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The Influence of Fraud Diamond, Beneish M-Score and Dechow F-Score in Detecting Financial Statement Fraud in Agricultural Companies in the Plantation Sub-Sector (Listed on the IDX)

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ABSTRACT

The study examines the Influence of Fraud Diamond, Beneish M-Score, and Dechow F-Score models in detecting financial statement fraud among agricultural companies in the plantation sub-sector listed on the Indonesia Stock Exchange during 2021–2024. The research aims to demonstrate how the application of theoretical and quantitative fraud detection models can identify potential financial manipulation and strengthen corporate transparency and accountability. This quantitative study uses secondary data obtained from company financial reports. The sample consists of 20 companies selected through purposive sampling. Data were analyzed using logistic regression with SPSS 26.0 software. The findings reveal that the Fraud Diamond, Beneish M-Score, and Dechow F-Score simultaneously have a significant effect on financial statement fraud. Partially, variables such as ACHANGE, ROA, RECEIVABLE, BDOUT, and AUDCHANGE significantly influence financial statement fraud, whereas LEV, DCHANGE, Beneish M-Score, and Dechow F-Score show no significant effect. These results indicate that combining theoretical fraud models provides a more comprehensive framework for detecting fraudulent financial reporting, thereby supporting improved corporate governance and investor confidence.

Keywords: *Agricultural Companies; Beneish M-Score; Dechow F-Score; Fraud Diamond; Financial Statement Fraud*

INTRODUCTION

The plantation sector holds a strategic position in Indonesia’s economic structure because of its substantial contribution to national output and export performance. According to the *Indikator Pertanian* 2023 published by Badan Pusat Statistik (2024), the Agriculture, Forestry, and Fisheries sector contributed 12,53 percent to Indonesia’s GDP in 2024, indicating the continuing importance of agricultural activities in supporting national economic performance.

Within this broader sector, the plantation subsector plays a dominant role. Official data from Badan Pusat Statistik (2024) show that plantation commodities contributed approximately 3.88 percent to Indonesia’s national GDP in 2023 and accounted for 30.97 percent of the GDP within the agricultural sector, making it the largest contributor among agricultural subsectors. This contribution highlights the critical role of plantation activities in maintaining economic stability and long-term growth, particularly in commodity driven regions.

Figure 1. Contribution of Agriculture to Gross Domestic Bruto, 2023

Financial statement fraud remains a persistent challenge in Indonesia. Oversight bodies in Indonesia, particularly the Audit Board of Indonesia (BPK), continue to report irregularities related to misstatements, weak internal controls, and non-compliance with reporting obligations across multiple industries, including the plantation sector. Concrete evidence of these issues can be seen in BPK's findings on PTPN VIII, a state-owned plantation company. BPK revealed that PTPN VIII failed to assess the financial capacity of its cooperative partners (KSU and KSS) and did not collect or record revenue-sharing obligations as mandated by cooperation agreements. These weaknesses resulted in a revenue shortfall of Rp19.44 billion, in addition to potential losses from unrecorded revenue-sharing between 2021 and 2023. Such findings demonstrate that fraud risks and reporting irregularities within plantation companies are not merely theoretical concerns but are empirically documented by national authorities, highlighting the need for more robust fraud detection mechanisms. Consistent with this situation, Yani et al. (2024) find that weaknesses in fraud detection and budget execution significantly reduce the quality of financial reporting, showing that misstatements often arise not only from technical accounting limitations but also from intentional manipulation. In line with this, Marpaung et al. (2023) highlight that auditor credibility and responsibility play an essential role in detecting fraud, emphasizing that auditors must exercise professional diligence and integrity to identify irregularities effectively. These findings collectively indicate that strong regulatory requirements must be supported by effective fraud detection mechanisms and competent auditors to ensure the reliability of financial statements. Fraudulent reporting also produces harmful organizational consequences, as "fraudulent financial reporting has an impact on poor external business relations, negative reputation, and decreased employee morale and performance" (Situmorang & Pane, 2024)**.** The issue becomes more critical considering that "If the action is done intentionally, it is called fraud" (Situmorang, 2023), indicating that fraudulent reporting involves intentional actions that directly compromise reporting integrity. Although regulatory frameworks such as POJK No. 29/POJK.04/2016 issued by Otoritas Jasa Keuangan (2016) on annual report transparency and the application of standardized financial reporting through PSAK aim to strengthen reporting quality, fraudulent practices continue to emerge in corporate environments. This condition indicates that regulatory compliance alone is insufficient to prevent fraud, thereby necessitating the use of more comprehensive analytical approaches for early detection.

In this context, the need for early detection is also influenced by the business realities of agricultural companies. Operations in such companies are typically characterized by long production cycles, seasonal harvesting, price volatility and high capital requirements for land development, replanting and processing facilities (McPhee et al., 2021; Vilani et al., 2024; Abokyi & Asiedu, 2021; Mustafa et al., 2023). Because of these, the pressure to project an image of stability and growth is stronger, especially when these companies depend on investors or lenders and therefore must fulfill their expectations and requirements. For this reason, financial statements do not act only as compliance reports but also as market signals that affect investor confidence and business relationships (Yetunde et al., 2025).

Credibility is a crucial and intangible asset for agricultural companies from a business perspective. A firm's reputation can be at stake if the reported company performance does not match its actual figures. This can result in weaker market reputation, stricter monitoring by stakeholders and decreased trust from key partners (Chen & Wei, 2024; Gu et al., 2022). Reputation is particularly critical in the plantation sub-sector because the inherent sensitivity to changes in weather and commodity cycles pushes stakeholders to closely monitor business performance and use the information to decide their level of confidence and willingness to continue investment in a company.

Fraud detection tools are more than just accounting control mechanisms. They can guide managerial supervision, develop tougher corporate governance, and aid in needed interventions before reporting issues develop into legal violations or reputational crises. This study therefore examines whether combining a behavioral framework such as Fraud diamond with quantitative models (Beneish M-Score and Dechow F-Score) strengthens detection of financial statement fraud among agricultural companies listed on the Indonesia Stock Exchange from 2021 to 2024.

