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Beneish Model for Financial Report Fraud Identification in the Manufacturing Sector During the COVID-19 Pandemic

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ABSTRACT

Financial statement fraud misleads stakeholders' judgments and erodes market confidence in corporate transparency, and this risk is particularly prominent during the period of high economic uncertainty brought by the COVID-19 pandemic. This study targets basic and chemical manufacturing companies listed on the Indonesia Stock Exchange (IDX), adopts the Beneish M-Score model, and focuses on the window period before and after the COVID-19 outbreak, aiming to analyze the impact of four categories of financial ratios—liquidity, solvency, profitability, and operating capacity—on fraud detection. The study adopts a quantitative explanatory design and processes data through panel data regression and the EViews software. Its sample consists of relevant data from 60 companies covering the period 2019–2022, totaling 240 firm-year observations. The empirical results show that liquidity (b=0.214, p=0.0001) and profitability (b=0.038, p=0.0000) have a significant positive impact, while solvency (b=-0.013, p=0.7128) and operating capacity (b=1.005, p=0.0596) have no significant impact; 89% of the annual reports have no likelihood of manipulation, and 11% carry potential manipulation. The conclusions can assist various stakeholders, including investors and regulators, in identifying early warning signals of fraud.

Keywords: Beneish M-Score; Financial Statement Fraud; Fraud Detection; Financial Ratios; Panel Data Regression; Manufacturing Sector

JEL Classification: C23; G32; M41; M4

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INTRODUCTION

Financial reports are professional documents that record the financial position of an accounting entity. They support users in conducting performance evaluations and reflect the fiduciary responsibility of management (Institute of Indonesia Chartered Accountants or Ikatan Akuntan Indonesia [IAI], 2021). The standards issued in 2021 by the Indonesian Institute of Chartered Accountants (IAI, 2021) explicitly stipulate that high-quality reports must meet five criteria: understandable, relevant, reliable, comparable, and capable of supporting decision-making.

Despite its critical importance, financial reporting still faces the risk of manipulation. As defined by Tuanakotta (2013) and Waromi et al. (2024), financial statement fraud is a serious issue that involves deception, concealment, and the misleading of stakeholders. According to literature including sources from ACFE Indonesia (ACFE Indonesia, 2020), Corporate Finance Institute (CFI, 2022), Davidson (2019), and Sacks & Reilly (2022), this type of fraud accounts for only 9% of global fraud cases, yet it produces the highest financial impact, outstripping that of asset misappropriation and corruption.

Numerous major cross-border financial fraud cases have sufficiently confirmed that financial reporting manipulation leads to severe negative consequences. Relevant studies have separately documented that leading companies including Waste Management, Enron, WorldCom, Tyco, HealthSouth, Freddie Mac, American International Group, Lehman Brothers, and Satyam (CFI, 2022); GE Capital (Damayanti, 2020); GE Power (Beanworks, 2021); Olympus, Toshiba, and Nissan-Mitsubishi-Renault (Integrity Indonesia, 2019); as well as Indonesian enterprises including PT Indofarma, PT Kimia Farma, PT KAI, PT Asuransi Jiwasraya, PT Hanson International, PT Garuda Indonesia, PT Envy Technologies Indonesia, and PT Tiga Pilar Sejahtera Food (Sandria, 2021; Supriyatna & Djaelani, 2021) were all involved in financial reporting fraud.

Fraud detection has long faced a core challenge, which stems from the fact that most fraud is exposed through various channels, rather than only uncovered by enterprises' internal formal review mechanisms. A 2020 survey by ACFE Indonesia (ACFE Indonesia, 2020) shows that 42% of fraud cases are exposed by news media, while only 16% are uncovered by internal audits; a 2022 study by Sacks & Reilly (2022) points out that 55% of fraud cases are disclosed by employees, and 18% by customers. Therefore, the current fraud detection field urgently needs analytical tools that can issue early warnings before cases are publicly exposed.

Most prior academic studies on financial statement fraud have been built on various financial indicators and fraud detection models, with existing findings covering dimensions including the influencing factors of fraud, detection tools, and cross-industry application scenarios: Yaramah and Hidayat (2022) proposed that the debt-to-equity ratio and asset-liability ratio affect accounting fraud detection; Durana et al. (2022) observed signs of financial report manipulation in sampled firms; Khatun et al. (2022) pointed out an abnormal trend of financial statement falsification in Bangladesh's banking industry; Basmar and Ruslan (2021) found a correlation between financial statement fraud and financial stability; Nugroho and Diyanty (2022) confirmed that rationalization factors impact accounting fraud; Grimaldi (2019) verified that the Beneish model can identify financial statement fraud; Alfian and Triani (2019) accurately classified 28 fraudulent entities among 55 manipulating companies; Irwandi et al. (2019) found that industry characteristics and financial stability have a significant impact on financial statement fraud.

However, prior research has not reached a unified conclusion on the validity of the Beneish model. While some existing studies confirm that the model's M-score can detect potential financial statement manipulation, five studies, including Deniswara et al. (2022), Harsanti & Mulyani (2021), Knežević et al. (2021), Lotfi & Chadegani (2017), and Wiszniowski (2020), found limited evidence supporting the model's ability to detect financial statement fraud. Current research still has gaps across the dimensions of industry, time period, and economic conditions.

This study has a clearly defined core test direction: it will verify the impact of four categories of financial ratios—liquidity, solvency, profitability, and operating capacity—on the effectiveness of the Beneish M-Score model in identifying financial statement fraud. The study also sets clear research boundaries, ties an exclusive innovation window period to this research topic, and highlights the unique academic value of this work.

This study conducts financial statement fraud detection targeting Indonesia's manufacturing sector (basic and chemical subsectors) listed on the Indonesia Stock Exchange (IDX) during 2019–2022. Theoretically, it enriches empirical evidence for the application of the Beneish model in identifying financial statement fraud. In periods of economic uncertainty, this study can provide early fraud warning for investors, regulators, and other relevant stakeholders, and can also remind enterprises to prioritize maintaining transparent and reliable financial reporting practices.

LITERATURE REVIEW

Financial Statement Fraud

Financial statement fraud refers to a non-compliant act in which corporate executives or institutional management intentionally manipulate the financial information disclosed in financial reports and conceal an entity's true financial position. Common motives for committing this fraud include obtaining specific benefits, creating a favorable impression of an enterprise's operating performance, and whitewashing financial statements or engaging in window dressing (Munidewi & Sunarsih, 2023; Suryandari & Endiana, 2019). This type of fraud occurs less frequently than other fraud types but causes the largest scale of financial losses, and it undermines the credibility of the financial information used by investors, creditors, regulators, and other stakeholders (Institute of Chartered Accountants in England and Wales [ICAEW], 2020; Ulfah et al., 2024).

