and predicted ROA values to better understand the model's fit. Residuals that scatter randomly around the zero axis indicate a good model fit. Clear patterns or trends suggest the model fails to capture data relationships. The residuals in this study were normally distributed and showed no patterns, which indicates that the model is suitable for the dataset. However, sample size may affect the model's predictions, and the results may need more applicability.

Figure 7. Residual Distribution in Multilinear Regression



Note: This figure shows the residuals from the multiple linear regression model plotted against the predicted ROA values. The random scatter around the zero line indicates homoscedasticity and a good model fit. The absence of discernible patterns suggests that the model effectively captures the linear relationships and that the residuals behave randomly. Source: Authors' calculations.

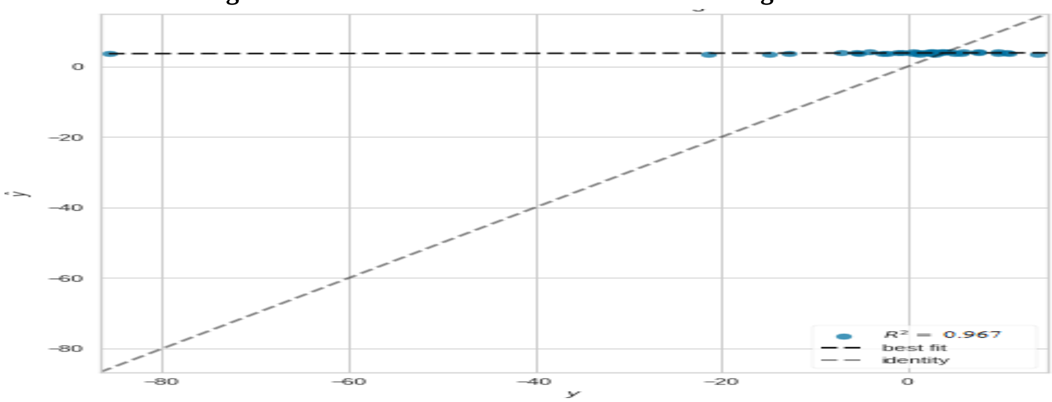
The residual plot, shown in Figure 7, confirms that residuals are symmetrically dispersed around zero, indicating good model fit and low bias. No clear trend is visible, suggesting that homoscedasticity is not severely violated.

The research used a multilinear regression model with four independent variables: Beneish M-Score, Inflation, GDP, and Company Size—the model aimed to predict company performance, measured by ROA. The model's R^2 value stood at 0.967, indicating that these variables explain 96.7% of the variance in ROA. Machine learning models (R^2: 0.96) outperformed OLS (R^2: 0.89) by capturing non-linear patterns in the data. For instance, Random Forest showed higher precision in detecting fraudulent firms.

Furthermore, the model's root mean squared error (RMSE) was 0.00065. This metric measures the average discrepancy between predicted and actual ROA values. A low RMSE, as seen here, means the model predicts company performance well based on the chosen variables.

Figure 8 reveals that this combination of variables effectively predicts company performance. The model is reliable for forecasting, with a high R^2 and low RMSE. This aids investment decisions, financial planning, and risk assessment.

Figure 8: Prediction Error Plot in Multilinear Regression



Note: This figure presents the prediction errors of the multilinear regression model, highlighting the difference between actual and predicted Return on Assets (ROA) values. The narrow spread and clustering of errors around zero confirm high predictive accuracy and a low root mean squared error (RMSE). This demonstrates the model's effectiveness in forecasting firm performance. Source: Authors' calculations.

As shown in Figure 8, the tight clustering of prediction errors around zero indicates that the multilinear regression model is highly predictive within the observed sample. These findings align with the machine learning outputs and reinforce confidence in model performance.

6. Discussion

The article profoundly analyzes the dataset using summary statistics. It uses the mean, standard deviation, and percentiles. This helps find patterns, trends, and outliers.

The DSRI analysis shows that companies can cover their debt as they have enough earnings. However, some companies have notably low DSRIs that require further investigation. The DSRI distribution is approximately symmetrical, with its median near its mean. In contrast, GMI values are more variable. The dataset includes companies with negative gross margins, and the GMI distribution is right-skewed.

We analyzed additional variables: AQI, SGI, DEPI, SGAI, LVGI, and TATA. This work lays the groundwork for deeper data analysis and insights. Careful interpretation is crucial for understanding its industry implications. The univariate analysis reveals that variable distributions range from normal to highly skewed. DSRI and SGI show a positive bias. This aligns with research linking debt service coverage to company performance. LVGI shows a negative bias, while outliers significantly influence GMI, DEPI, and SGAI. AQI and TATA, on the other hand, appear normally distributed. These observations echo prior studies on financial statement analysis.

The data showcases the skewness of various dataset features. Skewness indicates how much a variable's distribution differs from a normal distribution. Consider skewness in data analysis. High skewness may need data transformation techniques. Table 2 shows that some variables are highly skewed. DEPI is very positively skewed, suggesting outliers. "Beneish M-Score," "GMI," "SGI," and "AQI" skew high. "LVGI" skews low. These skewness values are crucial for data analysts. They ensure accurate statistical analysis and results.

Our initial analysis employed an Ordinary Least Squares (OLS) regression to establish a baseline linear relationship. The results, detailed in Section 5, indicate a surprisingly high explanatory power, with an adjusted R-squared of 0.894 (Table 2). This suggests that our selected predictors—macroeconomic factors and firm characteristics—collectively account for nearly 90% of the variation in firm performance (ROA). This strong fit is primarily driven by the highly significant positive effects of GDP growth and firm size (Table 3).