In addition to this conceptual gap, prior empirical studies also demonstrate that each model has been proven effective when applied individually. Beneish (1999) and later validations such as Adoboe-Mensah et al. (2023) confirm that the M Score accurately identifies earnings manipulation through abnormal financial ratio patterns. Similarly, Dechow et al. (2011) and Ratmono et al. (2020) provide strong evidence that the F Score is a reliable predictor of material misstatements by capturing inconsistencies between accruals, earnings, and cash flows. On the behavioral side, the Fraud Diamond framework has been empirically supported in various fraud contexts. Studies in Indonesia, including Rahma et al. (2022) and Purwani et al. (2024), show that pressure, opportunity, rationalization, and capability significantly influence the likelihood of fraud. Some researchers have also integrated behavioral indicators with financial ratio models. For example, Ratmono et al. (2020) and Putra & Dinarjito (2021) report that combining quantitative indicators with behavioral constructs improves the ability to detect fraudulent reporting. These empirical findings indicate that each model captures a different dimension of fraudulent behavior, and integrating them can create a more comprehensive and accurate approach for fraud detection, particularly in complex and high risk industries such as plantation companies.

Therefore, this study aims to empirically assess the effectiveness of the Fraud Diamond, Beneish M-Score, and Dechow F-Score in detecting potential financial statement fraud in plantation companies listed on the Indonesia Stock Exchange (IDX) for the 2021-2024 period. This research relies on secondary data obtained from annual reports published by IDX-listed plantation firms. By integrating behavioral frameworks and ratio-based fraud detection models, this study contributes to a more comprehensive understanding of fraud risk within the plantation sector and provides practical implications for auditors, regulators, and corporate governance.

LITERATURE REVIEW

Fraud Diamond

Fraud Diamond is a development of the fraud triangle by adding a capability element which plays a major role in determining whether fraud can actually occur even though the other three elements are present (Eksandy & Sari, 2022).

The Fraud Diamond model has the advantage of incorporating the capability element, which, as proposed by Wolfe & Hermanson (2004), explains why not all individuals who face pressure, opportunity, and rationalization ultimately commit fraud. The addition of capability makes this model more comprehensive than the Fraud Triangle, as it recognizes that fraudsters typically possess the position, authority, or technical competence to exploit internal control weaknesses. However, its weakness is the difficult-to-quantify nature of the indicators (Khamainy et al., 2022). Nevertheless, the Fraud Diamond remains relevant in the context of fraud detection in the plantation sector, as performance pressures, commodity price volatility, and supply chain complexity increase companies' vulnerability to financial statement manipulation (Prakoso & Setiyorini, 2021).

Table 1. Fraud Diamond Indicators

Element	Indicators	Measurements
Pressure	Financial Stability	ACHANGE = Total Assets$_t$ - Total Assets$_{t-1}$ / Total Assets$_{t-1}$
	Financial Target	ROA = Net Income / Total Assets
	External Pressure	LEV = Total Debt / Total Assets
Opportunity	Nature of Industry	RECEIVABLE = Receivables / Sales
	Ineffective Monitoring	BDOUT = Independent Commissioners / Total Commissioners
Rationalization	Change in Auditor	Dummy variable: 1 = auditor changed, 0 = otherwise
Capability	Change in Director	Dummy variable: 1 = director changed, 0 = otherwise

Interpretation of each Fraud Diamond indicator provides insight into the potential for fraud. An increased ACHANGE can reflect pressure to maintain financial stability, which, according to Rahma et al. (2022), often drives companies to engage in window dressing. A low ROA indicates an inability to achieve profit targets, thus reinforcing the motivation for earnings manipulation (Purwani et al., 2024). High leverage (LEV) indicates creditor pressure, which can trigger management to embellish performance (Putra & Dinarjito, 2021). An increased receivables ratio (RECEIVABLE) indicates the risk of fictitious revenue recognition (Ratmono et al., 2020). Meanwhile, a low BDOUT indicates weak oversight, which facilitates the occurrence of fraud (Indriani & Rohman, 2022). Auditor changes (AUDCHANGE) are often associated with perpetrators' attempts to cover up their fraud (Husein et al., 2023), while director changes (DCHANGE) may indicate the presence of figures with greater fraud-executing capabilities (Khamainy et al., 2022).

Beneish M-Score

Beneish M-Score is a model designed to capture distortions in financial reporting that may result from manipulation or preconditions that may encourage a company to engage in such activities (Kaab Omeir et al., 2023).

The Beneish M-Score was developed by Beneish (1999) to detect earnings manipulation using eight financial ratios sensitive to financial engineering. This model has empirical advantages because it has been proven effective in identifying companies engaging in earnings manipulation Adoboe-Mensah et al. (2023). However, this model also has limitations, particularly in industries with unstable earnings cycles such as plantations, where some ratios can provide biased signals (Marais et al., 2023). Nevertheless, the Beneish M-Score remains relevant as an initial screening tool because the numerical distortions detected by this model are often a direct consequence of fraud pressure or opportunity in the Diamond Fraud case (Kaab Omeir et al., 2023).

$$M = (-4{,}840) + (0{,}920 \times DSRI) + (0{,}528 \times GMI) + (0{,}404 \times AQI) + (0{,}892 \times SGI) + (0{,}115 \times DEPI) - (0{,}172 \times SGAI) + (4{,}679 \times TATA) - (0{,}327 \times LVGI)$$