According to Suryandari and Endiana (2019), financial statement fraud can be divided into several specific acts, including manipulating, falsifying, or altering accounting documents; concealing or omitting the effect of transactions; recording transactions without economic substance; misapplying accounting policies; and failing to disclose significant information. In addition, per the definition put forward by Turner and Weickgenannt (2013), misstatements in false financial records that intentionally mislead financial statement users are often associated with earnings management or financial reporting fraud.

To explain the root causes of financial statement fraud, core analysis must be grounded in the field's classic fraud theories. First is the Fraud Triangle Theory, proposed by Cressey and elaborated by Jonson and Geis (2010). Its three core elements: pressure, opportunity, and rationalization, correspond respectively to various types of internal and external pressures, weak internal controls, and the perpetrator's self-justification of their actions; these three elements work in tandem to spawn fraud. Later, the Fraud Diamond Theory adds a new element, "capability," suggesting that fraud occurs not only because

of pressure, opportunity, and rationalization, but also because individuals have the ability to execute and conceal fraudulent acts (Abdullahi & Mansor, 2015; Novita, 2019). When applied to the financial reporting scenario, financial pressure and management incentives may drive the manipulation of financial statements, and this tendency may be further strengthened during periods of economic instability.

Supporting Theories

Signaling theory, first proposed by Spence (1973), holds that enterprises can use financial statements to convey information such as their operational performance and development prospects to reduce information asymmetry. However, if a firm's management tampers with financial statement data, the signals transmitted will be misleading. Therefore, fraud detection is essential to distinguishing between true and false financial signals.

Principal-agent theory is the core foundational framework for understanding financial statement fraud. Within this theory, shareholders act as the principal, while managers serve as the agent. Jensen and Meckling (1976) point out that an inherent conflict of interest exists between these two parties. If managers have the motivation to whitewash their work performance, they will engage in earnings manipulation or fraudulent reporting. Eisenhardt (1989) further supplemented the two core conditions that give rise to agency problems.

The Pecking Order Theory can explain the financing choices and debt management logic of enterprises. Donaldson (1961) and Myers (1984) proposed that enterprises prioritize internal financing, and only then consider external debt or equity financing. This theory can support fraud detection research, as enterprises under debt repayment pressure have an incentive to embellish their financial statements.

Beneish M-Score Model

Developed by Messod D. Beneish for the finance field, the Beneish M-Score model is a professional analytical tool used to identify potential earnings manipulation by enterprises and distinguish between manipulated and non-manipulated financial statements. The model estimates the probability of manipulation using accounting and financial ratios, and its effectiveness has been corroborated by Beneish's (1999) original study, research by GMT Research (n.d.), and a follow-up study by Beneish et al. (2012).

Eight standard index ratios used to calculate the Beneish M-Score can capture abnormal changes in multiple types of financial indicators. These changes can serve as identification signals for corporate earnings manipulation. The core construction of this quantitative detection model originates from Beneish's original core research literature. Studies by Aghghaleh et al. (2016) and Beneish (1999) established the core judgment rules for the Beneish M-Score: with -2.22 set as the critical threshold, firms with scores above this value are classified as potential earnings manipulators. Some empirical studies further divide firms into three categories: non-manipulators, possible manipulators, and highly likely manipulators. Narsa et al. (2023) applied this model to fraud detection in Indonesia's manufacturing industry. This study affirms the practical operational value of this model.

Based on Beneish (1999), the M-Score formula is as follows:

$$M - Score = -4.84 + 0.920DSRI + 0.528GMI + 0.404AQI + 0.892SGI + 0.115DEPI - 0.172SGAI + 4.679TATA - 0.327LVGI$$

Table 1. Financial Report Fraud Formula (Beneish Model)

Index	Formula
Day Sales In Receivable Index (DSRI)	(Account Receivables$_t$ / Sales$_t$) / (Account Receivable$_{st-1}$) / Sales$_{t-1}$)
Gross Margin Index (GMI)	[(Sales$_{t-1}$ – Cost of Goods Sold$_{t-1}$) / Sales$_{t-1}$] / [(Sales$_t$ – Cost of Goods Sold$_t$) / Sales$_t$]
Asset Quality Index (AQI)	[1 – (Current Assets$_t$ + Net Fixed Assets$_t$) / Total Assets$_t$] / [1 – (Current Assets$_{t-1}$ + Net Fixed Assets$_{t-1}$) / Total Assets$_{t-1}$)]
Sales Growth Index (SGI)	(Sales$_t$ / Sales$_{t-1}$)
Depreciation Index (DEPI)	[Depreciation Expense$_{t-1}$ / (Depreciation Expense$_{t-1}$ + Net PPE$_{t-1}$)] / [Depreciation Expense$_t$ / (Depreciation Expense$_t$ + Net PPE$_t$)]
Sales, General and Administrative Expenses Index (SGAI)	Sales, General and Administrative Expenses$_t$ / Sales$_t$) / (Sales, General and Administrative Expenses$_{t-1}$ / Sales$_{t-1}$)
Total Accruals to Total Assets (TATA)	([Working Capital$_t$ – Working Capital$_{t-1}$] – [Cash$_t$ – Cash$_{t-1}$] + [Income Tax Payable$_t$ – Income Tax Payable$_{t-1}$] + [Current Maturities of Long Term Debt$_t$ – Current Maturities of Long Term Debt$_{t-1}$] – Depreciation Expense$_t$) / (Total Assets$_t$)
Leverage Index (LVGI)	[(Long Term Debt$_t$ + Current Liabilities$_t$) / Total Assets$_t$] / [(Long Term Debt$_{t-1}$ + Current Liabilities$_{t-1}$) / Total Assets$_{t-1}$]

Table 1 in this paper lists the 8 financial indicators of the Beneish M-Score model, which is used to detect financial statement manipulation. These indicators cover eight major dimensions, including changes in accounts receivable and gross profit margin, and the table also provides the calculation formula for computing the final M-value from the respective indicators.

Financial Ratios and Fraud Detection

Financial ratios are core analytical tools used to evaluate corporate performance, financial status, and abnormalities in financial statements. In financial fraud detection, they can flag potential manipulations through multi-dimensional anomalies. A study by Robiansyah et al. (2023) confirmed that combining relevant ratios with detection models can link those ratios to fraudulent financial statements, while a study by Narsa et al. (2023) conducted the same year also noted that these ratios can be integrated with theory to detect earnings management among Indonesian manufacturing enterprises.

This paper defines the connotation of corporate liquidity based on the research of Collier (2016). The market generally believes that enterprises with high liquidity boast strong financial strength, but in reality, this type of liquidity can generate incentives for management to engage in financial window dressing. Therefore, liquidity can serve as a reference dimension for identifying financial fraud.