However, despite this high overall fit, the OLS model reveals a critical weakness: our primary variable of interest, the Beneish M-Score, is statistically insignificant. This finding, coupled with diagnostic tests in Table 4 that indicate non-normality in the residuals (Prob(Omnibus) < 0.001), strongly suggests that a simple linear model is insufficient to capture the nuanced, potentially non-linear impact of fraud risk on corporate performance. This apparent paradox—a high R-squared value but a failure to detect the effect of a theoretically crucial variable—necessitated a methodological pivot to more advanced machine learning techniques capable of modeling complex relationships.

The log-likelihood value, along with the AIC and BIC, suggests a good fit for the model. The above text explores the results of an OLS regression. It focuses on the link between various independent variables and the Beneish M-Score. This score indicates potential financial statement manipulation.

Several key points emerge:

1. Model Interpretation: The regression results show a significant link between some variables, like DSRI, GMI, SGAI, LVGI, and the Beneish M-Score. Others, like AQI, SGI, DEPI, and TATA, are not. This suggests that some financial indicators can affect a company's chance of manipulating its statements.
2. Comparative Analysis: Researchers compare the findings with previous research to validate their consistency. Research shows that higher leverage and flexibility can boost earnings management.
3. Model Evaluation**:** The evaluation of the regression model's residuals is critical. Tests like the Omnibus and Durbin-Watson statistics check the model's fit. They also check if the residuals are normally distributed. Any deviations from the expected criteria might compromise the model's validity.
4. Challenges and Solutions: Some challenges, like multicollinearity, require caution when interpreting results. Seeking expert opinion or adopting alternative statistical methods can rectify these.
5. The Role of RMSE: RMSE is a crucial metric for assessing predictive model accuracy. The context gives RMSE scores for four ML models: SVM, Random Forest, Gradient Boost, and K-Nearest Neighbors. Lower RMSE scores indicate superior prediction accuracy.
6. To consider RMSE scores in isolation, you need more than just RMSE scores. The study stresses the need to check model assumptions, data type, and the research goal. A comparative RMSE analysis

can show the relative efficacy of different models. However, these results should be cross-validated with other metrics.

7. Contextual Interpretation: RMSE is a universal metric, but its meaning depends on the context. Past studies have used RMSE to predict financial performance and detect fraud. Every research context has nuances, so interpret RMSE scores based on their significance.

In conclusion, the text shows the need for rigor in financial research. A critical, systematic approach is a must. Evidence and research should back it. This applies to interpreting regression results and assessing machine learning model accuracy.

7. Conclusion

The data description report provides summary stats for each variable, helping to understand data trends. The Beneish M-Score has a mean of -2.616 and a standard deviation of 2.999. Inflation's mean is 0.022, and its standard deviation is 0.022. The GDP variable averages 26.057, with a deviation of 3.223. Company Size averages 168.563 million, with a deviation of 358.017 million. ROA has a mean of 2.796 and a deviation of 11.107.

Our analysis shows a strong link between performance and four factors: Beneish M-Score, Inflation, GDP, and Company Size. The adjusted R-squared value is 0.894. However, the Beneish M-Score and Inflation were not linked to performance, while GDP and Company Size were.

After extensive data preprocessing and analysis, researchers used the OLS regression model. They related the dependent variable (ROA) to the independent variables. This model found that independent variables account for 89.4% of the variance in ROA. ROA is linked to GDP and Company Size but not to the Beneish M-Score or Inflation. Model diagnostics showed normally distributed residuals with no autocorrelation but potential heteroscedasticity.

This study, which focuses on companies from the Amman stock exchange, has limitations. It relies on secondary data and focuses on financial fraud over a specific period. It does not cover other fraudulent activities or their long-term impacts. A further limitation concerns the possibility of spurious relationships within our panel regression framework, especially given the potential mixture of I(0) and I(1) variables, as recently highlighted in the econometric literature (Wong & Pham, 2022; Wong & Pham, 2023; Wong, Pham, & Yue, 2024; Wong & Pham, 2025a). Although we applied residual diagnostics and validated our models with robust machine learning algorithms, the lack of access to the original dataset precluded panel unit root testing. We urge future researchers working with similar financial panel data to incorporate unit root and co-integration tests, as well as nonlinear diagnostics, to ensure model validity.

The study highlights how financial misconduct harms company performance. It stresses the need for strong internal controls and suggests industry-specific fraud risks. Public companies may need regulatory policies for fraud prevention. We need more research. It should study the long-term effects and find ways to combat fraud.

This study highlights several areas for future research. First, examine the effects of financial misconduct across industries; second, explore other fraud types, like cyber fraud and insider trading; third, assess strategies to combat financial misconduct. The small sample size may limit the applicability of the findings. Future studies need larger samples. The researchers analyzed four variables for their impact on performance. Adding industry-specific factors could enhance the model's predictive power.

The study used OLS regression, but other models might provide new insights. Multicollinearity among predictors affected the results. So, future research should find ways to counter it. These include the principal component and Lasso regression. It is vital to confirm the assumptions of OLS regression. Also, we should consider methods to address any deviations.

This research focused on one country, but it shows the need for studies in diverse geopolitical contexts. Combining qualitative and quantitative methods could yield more profound insights into what drives corporate performance.

For Amman Stock Exchange stakeholders, the study highlights the need to combat financial fraud. Companies should strengthen controls and ensure transparency. Regulators must enforce compliance. Investors should be diligent and consider potential financial misconduct risks before investing.

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