Table 2. Beneish M-Score Indicators

Indicators	Description	Measurements
DSRI	Days Sales and Receivable Index	[Net Receivable$_t$ / Sales$_t$] / [Net Receivable$_{t-1}$ / Sales$_{t-1}$]
GMI	Gross Margin Index	[Sales$_{t-1}$ − Cost of goods sold$_{t-1}$] / [Sales$_t$ − Cost of goods sold$_t$]
AQI	Asset Quality Index	{1 − [(Current Assetst − netPPE$_t$) / Total Assets$_t$]} / {1 − [(Current Assets$_{t-1}$ − netPPE$_{t-1}$) / Total Assets$_{t-1}$]}
SGI	Sales Growth Index	Sales$_t$ / Sales$_{t-1}$
DEPI	Depreciation Index	[Depreciation$_{t-1}$ / (Depreciation$_{t-1}$ + netPPE$_{t-1}$)] / [Depreciation$_t$ / (Depreciation$_t$ + netPPE$_t$)]
SGAI	Expense Index	[SGAExpenses$_t$ / Sales$_t$] / [SGAExpenses$_{t-1}$ / Sales$_{t-1}$]
TATA	Total Accrual to Total Assets Index	[(ΔNet working capital − ΔCash and cash equivalents − ΔIncome tax − Depreciation) / Total Assets$_t$]
LVGI	Leverage Index	[LTD$_t$ + Current Liabilities$_t$] / Total Assets$_t$ / [LTD$_{t-1}$ + Current Liabilities$_{t-1}$] / Total Assets$_{t-1}$

Each indicator in the Beneish M-Score has a conceptual interpretation related to manipulation practices. An increase in the DSRI indicates sales manipulation through increased receivables (Beneish, 1999). An increase in the GMI indicates declining margins, increasing pressure on management to artificially improve earnings. A higher AQI reflects an increase in non-productive assets, which can stem from inappropriate cost capitalization. Excessively high sales growth (SGI) can signal pressure to maintain growth, which, according to Ratmono et al. (2020), is a trigger for earnings management. An increase in the DEPI indicates a slowdown in depreciation, which is often used to boost profits. An increase in the SGAI can signal inefficiencies that trigger earnings management. A high TATA indicates accrual aggressiveness, while an increased LVGI reflects financing pressures that encourage companies to embellish financial statements (Kaab Omeir et al., 2023).

Dechow F-Score

The Dechow F-Score represents a scaled probability measure that serves as an indicator or warning signal of potential earnings management or financial misstatement (Dechow et al., 2011).

The Dechow F-Score was introduced by Dechow et al. (2011) as a predictive model to identify the possibility of material misstatements using the accrual approach. This model excels because it can assess the consistency between changes in earnings, cash flow, and operating assets more comprehensively than traditional financial ratios. However, this model has limitations due to its calculation complexity and sensitivity to industry cycles, particularly in industries with fluctuating receivables and inventories, such as the plantation sector. Nevertheless, the F-Score remains relevant because many fraud cases involve accrual manipulation that is not captured by simple models (Ratmono et al., 2020).

Predicted Value = -7,893 + 0,790 × RSST + 2,518 × ΔREC + 1,191 × ΔINV + 1,979 × SOFTS ASSETS + 0,11 × ΔCASH SALES – 0,932 × ΔROA + 1,029 × ISSUE

Table 3. Dechow F-Score Indicators

Indicators	Description	Measurements
RSSTACC	Change in net non-cash operational assets	Change in net non-cash operational assets / Total assets
CHREC	Change in receivable accounts	Change in receivable account / Average total assets
CHINV	Change in inventory	Change in inventory / Average total assets
SOFTASSETS	Intangible assets	Intangible assets / Average total assets
CHCS	Change in cash sale	$Sales_t$ − Change in receivable $account_t$ / $Sales_{t-1}$ − Change in receivable $account_{t-1}$
CHROA	Change in asset return	Earning / Average total assets
ISSUE	If the company has issued a share certificate is 1, and otherwise, 0	

The F-Score indicator illustrates various accrual patterns that can lead to misstatements. A high RSST value indicates aggressive accruals, which, according to Dechow et al. (2011), is a key signal of earnings manipulation. Increases in CHREC and CHINV can indicate improper revenue and inventory recognition. High SOFTASSETS reflect subjective asset values that are easily manipulated (Marais et al., 2023). Inconsistent changes in CHCS indicate anomalies in sales cash flows. Fluctuating CHROA reflects unstable profitability that can mask earnings management practices. Meanwhile, ISSUE is often associated with window dressing practices to attract investors (Kaab Omeir et al., 2023).

The integration of the Fraud Diamond, Beneish M-Score, and Dechow F-Score provides a more comprehensive fraud detection approach. The Fraud Diamond explains the motivations and behavioral conditions that trigger fraud (Wolfe & Hermanson, 2004), while Beneish and Dechow capture the numerical manifestations of such behavior in the form of ratio anomalies and accrual inconsistencies Beneish (1999) and Dechow et al. (2011). This suggests that behavioral red flags often materialize in quantitative indicators, as Kaab Omeir et al. (2023) asserted that quantitative and behavioral models complement each other in detecting financial statement manipulation.

Financial Statement Fraud

Financial Statement Fraud is an act of fraud or manipulation carried out intentionally to cause misrepresentation or omission of material information in an organization's financial statements ACFE (2022)**.** Financial Statement Fraud shall be measured by way of a dummy variable where code 1 shall represent those companies which have restated their financial statements and 0 otherwise.

According to description provided, the variables for this study are illustrated by the following research framework image :