According to the definition proposed by Prastowo (2011), solvency refers to an enterprise's ability to fulfill its long-term debt obligations. High levels of indebtedness will trigger pressure from creditors and investors, giving rise to incentives for financial statement manipulation. Drawing on agency theory and the pecking order theory, solvency is correlated with opportunistic reporting behavior.

Collier (2016) defines profitability as an enterprise's ability to generate returns and achieve expected business performance. This metric can send a signal of positive business operations to stakeholders, but the pressure to maintain steady profit growth can create incentives for management to manipulate reported revenue.

Activity ratios are core financial metrics that measure a company's efficiency in using its assets to generate sales revenue. A related indicator, asset turnover (Collier, 2016), can reflect how effectively assets generate value. Two types of anomalies require vigilance: inefficient asset performance and overly aggressive asset utilization. This ratio helps to identify potential manipulation of financial statements.

Hypotheses Development

Liquidity and Financial Statement Fraud Detection

Liquidity refers to the degree to which an enterprise can repay its short-term debts. Based on Signaling Theory, it can convey signals of an enterprise's financial strength to investors and creditors. To maintain this positive image, management is prone to developing incentives to manipulate financial reports. Drawing on prior research by Robiansyah et al. (2023) and Yaramah and Hidayat (2022), this paper puts forward the presupposition that liquidity influences the detection of financial statement fraud.

H1: Liquidity has a significant effect on financial statement fraud detection.

Solvency and Financial Statement Fraud Detection

This study first defines solvency as a core indicator that reflects an enterprise's ability to fulfill its long-term debt obligations and captures its degree of reliance on debt financing. It draws on the agency theory proposed by Jensen and Meckling (1976), which holds that debt pressure elevates management's incentive to embellish the enterprise's financial status. Integrating this theoretical foundation with the conclusions of Narsa et al. (2023) and Robiansyah et al. (2023), which verified that debt indicators are associated with fraudulent reporting, the study derives and puts forward its core research hypothesis: solvency affects the detection of financial statement fraud.

H2: Solvency has a significant effect on financial statement fraud detection.

Profitability and Financial Statement Fraud Detection

This study defines profitability as an enterprise's ability to generate returns by relying on its own resources. This capability has dual attributes: it both reflects strong operational performance and exerts pressure on managers to increase profits. Drawing on signaling theory and referencing the conclusion proposed by Robiansyah et al. (2023) and Yaramah and Hidayat (2022) that the link between this indicator and fraudulent financial reporting has contextual heterogeneity, this study puts forward its core expectation: profitability has an impact on the detection of fraudulent financial statements.

H3: Profitability has a significant effect on financial statement fraud detection.

Activity and Financial Statement Fraud Detection

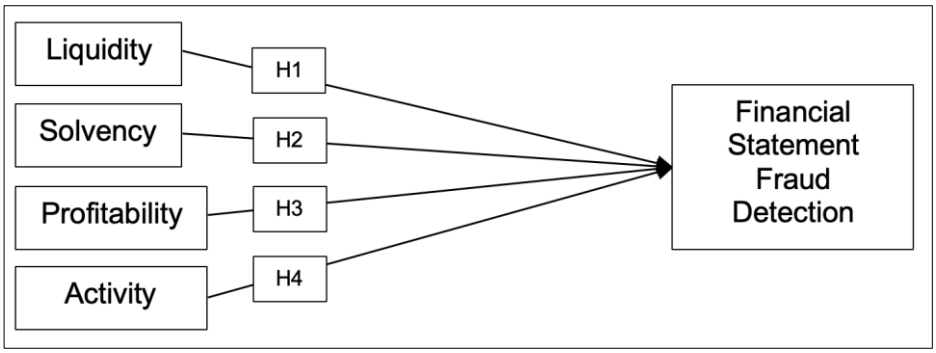
Activity ratios are core financial metrics that measure a company's efficiency in using its assets to generate sales. Abnormal patterns in these ratios may point to three categories of problems: operational pressure, aggressive revenue recognition, and inefficient asset use. Drawing on the core components of the classic Beneish model and citing the study by Robiansyah et al. (2023), this paper puts forward the research premise that activity-related factors can affect the detection of financial statement fraud.

H4: Activity has a significant effect on financial statement fraud detection.

Conceptual Framework

This study constructs a core conceptual framework to explain the association between financial ratios and the identification of financial statement fraud. Grounded in well-established signaling theory and agency theory, the study defines four categories of financial indicators as independent variables and adopts fraud identification measured by the Beneish M-Score as the dependent variable.

Figure 1. Research Framework



The research framework proposed in this paper centers on Figure 1. All financial ratios incorporated in the framework directly influence the detection of financial statement fraud. This study unpacks the connotations of four core types of financial ratios, including liquidity ratios, and leverages the Beneish M-Score model to identify potential financial reporting manipulation.

RESEARCH METHOD

Research Approach

This study adopts a quantitative research method, drawing on supporting research from Sugiyono (2017). Relying on numerical data and statistical analysis, the study tests the association between four categories of financial ratios and the identification of financial statement fraud, and this method is well-suited to the core objective of this study.

Research Design

This study is an explanatory quantitative empirical study. It takes financial statement fraud detection as its dependent variable, which is measured using the Beneish M-Score model. Four categories of financial ratios, including liquidity and solvency, are selected as independent variables. The data adopted in this study is corporate panel data that integrates cross-sectional and time-series dimensions, covering the period from 2019 to 2022.

Population and Sampling Method

The population of this study comprises manufacturing firms in the basic industry and chemical sub-sectors listed on the IDX between 2019 and 2022. This study adopts purposive sampling, a form of non-probability sampling defined by Sekaran and Bougie (2013). Eligible samples must meet two criteria: they must have continuously released complete annual reports, and they must have reported net profits throughout the observation period.

Table 2. Population and Sample Selection

Criteria	Number
Population: Manufacturing companies in the basic and chemical industry subsector listed on the IDX during 2019–2022	According to IDX listing
Companies that published complete annual financial statements consecutively during 2019–2022	Included based on screening
Companies that reported net profit during the observation period	Included based on screening
Final sample companies	60 companies
Observation period	4 years
Total firm-year observations	240 observations

Table 2 details the population and sample selection process used in this research. It outlines the total study population, the criteria for purposive sampling, the final count of selected firms, the duration of the observation period, and total firm-year observations for the panel data analysis. The final sample comprised 60 manufacturing firms from the basic and chemical industry subsector, covering four years' time, and 240 firm-year observations as presented in Table 2. This sample design is adequate for panel data regression, as it incorporates time-series data for the years 2019–2022 along with cross-sectional data from firms.