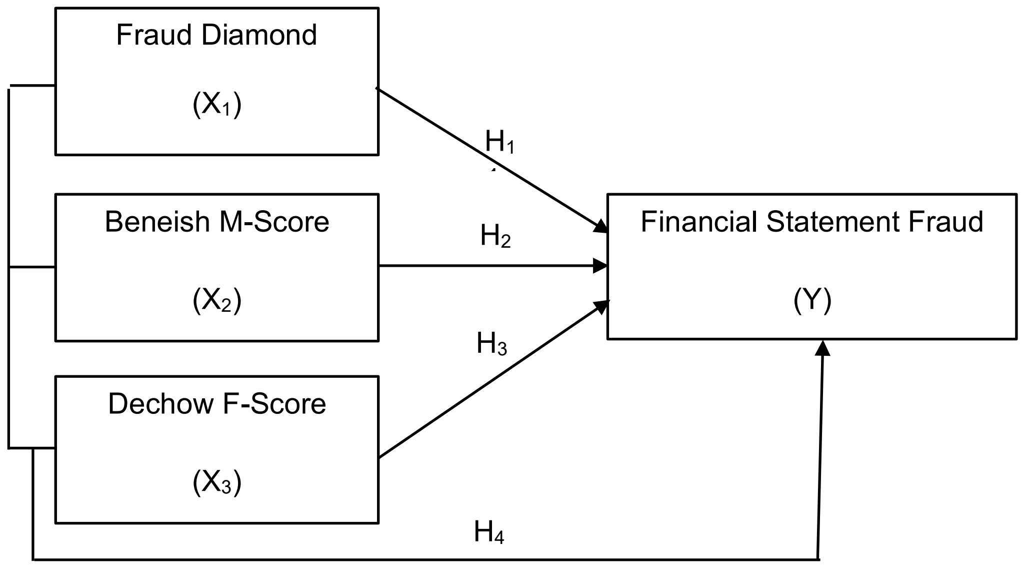

Figure 2. Research Framework

Hypotheses Development

The Influence of Fraud Diamond on Financial Statement Fraud

The fraud diamond explains that there are four elements that drive someone to commit fraud: pressure, opportunity, rationalization, and capability. A person who is under pressure from various parties, sees an opportunity to commit fraud, has a justification, and is capable of doing so, will increase the likelihood of committing financial statement fraud. Research by Wolfe & Hermanson (2004), who first developed the Fraud Diamond model, and subsequent studies by Rahma et al. (2022) and Purwani et al. (2024) show that these four elements significantly influence the occurrence of fraud in financial statements.

The Influence of Beneish M-Score on Financial Statement Fraud

The Beneish M-Score model explains that financial statement fraud can be detected through patterns of earnings manipulation reflected in certain financial ratios. It identifies anomalies in revenue recognition, depreciation, and expense management that deviate from normal accounting behavior. A higher M-Score indicates a greater probability that a company has manipulated its earnings to achieve specific financial targets or conceal poor performance. Research by Beneish (1999) and Kaab Omeir et al. (2023) found that the Beneish M-Score is effective in identifying companies engaged in earnings manipulation, as it captures the financial distortions commonly associated with fraudulent reporting.

The Influence of Dechow F-Score on Financial Statement Fraud

The Dechow F-Score model explains that fraud or material misstatement in financial reports can be detected through accrual-based indicators. This model evaluates the consistency between reported earnings, cash flows, and changes in working capital. A higher F-Score suggests a higher likelihood that a company's earnings have been overstated due to aggressive accounting practices or intentional misstatements. Research by Dechow et al. (2011) introduced this model as a predictive tool for identifying firms likely to issue restatements due to accounting errors or fraud. Subsequent studies, such as Ratmono et al. (2020) and Kaab Omeir et al. (2023) demonstrated that the F-Score can effectively signal financial misstatements by highlighting discrepancies between accruals and actual cash flows.

RESEARCH METHOD

The study employs a quantitative approach method. Quantitative research is the research process of discovering knowledge that uses numerical data as a tool to analyze information about what one wants to know (Sinaga, 2022).

The data used in this study were obtained from the annual reports audited and can be accessed at the official website of the Indonesia Stock Exchange (*www.Idx.co.id*). The observation period covers financial statements from 2021 to 2024. The sampling technique used in this study was purposive sampling, which was chosen to ensure only companies that met certain criteria, such as consistently publishing financial statements during the observation period.

The analytical method used in this study is binary logistic regression because the dependent variable is dichotomous (fraud = 1, non-fraud = 0). Logistic regression is recommended when the dependent variable is categorical and the independent variables may consist of continuous or categorical predictors, without requiring the assumption of multivariate normality (Ghozali, 2018). Mathematically, logistic regression is formulated as follows:

$$Logit\ (Fraud) = \beta_0 + \beta_1 FD + \beta_2 BM + \beta_3 DF + \epsilon$$

where p is the probability of financial statement fraud, FD is the Fraud Diamond, BM is the Beneish M-Score, and DF is the Dechow F-Score. The equation shows a logarithmic relationship between the probability of fraud and the predictor variables.

Although the indicators of Fraud Diamond, Beneish M-Score, and Dechow F-Score have been conceptually defined and presented in the Literature Review, this study employs those indicators as operational measures for each independent variable and uses a dummy variable to represent the presence or absence of financial statement fraud.

The logistic regression analysis in this study follows several statistical testing stages, including:

1. Descriptive Statistics
2. Overall Model Fit Test
3. Goodness of Fit Test
4. Coefficient of Determination Test
5. Multicollinearity Test
6. Classification Accuracy Test
7. Wald Test
8. Omnibus Test of Model Coefficients

Data processing and statistical analyses were conducted using Statistical Package for the Social Sciences (SPSS) Version 26.0.

Table 4. Sample Selection Criteria

Description	Amount
Companies Listed on IDX report between 2021-2024	32
Companies who do not present a Financial Report between 2021-2024	(12)
Number of companies selected as research samples	20
Total number of research samples (20 x 4)	80

RESULTS

Descriptive Statistics

Table 5. Descriptive Statistics Results (N = 80)

	Min.	Max.	Mean	Std. Deviation
ACHANGE (X1.1)	-0,45	0,71	0,0434	0,14739
ROA(X1.2)	-0,15	0,23	0,0548	0,7151
LEV (X1.3)	0,09	2,64	5,641	0,44283
RECEIVABLE (X1.4)	-11,24	6,30	-0,0126	1,53630
BDOUT (X1.5)	0,00	0,67	0,3873	0,12324
AUDCHANGE (X1.6)	0,00	1,00	0,1000	0,30189
DCHANGE (X1.7)	0,00	1,00	0,1375	0,34655
Beneish M-Score (X2)	-5,38	31,95	-1,6387	4,26840
Dechow F-Score(X3)	-11,17	-3,68	-6,4718	0,93211
FSF (Y)	0,00	1,00	0,3000	0,46115

Source: Processed using SPSS 26.0

Based on the descriptive statistics presented in the table, several important characteristics of plantation companies listed on the Indonesia Stock Exchange (IDX) during 2021–2024 can be observed. The ACHANGE variable shows a minimum value of –0.45, a maximum of 0.71, and a mean of 0.0434. This indicates that on average, plantation companies experienced modest asset growth, while some firms faced significant decreases in total assets. Such fluctuations may reflect the capital-intensive and cyclical nature of plantation operations, where biological asset revaluation can materially affect asset levels.