Data Collection

The information for this research was gathered from the IDX website and the chosen companies' annual financial reports. The documentation process involved collecting, noting, and computing financial statement information needed to assess the Beneish M-Score and the independent variables. The data set spans the years 2019-2022, accounting for the years prior to COVID-19 and the years during COVID-19.

Variable Measurement

This study introduces the M-Score model proposed by Beneish (1999) as a tool for detecting financial statement fraud. This model is generated through calculations of eight proprietary financial indicators, and its core judgment logic holds that the higher the M-Score, the greater the likelihood that an enterprise's financial statements have been manipulated.

This study first outlines the core basic indicators of financial analysis, then sorts out four core dimensions in sequence: Liquidity uses the current ratio to measure short-term solvency; Solvency uses the debt-to-equity ratio to measure the degree of reliance on debt; Profitability uses return on equity to measure the profit-generating capacity of shareholders' equity; Activity uses total asset turnover to measure asset utilization efficiency.

The measurement methods for all variables in this study are summarized in Table 3. The dependent variable, financial statement fraud identification, uses the Beneish M-Score, and the independent variables are divided into four categories of core financial ratios.

Table 3. Variable Measurement

Variable	Measurement	Formula
Financial Statement Fraud Detection (Y)	Beneish M-Score	M-Score = -4.84 + 0.920DSRI + 0.528GMI + 0.404AQI + 0.892SGI + 0.115DEPI - 0.172SGAI + 4.679TATA - 0.327LVGI
Liquidity (X1)	Current Ratio	Current Assets / Current Liabilities
Solvency (X2)	Debt-to-Equity Ratio	Total Liabilities / Total Equity
Profitability (X3)	Return on Equity	Net Income / Total Equity
Activity (X4)	Total Asset Turnover	Sales / Total Assets

As presented in Table 3, financial statement fraud detection is measured using the Beneish M-Score formula, while liquidity, solvency, profitability, and activity are measured using financial ratios derived from company financial statements. These measurements are used as the basis for panel data regression analysis.

Data Analysis

This study conducts data analysis relying on the EViews software. It uses descriptive statistics to characterize the mean, median, maximum, minimum, and standard deviation of all variables, and additionally adopts panel data regression, a method that can integrate cross-sectional differences across sample enterprises and the time-series changes spanning 2019 to 2022.

The panel data regression model used in this study is formulated as follows:

$$Yit = \alpha + \beta1X1it + \beta2X2it + \beta3X3it + \beta4X4it + \varepsilon it$$

Where Yit represents financial statement fraud detection for company i in year t, α is the constant, β1–β4 are regression coefficients, X1it is liquidity, X2it is solvency, X3it is profitability, X4it is activity, and εit is the error term.

This paper's empirical analysis uses three types of panel data estimation models: the common effects model (CEM), which has constant intercepts and slopes across all dimensions; the fixed effects model (FEM), which controls for firm-level heterogeneity; and the random effects model (REM), whose individual effects are random and uncorrelated with independent variables.

This study uses three types of tests to complete panel model selection: first, the Chow test is applied to select between the CEM and the FEM; next, the Hausman test is used to choose between FEM and the REM; finally, the Lagrange Multiplier (LM) test is conducted for verification. The significance threshold for all tests is uniformly set at $p<0.05$, and every step produces a clear binary choice between the two candidate models.

This study employs four categories of classical assumption tests: normality test, multicollinearity test, heteroscedasticity test, and autocorrelation test, to assess the quality of its regression models. Although these diagnostic tools have inherent functional boundaries and limitations, we still relied on this set of core screening criteria to determine the final panel model adopted in this study.

This study conducts hypothesis testing for financial statement fraud detection, employing three types of statistical tools: the coefficient of determination, the F-test, and the t-test, which are used to separately test model goodness of fit, overall model significance, and individual variable significance. Four categories of independent variables are

incorporated into the analysis: liquidity, solvency, profitability, and operating capacity. This study adopts a 5% significance threshold, and this p-value judgment criterion is cited from the existing study by Ghozali (2018).

RESULTS

Descriptive Statistics

Table 4 presents the descriptive statistics of the research variables, consisting of liquidity, solvency, profitability, activity, and financial statement fraud detection measured using the Beneish M-Score. The descriptive statistics include the mean, median, maximum, minimum, standard deviation, skewness, kurtosis, Jarque-Bera value, probability, and number of observations.

Table 4. Descriptive Statistics

Statistic	Liquidity	Solvency	Profitability	Activity	Beneish Score
Mean	2.334875	1.312708	0.527625	0.858000	-3.090333
Median	1.575000	0.860000	0.040000	0.685000	-3.075000
Maximum	24.80000	23.92000	167.3600	4.900000	8.120000
Minimum	0.020000	-10.18000	-33.42000	0.000000	-9.150000
Std. Dev.	2.709764	3.037485	11.04655	0.639285	1.529507
Skewness	4.668022	3.908990	14.31889	2.417962	2.007794
Kurtosis	33.19378	29.81302	218.9669	12.44855	23.28090
Jarque-Bera	9988.263	7800.587	474618.2	1126.613	4274.398
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	240	240	240	240	240

Based on the statistical results presented in Table 4, the authors of this paper sequentially interpret four basic financial indicators of the sampled enterprises: the average liquidity is 2.334875, with current assets generally exceeding current liabilities; the average solvency is 1.312708, indicating that the enterprises use a certain amount of debt financing; the average profitability is 0.527625; and the average operating capacity is 0.858. The paper then proceeds to analyze the Beneish score, whose average value of -3.09 falls below the threshold of -2.22, meaning most samples show no suspicion of financial manipulation. Only a small number of samples with the highest score of 8.12 exhibit strong signs of such manipulation.

This study relies on the data from Table 4 of this empirical research. The p-values of the Jarque-Bera test for all variables are all lower than 0.05, from which we derive that the variables do not follow a normal distribution. This pattern is very common in corporate financial ratio data. The excessively high maximum values, skewness, and kurtosis can corroborate the causes of extreme values that may occur across firms.

Classical Assumption Tests

Classical assumption tests were conducted as diagnostic procedures to evaluate potential estimation problems in the regression model. The tests include autocorrelation, heteroscedasticity, and multicollinearity tests. The normality condition is reflected in the Jarque-Bera values reported in Table 4.

Autocorrelation Test

Table 5 presents the autocorrelation test result using the Durbin-Watson statistic. The Durbin-Watson value was compared with the lower and upper critical values to determine whether autocorrelation exists in the regression model.