The ROA variable ranges from –0.15 to 0.23, with a mean of 0.0548. This suggests that most plantation companies maintain relatively moderate profitability. The presence of negative ROA values indicates that a portion of firms experienced losses, possibly due to seasonal production challenges or volatile commodity prices commonly observed in the plantation sector.

The LEV variable shows substantial variation, ranging from 0.09 to 2.64, with a mean of 5.641. This relatively high average leverage suggests that plantation firms tend to rely heavily on debt financing, likely due to the long-term investment needs of developing and maintaining plantation estates. Firms with higher leverage may face stronger external pressure from creditors, potentially increasing incentives for earnings management.

The RECEIVABLE variable ranges widely from –11.24 to 6.30, with a mean of –0.0126. The large spread indicates significant differences in receivable management across firms. Negative values may reflect adjustments or write-offs, while high positive values may signal slower collection cycles. Such variability is consistent with plantation companies, which often engage in long-term contracts and experience seasonal cash inflows.

The BDOUT variable ranges from 0.00 to 0.67 and has a mean of 0.3873. This indicates that, on average, companies have a moderate proportion of independent commissioners. Firms with lower values may have weaker oversight structures, which can elevate fraud risks, whereas higher values may indicate stronger governance mechanisms.

The AUDCHANGE variable has values between 0.00 and 1.00 with a mean of 0.1000. This suggests that auditor changes occurred in 10 percent of the observations. Auditor turnover may indicate disagreements with auditors or attempts to seek more lenient audit environments, although the relatively low frequency suggests that most firms maintain consistent auditor relationships.

The DCHANGE variable also ranges from 0.00 to 1.00 with a mean of 0.1375. This implies that 13.75 percent of firms experienced changes in directors. Leadership changes can disrupt internal controls and create opportunities for new management to override existing procedures, although the overall frequency remains relatively low.

The Beneish M-Score ranges significantly from –5.38 to 31.95, with a mean of –1.6387. While the mean score is below the threshold of –1.78, indicating low average manipulation risk, the very high maximum value suggests that a few companies exhibit unusual financial ratio patterns. These extremes likely arise from unique plantation accounting practices, such as biological asset revaluation and seasonal cost fluctuations, which can distort Beneish ratios.

The Dechow F-Score ranges from –11.17 to –3.68, with a mean of –6.4718. Lower values generally imply lower misstatement risk. However, the variability still indicates that some firms exhibit more aggressive accrual patterns than others. Such variations can be attributed to differences in inventory cycles, production stages, and fair value adjustments common in plantation accounting.

Finally, the FSF dummy variable ranges from 0 to 1, with a mean of 0.3000. This indicates that 30 percent of the observations were classified as fraud cases based on restatement criteria. Although financial statement fraud remains relatively rare, the proportion is sufficiently meaningful to justify further analysis using predictive models.

Overall Model Fit Test

The comparison between the initial -2 Log Likelihood value (block 0) and the final -2 Log Likelihood value (block 1) is conducted to assess model improvement. A higher initial -2 Log Likelihood relative to the final value indicates a decrease, which reflects a better fit of the regression model (Ghozali, 2018).
The hypothesis used to evaluate the overall model fit is formulated as follows:
H0 : The hypothesized model fits the data.
H1 : The hypothesized model does not fit the data.

Table 6. Overall Model Fit Results

-2 Initial logL (block number = 0)	97,738
-2 Final logL (block number = 1)	61,461

Source: Processed using SPSS 26.0

The study results indicate that the initial -2 Log Likelihood value (block 0) decreased by 36,277, indicating a significant improvement in the model compared to the final value (block 1). This decrease indicates that the proposed model fits the data. Consequently, the incorporation of independent variables improves the regression model, meaning H_0 is accepted.

Goodness of Fit Test

The Hosmer and Lemeshow Goodness-of-Fit Test applies the Chi-square statistic to evaluate whether the observed data align with the model. If no significant difference exists between the model and the data, it indicates that the model demonstrates a good fit (Ghozali, 2018). A p-value of 0.05 or higher from the test indicates that the model does not significantly differ from the observed data, suggesting that the model is appropriate for making predictions.

Table 7. Goodness of Fit Test Results

Step	Chi-square	df	Sig.
1	9,251	8	0,322

Source: Processed using SPSS 26.0

The results show that the chi-square value for df 9 is 9.251 with a significance level of 0.322. Since Sig. = 0.322 > 0.05, the model fits the data, indicating no significant difference between the observed and predicted values.

Coefficient of Determination Test

The coefficient of determination measures the ability of the independent variable in explaining variations that occur in the dependent variable. This is expressed through the Nagelkerke R Square value. The Nagelkerke R-Square value is interpreted in much the same way as the R-Square value in multiple regression analysis (Ghozali, 2018).

Table 8. Coefficient of Determination Test Results

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	61,461[a]	0,365	0,517

a. The estimation process was terminated at the 7th iteration, as the parameter estimates had changed by less than 0.001.
Source: Processed using SPSS 26.0

The regression analysis produced a Nagelkerke R-Square value of 0.517, which explains 51.7% of the variation in financial reporting fraud, indicating a moderately strong explanatory power, while the remaining 48.3% is due to other factors not included in this research model.