Table 5. Autocorrelation Test Results

Indicator	Value
Durbin-Watson statistic	1.993647
dL	1.7279
dU	1.8904
4 - dU	2.1096
Conclusion	No autocorrelation

As shown in Table 5, the Durbin-Watson statistic is 1.993647. Since the value lies between dU and 4 - dU, namely 1.8904 < 1.993647 < 2.1096, the model does not indicate autocorrelation.

Heteroscedasticity Test

Table 6 presents the heteroscedasticity test result using the Glejser test. The decision is based on the probability value of Obs*R-squared.

Table 6. Heteroscedasticity Test Results

Test Indicator	Statistic	Probability
F-statistic	2.320545	0.0576
Obs*R-squared	9.119467	0.0582
Scaled explained SS	17.28739	0.0017

As presented in Table 6, the probability value of Obs*R-squared is 0.0582, which is greater than 0.05. This indicates that the regression model does not have a heteroscedasticity problem based on the Glejser test.

Multicollinearity Test

Table 7 presents the multicollinearity test result using the Variance Inflation Factor (VIF). The centered VIF value is used to assess whether there is a high correlation among the independent variables.

Table 7. Multicollinearity Test Results

Variable	Centered VIF
Liquidity (X1)	1.019454
Solvency (X2)	1.040426
Profitability (X3)	1.010436
Activity (X4)	1.020091

As shown in Table 7, all independent variables have centered VIF values below 10. This indicates that the model does not have a multicollinearity problem.

Panel Data Regression Model Selection

Panel data regression model selection was conducted to determine the most appropriate estimation model. The Chow test was used to compare the CEM and FEM, while the Hausman test was used to compare FEM and REM. Since both tests support FEM, the Lagrange Multiplier test is not required for final model selection.

Chow Test

Table 8 presents the Chow test result used to determine whether CEM or FEM is more appropriate for estimating the panel data regression model.

Table 8. Chow Test Results

Effects Test	Statistic	d.f.	Probability
Cross-section F	1.619528	(59,176)	0.0086
Cross-section Chi-square	104.080875	59	0.0003

As shown in Table 8, the probability value of the cross-section Chi-square is 0.0003, which is below 0.05. Therefore, FEM is more appropriate than CEM.

Hausman Test

Table 9 presents the Hausman test result used to determine whether FEM or REM is more appropriate.

Table 9. Hausman Test Results

Test Summary	Chi-Square Statistic	Chi-Square d.f.	Probability
Cross-section random	49.309524	4	0.0000

As shown in Table 9, the probability value is 0.0000, which is below 0.05. This indicates that FEM is more appropriate than REM. Therefore, the final model used for hypothesis testing is FEM.

Panel Data Regression Results

Table 10 presents the panel data regression results using FEM. The table reports the coefficient, standard error, t-statistic, probability value, and hypothesis decision for each independent variable.

Table 10. Panel Data Regression Results Using FEM

Variable	Coefficient	Std. Error	t-Statistic	Probability	Decision
Constant	-4.455714	0.477258	-9.336062	0.0000	—
Liquidity (X1)	0.214446	0.052745	4.065673	0.0001	Supported
Solvency (X2)	-0.013295	0.036059	-0.368690	0.7128	Not supported
Profitability (X3)	0.037543	0.008234	4.559400	0.0000	Supported
Activity (X4)	1.005035	0.530159	1.895722	0.0596	Not supported

This study relies on the regression data in Table 10 to sequentially test the impact of four core categories of financial indicators on financial statement fraud detection, and verify four pre-set hypotheses: Liquidity has a significant positive effect (0.214446, p=0.0001), so H1 holds; Solvency has an insignificant negative effect (-0.013295, p=0.7128), so H2 does not hold; Profitability has a significant positive effect (0.037543, p=0.0000), so H3 holds; Operating activity has an insignificant positive effect (1.005035, p=0.0596), so H4 does not hold at the 5% significance level.

Based on Table 10, the panel data regression equation is formulated as follows:

$$Y = -4.456 + 0.214X1 – 0.013X2 + 0.037X3 + 1.005X4$$

This equation indicates that liquidity and profitability increase the Beneish Score significantly, while solvency and activity do not significantly explain changes in the Beneish Score. Because a higher Beneish Score indicates a greater likelihood of financial statement manipulation, the significant positive coefficients of liquidity and

profitability suggest that these variables are associated with higher fraud-detection scores in the sampled companies.

Model Summary and Simultaneous Test

Table 11 presents the model summary and the simultaneous test result. This table reports the R-squared, adjusted R-squared, F-statistic, and probability of the F-statistic.

Table 11. Model Summary and Simultaneous Test

Indicator	Value
R-squared	0.466950
Adjusted R-squared	0.276142
F-statistic	2.447227
Prob(F-statistic)	0.000002

According to the statistical data from Table 11 of this paper, the R^2 of this regression model is 0.466950. The four categories of independent variables, including liquidity, can explain 46.7% of the variation in the financial fraud detection indicator. The p-value of the F-statistic is 0.000002, which is less than 0.05, confirming that the independent variables have a jointly significant effect on the dependent variable.

Financial Statement Fraud Classification Using the Beneish Model

Table 12. Financial Report Manipulation Classification

Classification	Frequency	Percentage
Unlikely profit manipulation	213	89%
Possible manipulation	14	6%
Likely profit manipulation	13	5%

This study draws on Table 12 and uses the Beneish M-Score tool to classify the financial statement manipulation risk of 240 annual financial reports from manufacturing enterprises in the basic chemical sub-industry, covering the period 2019–2022. The study first defines the rules for the three classification categories. Statistical results show that 213 samples, accounting for 89% of all observations, are classified as unlikely to have manipulated their financial statements; 14 samples, or 6% of the total, are classified as possibly manipulative; and 13 samples, or 5% of the total, are classified as highly likely to be manipulative. In total, around 11% of all samples show signs of manipulation. While most samples from this sub-industry show no signs of manipulation, the risk of financial statement fraud still exists.

DISCUSSION

The Effect of Liquidity on Fraud Detection

Empirical tests conducted in this study find that liquidity has a significant positive impact on the detection of financial statement fraud. The study's core statistical parameters meet qualification standards; the original hypothesis H1 holds, this conclusion conforms to standard empirical research norms, and it can provide solid support for the prevention and control of financial fraud.

This paper interprets the aforementioned research findings using signaling theory. The industry generally regards corporate liquidity as a positive signal, as it can reflect an enterprise's short-term solvency. However, if this indicator becomes the core evaluation basis, it will create incentives for management to window-dress liquidity. The Beneish model can capture changes in accounts receivable and accrual items, and support the identification of financial manipulation.

Robiansyah et al. (2023) found in their research that among enterprises classified by fraud detection models, there is an association between liquidity and fraudulent financial reporting; Yaramah and Hidayat (2022) also point out that financial ratios can be used to identify accounting fraud. This study finds that liquidity has a significant positive impact on financial fraud risk and proposes that liquidity should not only function as an indicator of financial health. When accompanied by abnormal financial reporting patterns, it can also serve as a potential early warning signal for accounting fraud.

The Effect of Solvency on Fraud Detection

This study conducted regression tests on a model with the Beneish Score as the dependent variable. The coefficient for solvency is -0.013295, with a t-value of -0.368690 and a p-value of 0.7128. The null hypothesis H2 is not supported. The research sample consists of enterprises in the basic and chemical manufacturing industries covering the period 2019–2022.

This study finds that long-term debt pressure has not become the dominant influencing factor for fraud detection signals among sample firms. Drawing on the agency theory proposed by Jensen and Meckling (1976), debt should, in principle, force management to improve financial performance. Yet this pressure did not produce a significant impact on Beneish scores, an outcome that may be associated with heterogeneity in the sample's debt structure, creditor oversight, and financial policies during the pandemic.

The core empirical findings of this study diverge from two accounting studies published in 2023. Narsa et al. (2023) used a sample of Indonesian manufacturing firms and the modified M-Score model and concluded that the debt ratio is positively correlated with earnings management. Robiansyah et al. (2023) proposed that leverage indicators influence fraudulent financial reporting. This study finds no significant correlation between solvency and financial fraud, because firms that manage their debts in compliance with regulations have no need to falsify their performance. In the context of this study, solvency is a potential rather than a consistently significant indicator for fraud detection.

The Effect of Profitability on Fraud Detection

The regression results of this study show that profitability has a significant positive impact on the detection of financial statement fraud, with a corresponding regression coefficient of 0.037543, t-statistic of 4.559400, and p-value of 0.0000. On this basis, Hypothesis H3 of this study is verified. Higher profitability corresponds to a higher Beneish Score, meaning that firms with higher profit levels are more likely to exhibit potential signs of financial statement manipulation. This result can be explained by signaling theory: high profitability is a core indicator used by stakeholders to evaluate firms. Firms face pressure to maintain their profit trend, which generates incentives to submit untruthful financial reports, a dynamic that aligns with the earnings management logic of the Beneish model.

First, the core findings of this study align with the conclusions proposed by Robiansyah et al. (2023) regarding the correlation between profitability and fraudulent financial reporting. They also support the research of Alfian & Triani (2019) and Grimaldi (2019), which confirms that the Beneish model is able to identify and classify financial manipulation. These findings remind investors and regulators to prudently evaluate enterprises' profitability, as strong earnings cannot rule out the risk of corporate manipulation.

The Effect of Activity on Fraud Detection

This quantitative empirical study applies the Beneish score test to identify financial statement fraud. The regression coefficient for the activity variable is 1.005035, its t-value is 1.895722, and its p-value is 0.0596. This variable failed to pass the 5% significance test, so its positive effect is not statistically significant. The original hypothesis H4 does not hold, which corrects the prior misinterpretation that this variable exerts a negative impact.

The empirical results of this study, which use basic and chemical manufacturing firms from 2019 to 2022 as the research sample, show that asset utilization efficiency has insufficient explanatory power for financial statement fraud detection signals. The activity ratio refers to the efficiency with which assets generate revenue; existing theories hold that abnormal operating activities signal risk, but this indicator is not a core basis for identifying fraud in the sample of this study.

The core findings of this study diverge from the conclusion proposed by Robiansyah et al. (2023) that capital turnover has an impact on fraudulent financial reporting. This divergence stems from three types of differences: industry characteristics, measurement methods, and observation periods. Compounding these factors, the shock of the COVID-19 pandemic on the manufacturing industry weakened the explanatory power of activity ratios. Ultimately, this study concludes that operating activity only functions as a supportive auxiliary indicator and cannot act as a significant determinant of fraud detection in this research.

Financial Statement Fraud Detection Using the Beneish Model

The findings of this study partially rely on the Beneish classification model to assign risk levels to a sample of 240 annual financial reports: 213 reports have no suspicion of manipulation, accounting for 89% of the total sample; 14 reports show possible manipulation, accounting for 6%; 13 reports have a high likelihood of manipulation, accounting for 5%. In total, 11% of the sample exhibits signs of potential manipulation.

The financial statement manipulation detection conducted in this study targeting IDX-listed manufacturing enterprises shows that the financial disclosures of most sample firms meet compliance requirements. However, the cascading risks hidden in the extremely small share of abnormal samples are highly prone to being underestimated. Existing authoritative studies have clearly pointed out that the risk priority of these small-proportion abnormal samples must never be lower than that of samples with conventional problems (ICAEW, 2020).

The conclusions of this study align with the established field consensus that the Beneish model can identify potential earnings manipulation. Durana et al. (2022) applied the model's M-score to identify creative accounting practices, Khatun et al. (2022) used the model to study earnings manipulation in the banking industry, Narsa et al. (2023) validated the applicability of a modified M-score for detecting earnings management in the manufacturing sector within the Indonesian context, and Hernadi and Meiden (2023) defined financial statement fraud as intentional acts that mislead users of financial reports, further reinforcing the application value of financial fraud detection frameworks. Within the scope of this study, only liquidity and profitability are significant indicators for financial statement fraud detection, while solvency and operating capacity lack statistical significance. It can be inferred from this finding that not all financial ratios have equal explanatory power for fraud detection, and three categories of supplementary analysis must be incorporated when applying the Beneish model.

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CONCLUSION

This study aims to analyze the impact of four major financial dimensions: liquidity, solvency, profitability, and operating capability, on financial fraud detection. It adopts the Beneish M-Score model, takes manufacturing firms in the basic industry and chemical sub-sectors listed on the IDX from 2019 to 2022 as its research sample, and its study period covers the COVID-19 pandemic.

The empirical results of this study show that liquidity and profitability have a significant positive impact on the detection of financial fraud, and relevant fraud signals can be captured via the Beneish M-Score; the effects of solvency and operating capacity do not reach a statistically significant level. This conclusion applies only to the context of this study, and cannot be generalized or extrapolated to other settings.

This paper uses the Beneish classification method to conduct the detection of the likelihood of financial statement manipulation. Most observed samples are classified as having no risk of manipulation, yet 11% still show signs of possible or highly probable manipulation. It is critical not to ignore potential financial fraud risks simply because most samples do not exhibit strong manipulation signals.

The conclusions of this study can serve multiple types of market entities, including investors and regulatory authorities. The core detection tool adopted in this study, the Beneish M-Score, is able to identify financial statement fraud, but this tool has clear usage boundaries and cannot be over-relied on. Future research can advance along three specific directions to further improve the accuracy and applicability of financial statement fraud detection.