Multicollinearity Test

The multicollinearity test is used to determine whether the independent variables in the regression model are highly correlated with one another. Multicollinearity may reduce the reliability of regression coefficients and weaken the explanatory power of the model. In logistic regression, multicollinearity can be assessed using the Tolerance and Variance Inflation Factor (VIF) values (Ghozali, 2018).The criteria for determining whether multicollinearity is present in the regression model are:

1. If Tolerance value < 0.10 or VIF value >10, the model indicates multicollinearity.
2. If Tolerance value > 0.10 and VIF value < 10, the model is free from multicollinearity.

Table 9. Multicollinearity Test Results

Model		Collinearity Statistics	
		Tolerance	VIF
1	(Constant)		
	ACHANGE (X1.1)	0,797	1,254
	ROA(X1.2)	0,797	1,254
	LEV (X1.3)	0,637	1,571
	RECEIVABLE (X1.4)	0,982	1,018
	BDOUT (X1.5)	0,943	1,060
	AUDCHANGE (X1.6)	0,858	1,165
	DCHANGE (X1.7)	0,968	1,033
	Beneish M-Score (X2)	0,923	1,083
	Dechow F-Score(X3)	0,599	1,669

a. Dependent Variable: FSF (Y)
Source: Processed using SPSS 26.0

Based on the results, all variables show Tolerance values between 0.599 and 0.982 and VIF values between 1.018 and 1.669. These results indicate that every independent variable has a Tolerance value greater than 0.10 and a VIF value less than 10. Therefore, the regression model does not exhibit multicollinearity.

This means that the independent variables used in the model do not have strong intercorrelations and are appropriate for inclusion in the logistic regression analysis. As a result, each variable can be interpreted independently without concern for inflated standard errors or unstable coefficient estimates.

Classification Accuracy Test

The classification matrix demonstrates how accurately the logistic regression model can predict the probability of respondents having FSF (Y). The following table presents the classification matrix:

Table 10. Classification Accuracy Test Results

Observed			Predicted		
			FSF (Y)		Percentage Correct
			Restatement	No Restatement	
Step 1	FSF (Y)	Restatement	51	5	91,1
		No Restatement	9	15	62,5
	Overall Percentage				82,5

a. The cut value is 0,500
Source: Processed using SPSS 26.0

Regression analysis output reveals that the general probability of FSF (Y) prediction from the model is at 82.5%. From the above table, the probability of FSF (Y) being "No Restatement" comes to be 62.5% out of a total sample size of 24 data points. Whereas

"Restatement" is 91.1% from a total sample size of 56 data points.

Binary Logistic Regression Analysis

The binary logistic regression model in this study is used to examine the effect of the Fraud Diamond indicators, the Beneish M-Score, and the Dechow F-Score on the likelihood of Financial Statement Fraud (FSF). The general logistic regression equation is expressed as follows:

$$ln\left(\frac{p}{1-p}\right) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon$$

Explanation:

p = probability of financial statement fraud (FSF = 1)
$\frac{1}{p}$ = probability of non-fraud (FSF = 0)
α = contant
$\beta_1, \beta_2, \beta_3$,... = regression coefficients
X_1, X_2, X_3,... = independent variables
ε = error

Table 11. Binary Logistic Regression Analysis Results

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	ACHANGE (X1.1)	7,072	2,845	6,181	1	0,013	1178,823	4,467	311071,740
	ROA(X1.2)	-15,902	6,180	6,622	1	0,010	0,000	0,000	0,023
	LEV (X1.3)	-0,594	1,085	0,300	1	0,584	0,552	0,066	4,625
	RECEIVABLE (X1.4)	2,524	1,030	6,003	1	0,014	12,480	1,657	94,014
	BDOUT (X1.5)	-7,982	3,416	5,460	1	0,019	0,000	0,000	0,276
	AUDCHANGE (X1.6)	2,843	1,231	5,337	1	0,021	17,171	1,539	191,606
	DCHANGE (X1.7)	-0,866	1,209	0,514	1	0,474	0,421	0,039	4,494
	Beneish M-Score (X2)	-0,085	0,117	0,532	1	0,466	0,918	0,731	1,154
	Dechow F-Score(X3)	-0,388	0,386	1,010	1	0,315	0,678	0,318	1,446
	Constant	-0,484	2,657	0,033	1	0,855	0,616		

Source: Processed using SPSS 26.0

Based on the coefficients in the table above, the logistic regression model is:

$$ln\left(\frac{p}{1-p}\right) = -0.484 + 7.072X_{1.1} - 15.902X_{1.2} - 0.594X_{1.3} + 2.524X_{1.4} - 7.982X_{1.5} + 2.843X_{1.6} - 0.866X_{1.7} - 0.085X_2 - 0.388X_3 + \varepsilon$$

Model Fit Assessment (Integrated as Required by Reviewer)
The model has been tested using several fit measures:
1. Omnibus Test of Model Coefficients: $\chi^2 = 36.277$, p = 0.000 → the model significantly improves prediction.
2. Hosmer and Lemeshow Test: p = 0.322 (> 0.05) → no significant difference between observed and predicted values; model fits the data well.
3. Nagelkerke $R^2 = 0.517$ → 51.7% of the variation in FSF is explained by the model.

These results collectively demonstrate that the logistic regression model is statistically appropriate and has moderately strong explanatory power.

Interpretation of Significant Variables
a. ACHANGE (X1.1) – Significant (p = 0.013)
   The positive coefficient (B = 7.072) and very large Exp(B) = 1178.823 indicate that increases in asset change substantially raise the odds of fraud.
   This finding aligns with the “pressure” element of the Fraud Diamond, where firms experiencing unstable asset growth may manipulate performance.
b. ROA (X1.2) – Significant (p = 0.010)
   ROA has a negative coefficient (B = –15.902) with Exp(B) ≈ 0.000, implying that higher profitability drastically reduces the likelihood of fraud.
   This suggests that profitable firms face lower pressure to manipulate earnings, consistent with prior fraud risk theory.
c. RECEIVABLE (X1.4) – Significant (p = 0.014)
   With Exp(B) = 12.480, firms with higher receivables ratios are more likely to engage in fraud.
   This supports the notion that inflated receivables are frequently used for fictitious sales or aggressive revenue recognition.
d. BDOUT (X1.5) – Significant (p = 0.019)
   The negative coefficient and Exp(B) ≈ 0 indicate that strong board independence reduces fraud risk.
   This is consistent with the “opportunity” element of the Fraud Diamond.
e. AUDCHANGE (X1.6) – Significant (p = 0.021)
   Exp(B) = 17.171 indicates that firms changing auditors are over 17 times more likely to commit fraud.
   This is often associated with rationalization (seeking a more lenient auditor) or attempts to conceal manipulation.