LIMITATION

This study has several limitations. First, the research sample only focuses on manufacturing enterprises in the basic industry and chemical sub-sectors listed on the IDX. Its conclusions cannot be generalized to cross-industry firms, and the remaining limitations will be disclosed in subsequent research.

This study limits its observation period to 2019–2022, a special period spanning before and after the outbreak of the COVID-19 pandemic. This limitation in the study's design may interfere with indicators of corporate performance, financial reporting behavior, and fraud risk, and the study's conclusions cannot be applied to normal economic environments or the post-pandemic period.

This study carries out its analysis solely relying on secondary data sourced from public financial statements. Limited by the constraints of this data source, the study cannot capture the four core internal dimensions that influence fraudulent reporting: internal management motives, internal control quality, audit findings, and corporate governance practices.

This study only selected four categories of financial indicators: liquidity, solvency, profitability, and operating capacity, as explanatory variables, and did not incorporate eight categories of potential influencing factors, such as firm size. Follow-up research may supplement these variables to improve the comprehensiveness of financial statement fraud detection.

The Beneish M-Score model can identify potential signs of manipulation in financial statements, but it cannot prove that fraud has actually occurred. It can only serve as an

early warning signal that requires further investigation, rather than conclusive evidence confirming the existence of fraud.

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DECLARATION OF CONFLICTING INTERESTS
The authors of this study declare that no conflicts of interest related to this research or the publication of its findings exist. All analytical conclusions are built upon objective data, and no factors that would interfere with the interpretation of the study results have exerted any influence over this work.

REFERENCES

Abdullahi, R., & Mansor, N. (2015). Fraud triangle theory and fraud diamond theory: Understanding the convergent and divergent for future research. *International Journal of Academic Research in Accounting, Finance and Management Sciences, 5*(4), 38–45. https://doi.org/10.6007/IJARAFMS/v5-i4/1823

Aghghaleh, S. F., Mohamed, Z. M., & Rahmat, M. M. (2016). Detecting financial statement frauds in Malaysia: Comparing the abilities of Beneish and Dechow models. *Asian Journal of Accounting and Governance, 7*, 57–65. https://doi.org/10.17576/AJAG-2016-07-05

Alfian, F., & Triani, N. A. (2019). Fraudulent financial reporting detection using Beneish M-Score model in public companies in 2012–2016. *Asia Pacific Fraud Journal, 4*(1). https://doi.org/10.21532/apfj.001.19.04.01.03

Association of Certified Fraud Examiners Indonesia (ACFE Indonesia). (2020). *Survei fraud Indonesia 2019*. ACFE Indonesia https://acfe-indonesia.or.id/wp-content/uploads/2021/02/Survei-Fraud-Indonesia-2019.pdf

Basmar, N. A., & Ruslan. (2021). Analisis perbandingan model Beneish M-Score dan fraud score dalam mendeteksi kecurangan laporan keuangan. *SEIKO: Journal of Management & Business, 4*(2), 428–440. https://doi.org/10.37531/sejaman.v4i2.1439

Beanworks. (2021). *The most shocking cases of accounting fraud in 2021 and how to protect your business*. Beanworks. https://www.beanworks.com/blog/the-most-shocking-cases-of-accounting-fraud-in-2021-and-how-to-protect-your-business/

Beneish, M. D. (1999). The detection of earnings manipulation. *Financial Analysts Journal, 55*(5), 24–36. https://doi.org/10.2469/faj.v55.n5.2296

Beneish, M. D., Lee, C. M. C., & Nichols, D. C. (2012). Fraud detection and expected returns. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1998387

Collier, P. M. (2016). *Accounting for Managers: Interpreting Accounting Information for Decision Making*. John Wiley & Sons.

Corporate Finance Institute (CFI). (2022). *Top accounting scandals*. CFI. https://corporatefinanceinstitute.com/resources/knowledge/other/top-accounting-scandals/

Damayanti, A. (2020, December 10). *Diduga manipulasi laporan keuangan, GE didenda Rp 2,8 T*. detikFinance. https://finance.detik.com/berita-ekonomi-bisnis/d-5289429/diduga-manipulasi-laporan-keuangan-ge-didenda-rp-28-t

Davidson, W. (2019). *Financial Statement Analysis: Basis for Management Advice*. Association of International Certified Professional Accountants.

Deniswara, K., Kesuma, J. T., & Louis, V. (2022). Forensic accounting on Indonesian energy sector with Beneish M-Score model analysis. In *Proceedings of the 2022 6th International Conference on E-Commerce, E-Business and E-Government (ICEEG 2022)*. Association for Computing Machinery. https://doi.org/10.1145/3537693.3537709

Donaldson, G. (1961). *Corporate Debt Capacity: A Study of Corporate Debt Policy and The Determination of Corporate Debt Capacity*. Harvard University, Division of Research, Graduate School of Business Administration.

Durana, P., Blazek, R., Machova, V., & Krasnan, M. (2022). The use of Beneish M-scores to reveal creative accounting: Evidence from Slovakia. *Equilibrium. Quarterly Journal of Economics and Economic Policy, 17*(2), 481–510. https://doi.org/10.24136/eq.2022.017

Eisenhardt, K. M. (1989). Agency theory: An assessment and review. *Academy of Management Review, 14*(1), 57–74. https://doi.org/10.5465/amr.1989.4279003

Ghozali, I. (2018). *Aplikasi Analisis Multivariate Dengan Program IBM SPSS* (9th ed.). Badan Penerbit Universitas Diponegoro.

GMT Research. (n.d.). *Beneish's M-Score*. GMT Research. https://www.gmtresearch.com/en/accounting-ratio/beneishs-m-score/

Grimaldi, F. (2019). The relationship between financial crisis and earnings management: Some evidence from the Italian context. *Corporate Ownership & Control, 17*(1), 325–335. https://doi.org/10.22495/cocv17i1siart13

Harsanti, P., & Mulyani, U. R. (2021). Testing of fraudulent financial statements with the Beneish M-Score model for manufacturing companies listed in the Indonesian Stock Exchange. *KnE Social Sciences, 5*(7), 125–133. https://doi.org/10.18502/kss.v5i7.9328

Hernadi, K. N., & Meiden, C. (2023). The effect of fraud pentagon on fraudulent financial statements: A meta-analysis. *Journal of International Conference Proceedings, 6*(1), 242–251. https://doi.org/10.32535/jicp.v6i1.2264

Institute of Chartered Accountants in England and Wales (ICAEW). (2020). *Fraudulent financial reporting: Fresh thinking*. ICAEW. https://www.icaew.com/-/media/corporate/files/technical/audit-and-assurance/the-future-of-audit/fraudulent-financial-reporting-fresh-thinking.ashx

Institute of Indonesia Chartered Accountants (Ikatan Akuntan Indonesia/IAI). (2021). *Standar Akuntansi Keuangan: PSAK 1*. IAI.