Interpretation of Non-Significant Variables
Not significant (p > 0.05):
- LEV
- DCHANGE
- Beneish M-Score
- Dechow F-Score

The insignificance of Beneish and Dechow models may reflect the unique characteristics of plantation accounting—such as biological asset valuation and seasonal production—making ratio-based red flags less sensitive in this sector.

Overall, the logistic regression results show that five Fraud Diamond indicators—ACHANGE, ROA, RECEIVABLE, BDOUT, and AUDCHANGE—significantly influence the likelihood of financial statement fraud in plantation companies. Meanwhile, the

Beneish M-Score and Dechow F-Score do not significantly predict fraud in this context. The model demonstrates good overall fit and explains 51.7% of the variance in fraud likelihood. These findings imply that behavioral and governance-related factors are more influential predictors of fraud in plantation firms than financial ratio-based models.

Wald Test (Partial Significance Test)

Wald testing is used in this research work to evaluate the competencies of individual independent variables in explaining the variation of the dependent variable, FSF (Y). The decision regarding whether the hypothesis will be accepted or not is made by comparing the calculated alpha value with a significance level on an undermentioned criterion:
1. If p-value < 0.05 → Reject H_0 (the variable significantly affects FSF).
2. If p-value ≥ 0.05 → Fail to reject H_0 (the variable has no significant effect).

Table 12. Wald Test Results

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	ACHANGE (X1.1)	7,072	2,845	6,181	1	0,013	1178,823	4,467	311071,740
	ROA(X1.2)	-15,902	6,180	6,622	1	0,010	0,000	0,000	0,023
	LEV (X1.3)	-0,594	1,085	0,300	1	0,584	0,552	66	4,625
	RECEIVABLE (X1.4)	2,524	1,030	6,003	1	0,014	12,480	1,657	94,014
	BDOUT (X1.5)	-7,982	3,416	5,460	1	0,019	0,000	0,000	0,276
	AUDCHANGE (X1.6)	2,843	1,231	5,337	1	0,021	17,171	1,539	191,606
	DCHANGE (X1.7)	-0,866	1,209	0,514	1	0,474	0,421	0,039	4,494
	Beneish M-Score (X2)	-0,085	0,117	0,532	1	0,466	0,918	0,731	1,154
	Dechow F-Score(X3)	-0,388	0,386	1,010	1	0,315	0,678	0,318	1,446
	Constant	-0,484	2,657	0,033	1	0,855	0,616		

a. Variable(s) entered on step 1: ACHANGE (X1.1), ROA(X1.2), LEV (X1.3), RECEIVABLE (X1.4), BDOUT (X1.5), AUDCHANGE (X1.6), DCHANGE (X1.7), Beneish M-Score (X2), Dechow F-Score(X3).
Source: Processed using SPSS 26.0

The Wald test results show that ACHANGE, ROA, RECEIVABLE, BDOUT, and AUDCHANGE have a statistically significant effect on Financial Statement Fraud (p < 0,05). These findings are consistent with the Fraud Diamond theory, where financial pressure, opportunity, monitoring effectiveness, and rationalization influence fraudulent behavior. The Exp(B) values indicate that increases in ACHANGE, RECEIVABLE, AUDCHANGE substantially raise the odds of fraud, whereas stronger profitability (ROA) and better board independence (BDOUT) reduce fraud risk. Extremely large odds ratios should be interpreted cautiously due to the potential impact of outliers or variable scaling. Meanwhile, non-significant variables may reflect sector characteristics or limited sample variation, aligning with previous studies that find behavioral factors more influential than purely ratio-based fraud indicators.

Omnibus Test of Model Coefficients (Simultaneous Test)

The Omnibus Test of Model Coefficients is used to assess whether all independent variables, when considered jointly, significantly improve the prediction of financial statement fraud (FSF) compared to the null model. In logistic regression, this test is based on the Chi-square statistic rather than an F-test, and the decision criterion relies solely on the p-value, decision rule:
1. If p-value < 0.05 → Reject H_0 (the independent variables collectively have a significant effect on FSF)
2. If p-value ≥ 0.05 → Fail to reject H_0 (the independent variables do not collectively influence FSF)

Table 13. Omnibus Test of Model Coefficients Results

		Chi-square	df	Sig.
Step 1	Step	36,277	9	0
	Block	36,277	9	0
	Model	36,277	9	0

Source: Processed using SPSS 26.0

The Omnibus Test produces a Chi-square value of 36.277 with a significance level of p = 0.000 (< 0.05). Based on this result, H_0 is rejected, meaning that the full logistic regression model provides a significantly better fit than the null model. This indicates that the independent variables—Fraud Diamond indicators, Beneish M-Score, and Dechow F-Score—collectively contribute to explaining the likelihood of financial statement fraud in plantation companies.

This result confirms that fraud risk is influenced by a combination of behavioral pressures (fraud motivation and opportunity) and quantitative manipulation indicators. However, because the sample size is relatively small (n = 80) and logistic regression is sensitive to outliers and extreme ratio values, the Chi-square statistic may be influenced by data distribution or scaling issues. These limitations should be considered when generalizing the findings.

This finding suggests that behavioral fraud indicators (Fraud Diamond) together with quantitative manipulation measures (Beneish M-Score and Dechow F-Score) jointly contribute to explaining fraud risk in plantation companies, supporting the conceptual framework of the study.