Integrity Indonesia. (2019). *3 skandal kecurangan yang libatkan perusahaan Jepang*. Integrity Indonesia. https://www.integrity-indonesia.com/id/blog/2019/08/01/3-skandal-kecurangan-yang-libatkan-perusahaan-jepang/

Irwandi, S. A., Ghozali, I., Faisal, & Pamungkas, I. D. (2019). Detection fraudulent financial statement: Beneish M-Score model. *WSEAS Transactions on Business and Economics, 16*, 271–281. https://www.wseas.org/multimedia/journals/economics/2019/a545107-731.php

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs, and ownership structure. *Journal of Financial Economics, 3*(4), 305–360. https://doi.org/10.1016/0304-405X(76)90026-X

Jonson, C. L., & Geis, G. (2010). Cressey, Donald R.: Embezzlement and white-collar crime. In F. T. Cullen & P. Wilcox (Eds.), *Encyclopedia of Criminological Theory*. SAGE Publications. https://doi.org/10.4135/9781412959193.n62

Khatun, A., Ghosh, R. K., & Kabir, S. (2022). Earnings manipulation behavior in the banking industry of Bangladesh: The strategical implication of Beneish M-score model. *Arab Gulf Journal of Scientific Research, 40*(3), 302–328. https://doi.org/10.1108/AGJSR-03-2022-0001

Knežević, S., Špiler, M., Milašinović, M., Mitrović, A., Milojević, S., & Travica, J. (2021). Using Beneish M-Score and Altman Z-Score models to detect financial fraud and

company failure. *Tekstilna Industrija, 69*(4), 20–29. https://doi.org/10.5937/tekstind2104020K

Lotfi, N., & Chadegani, A. A. (2017). Detecting corporate financial fraud using Beneish M-Score model. *International Journal of Finance and Managerial Accounting, 2*(8), 29–34. https://ijfma.ir/article_11799.html

Munidewi, I. A. B., & Sunarsih, N. M. (2023). *Time budget pressure effect, auditor ethics, audit fee and auditor's working experience on audit quality*. *International Journal of Accounting and Finance in Asia Pacific,* **6**(3). https://doi.org/10.32535/ijafap.v6i3.1884

Myers, S. C. (1984). The capital structure puzzle. *The Journal of Finance, 39*(3), 575–592. https://doi.org/10.1111/j.1540-6261.1984.tb03646.x

Narsa, N. P. D. R. H., Afifa, L. M. E., & Wardhaningrum, O. A. (2023). Fraud triangle and earnings management based on the modified M-score: A study on manufacturing company in Indonesia. *Heliyon, 9*(2), e13649. https://doi.org/10.1016/j.heliyon.2023.e13649

Novita, N. (2019). Teori fraud pentagon dan deteksi kecurangan pelaporan keuangan. *Jurnal Akuntansi Kontemporer, 11*(2), 64–73. https://doi.org/10.33508/jako.v11i2.2077

Nugroho, D. S., & Diyanty, V. (2022). Fraud hexagon and fraudulent financial statement: Comparison between OMI and Beneish model. In *Proceedings of the International Conference on Economics, Management and Accounting (ICEMAC 2021)* (Vol. 207, pp. 1–10). Atlantis Press. https://doi.org/10.2991/aebmr.k.220204.001

Prastowo, D. (2011). *Analisis Laporan Keuangan*. UPP STIM YKPN.

Robiansyah, A., Suranta, E., Midiastuty, P. P., & Fachruzzaman. (2023). The effect of leverage, profitability, asset composition, liquidity, capital turnover, and cash flow on fraudulent financial reporting. *Al-Mal: Jurnal Akuntansi dan Keuangan Islam, 4*(1). https://doi.org/10.24042/al-mal.v4i01.16201

Sacks, J., & Reilly, R. (2022). *2022 ACFE report to the nations: Fraud trends and key takeaways*. Withum. https://www.withum.com/resources/2022-acfe-report-to-the-nations-fraud-trends-and-key-takeaways/

Sandria, F. (2021, July 27). *Deretan skandal lapkeu di pasar saham RI, Indofarma-Hanson!*. CNBC Indonesia. https://www.cnbcindonesia.com/market/20210726191301-17-263827/deretan-skandal-lapkeu-di-pasar-saham-ri-indofarma-hanson

Sekaran, U., & Bougie, R. (2013). *Research Methods for Business: A Skill-Building Approach* (6th ed.). Wiley.

Spence, M. (1973). Job market signaling. *The Quarterly Journal of Economics, 87*(3), 355–374. https://doi.org/10.2307/1882010

Sugiyono, S. (2017). *Metode Penelitian Kuantitatif, Kualitatif, dan R&D*. Alfabeta.

Supriyatna, I., & Djaelani, M. (2021, June 4). *Manipulasi laporan keuangan, 2 mantan direksi AISA dituntut 7 tahun penjara*. Suara. https://www.suara.com/bisnis/2021/06/04/132347/manipulasi-laporan-keuangan-2-mantan-direksi-aisa-dituntut-7-tahun-penjara?page=all

Suryandari, N. N. A., & Endiana, I. D. M. (2019). *Fraudulent Financial Statement*. CV Noah Aletheia.

Tuanakotta, T. M. (2013). *Mendeteksi Manipulasi Laporan Keuangan*. Salemba Empat.

Turner, L., & Weickgenannt, A. (2013). *Accounting Information Systems: Controls and Processes*. John Wiley & Sons.

Ulfah, S. M., Rusydi, M. K., & Prihatiningtias, Y. W. (2024). *Determinants of government procurement fraud prevention with organizational commitment and ethical culture as moderating variables*. *International Journal of Accounting and Finance in Asia Pacific, 7*(3), 317–341. https://doi.org/10.32535/ijafap.v7i3.3602

Waromi, J., Salle, A., & Fonataba, N. A. (2024). The effect of whistleblowing and professional skepticism on fraud detection audit with fraud audit training as a moderating variable. *International Journal of Accounting and Finance in Asia Pacific, 7*(1). https://doi.org/10.32535/ijafap.v7i1.2911

Wiszniowski, E. (2020). Accuracy of the Beneish Model as applied to polish enterprises known to manipulate financial reports. In *Proceedings of the 35th International Business Information Management Association Conference IBIMA 2020* (pp. 9218-9222). International Business Information Management Association.

Yaramah, W., & Hidayat, I. (2022). Mendeteksi kecurangan laporan keuangan dengan analisis rasio keuangan. *Competitive Jurnal Akuntansi Dan Keuangan*, *6*(1), 191-202.

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