DISCUSSION

The partial effect analysis shows that ACHANGE, ROA, RECEIVABLE, BDOUT, and AUDCHANGE significantly influence Financial Statement Fraud, indicating that indicators related to pressure, opportunity, and rationalization are important in explaining fraudulent financial reporting among plantation companies. In contrast, LEV and DCHANGE do not show significant effects, which suggests that leverage and changes in key management positions are less relevant predictors of fraud in this industry. These results are consistent with the findings of Ratmono et al. (2020) and Purwani et al. (2024), who state that behavioral indicators tend to be stronger and more consistent predictors of fraud than purely quantitative financial ratios. This supports the argument that fraudulent behavior is closely linked to human motivation and internal governance rather than solely numerical outcomes. The significant effect of ACHANGE suggests rapid asset expansion leading to overstatement dues to aggressive capitalization, while RECEIVABLE increases may signal revenue manipulation through premature recognition. AUDCHANGE also reflects weak monitoring where auditor turnover disrupts continuity and reduces the likelihood of fraud detection.

The analysis also indicates that the Beneish M-Score does not significantly affect Financial Statement Fraud. This outcome differs from the studies of Beneish (1999) and Kaab Omeir et al. (2023), which reported strong predictive power of the model in detecting earnings manipulation. The difference in this research may be explained by the contextual characteristics of plantation companies. Firms in this sector are influenced by fair value adjustments on biological assets, seasonal harvesting cycles, and fluctuations in production that naturally affect financial ratios such as DSRI, SGI, and AQI. These variations may resemble manipulation signals in the Beneish model, even when no fraud occurs, reducing the model's accuracy in this particular industry. Additionally, the lack of significance may reflect the model's original reference using the U.S. Manufacturing firms, which may differ from Indonesian plantation companies. Also, M-Score may not be sensitive to the unique accounting practices in agriculture.

Similarly, the Dechow F-Score does not show significant influence on Financial Statement Fraud. This contrasts with findings by Dechow et al. (2011) and Kaab Omeir et al. (2023), who reported that the F-Score was effective in identifying firms with misstatement risks. The weak significance of the F-Score in this study suggests that accrual-based indicators may be less reliable for plantation firms. Biological asset valuation techniques, long production cycles, and revenue seasonality generate natural accrual volatility, making it difficult to distinguish normal accounting patterns from manipulated ones. This indicates that the F-Score alone is insufficient for detecting fraud in plantation companies and may need to be complemented with behavioral indicators from the Fraud Diamond. Moreso, Plantation companies may exhibit moderate accrual distortions attributed to operations rather than fraud, making it ambiguous, where F-Score cannot aggressive but legal accounting from manipulation.

The simultaneous effect analysis shows that the combined model consisting of the Fraud Diamond, Beneish M-Score, and Dechow F-Score significantly enhances the ability to detect Financial Statement Fraud. This result indicates that even though some indicators are not individually significant, the integration of behavioral characteristics and financial ratio analysis provides meaningful explanatory power. The combined model captures multiple dimensions of fraud risk, including managerial pressure, governance weaknesses, accrual aggressiveness, and financial anomalies, leading to a more comprehensive fraud detection approach. The significant performance of the model triangulates multiple measures, converging together to reduce fraud. Behavioral indicators address the human element while ratio-based indicators detect financial anomalies, compensating for each model's weaknesses.

These findings provide practical implications for auditors, regulators, and corporate governance practitioners. Behavioral indicators such as asset growth, auditor turnover, and weak oversight should be treated as early warning signals for fraud risk. For plantation companies, rapid changes in receivables or repeated auditor replacement may warrant enhanced audit procedures. The results also suggest that ratio-based models alone are insufficient in this industry and should be combined with behavioral assessments to improve fraud detection accuracy. Regulators could also consider developing industry specific fraud risk guidelines for agricultural asset valuation and audit inspection.

Overall, the results reinforce the theoretical foundation of this study by demonstrating that an integrated model combining the Fraud Diamond with the Beneish and Dechow frameworks offers stronger explanatory value than using these models independently. This integration not only advances fraud detection strategies but also provides a practical view for adapting general fraud models to industry specific, contributing to better reporting integrity particularly in the plantation sector.

CONCLUSION

This study demonstrates that behavioral indicators represented by the Fraud Diamond model play a significant role in predicting financial statement fraud in the plantation sector, while ratio-based detection models such as the Beneish M-Score and Dechow F-Score show limited explanatory power. These results suggest that fraud in this industry is more strongly driven by internal behavioral pressures, opportunities, rationalization, and capability rather than numerical irregularities detectable through financial ratios.This confirms that behavioral- financial models are more sensitive in industries with unique accounting characteristics.

The findings also indicate that changes in assets, profitability patterns, monitoring effectiveness, and auditor rotation may serve as meaningful early warning signals for fraud. Practically, this implies that auditors, regulators, and corporate governance bodies should strengthen fraud assessment procedures by focusing on behavioral and governance-related red flags rather than relying solely on accounting-based detection tools. Ratios such as ACHANGE and ROA may be particularly useful as preliminary screening indicators when assessing potential irregularities in financial statements. Also, Audit programs should incorporate mandatory risk assessments when ACHANGE exceeds the benchmarks or auditor changes happen frequently.

Furthermore, the limited effect of ratio-based models in this study suggests that industry characteristics, accounting homogeneity, and valuation methods may affect the sensitivity of financial manipulation indicators. This highlights the importance of aligning fraud detection tools with contextual factors rather than applying them uniformly across industries. Regulators should also provide clearer guidelines while audit rotation policies should be complemented with transition protocols to maintain oversight continuity.

Future studies are encouraged to expand the scope of analysis by incorporating broader samples, additional fraud frameworks, and complementary qualitative approaches. Such efforts may help refine fraud detection models and strengthen their applicability across different organizational and industrial environments. Ultimately, Fraud detection requires context - aware, and behaviorally - informed frameworks that reflects unique industry conditions while ensuring analytical validity.

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