Analysis of Financial Statement Manipulation Indications Using Beneish M-Score among Late IDX Filers, 2021-2024

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Abstract
This study aims to analyze the indications of financial statement manipulation among companies that filed their financial statements late with the Indonesia Stock Exchange during 2021-2024, classify company-year observations, and identify the Beneish ratios that most frequently exceeded their respective indicative thresholds. This study used a descriptive quantitative approach and secondary data. Of the 491 company-year observations in the population, 213 were selected using purposive sampling. The results showed that 98 observations (46.01%) were classified as potential manipulators and 115 observations (53.99%) were classified as non-manipulators. The highest proportion of potential manipulation occurred in 2023 (54.55 %). The Selling, General, and Administrative Expenses Index (SGAI), Gross Margin Index (GMI), and Days' Sales in Receivables Index (DSRI) were the ratios that most frequently exceeded their respective indicative thresholds. Late filing alone does not establish manipulation, but it strengthens the risk signal when accompanied by an M-score above the threshold. This study is limited to late-reporting Indonesia Stock Exchange (IDX) listed companies during 2021-2024 and uses the Beneish M-Score as an initial screening tool rather than definitive evidence of financial statement manipulation. The novelty of this study lies in the two-stage risk-screening framework that combines an observable reporting-timeliness signal, namely late filing, with an accounting-anomaly measure, namely the Beneish M-Score. These two issues have generally been examined separately in the literature. Their integration provides an empirically grounded assessment of financial reporting risk and supports the prioritization of follow-up reviews by investors, auditors and regulators.

Keywords: *Beneish M-Score, Earnings Manipulation Detection, Financial Reporting Risk, Financial Statement Manipulation, Late Filing*

1. INTRODUCTION

Financial statements are a primary source of information for investors, creditors, regulators, and other stakeholders to assess a company's financial position, performance, changes in equity, and cash flows. Such information is most useful when presented reliably and on time, as delayed publication may reduce its relevance to economic decision-making (Larasati, Kencana, & Sihono, 2024). Accordingly, timely financial statement filing is not merely an administrative obligation; it also reflects a company's transparency and accountability to the public. In Indonesia, issuers and public companies are required to file and publish their annual financial statements no later than the end of the third month after the annual reporting date. Despite the prescribed deadline, late filing remains a recurring issue among companies listed on the Indonesia Stock Exchange (IDX). In the 2021 reporting year, 91 issuers failed to file their annual financial statements on time. For the 2022 reporting year, the number of late filers increased to 143. In the 2023 reporting year, 129 issuers missed the filing deadline. For the 2024 reporting year, 128 issuers were recorded as having failed to file on time.

Late financial reporting may be influenced by a company's financial condition and audit procedures that require more time. Pangestuti, Wijayanti, and Samrotun (2020) found that leverage and audit opinions affect financial reporting timeliness. Videsia, Agung, and Nurcahyono (2022) showed that profitability, firm size, firm age, and audit opinion affect the timely filing of financial statements. From a signaling theory perspective, external parties may also perceive late filing as a negative signal because the company does not promptly provide the information needed to reduce uncertainty (Spence 1973). Late filing does not directly prove manipulation, but it may serve as an early indicator of heightened information risk, warranting a more in-depth analysis of the figures reported in the financial statements.

Although audit report lag and filing delay with the stock exchange are not identical concepts, the completion of the external audit is a major component of reporting timeliness. From an information asymmetry perspective, an extended reporting process may indicate unresolved accounting judgments, complex transactions, internal control weaknesses, or the need for auditors to expand their examination procedures. Because these conditions may also arise from legitimate business circumstances, delays should be treated as noisy signals rather than evidence of manipulation. Singh, Sultana, Islam, and Singh (2022) found that audit partners handling multiple clients took longer to complete their audits, and that longer audit completion was associated with lower financial reporting quality. This evidence strengthens the rationale for combining the delay signal with accounting-anomaly indicators before identifying observations that require further review (Anggelina, Rohmi, Islami, Rahma, & Zuhdi, 2025).

Attention to financial reporting quality is increasingly important because manipulation may involve misstatements or the omission of material information that misleads users (Oranefo & Egbunike, 2022). Such practices may involve improper revenue recognition, understatement of expenses, or overstatement of assets, all of which can distort financial reports and create an inaccurate perception of a company's financial performance and position. Although financial statement fraud accounts for only approximately 5% of the fraud cases analyzed by the Association of Certified Fraud Examiners (ACFE), it produces the highest median loss of USD 766,000 per case. The magnitude of these losses underscores the importance of early detection by investors, creditors, auditors, and regulators.

One early detection method is the Beneish M-score. The model identifies the likelihood of earnings manipulation through eight indices that capture changes in receivables, gross margin, asset quality, sales growth, depreciation, selling and administrative expenses, leverage, and corporate accruals (Beneish, 1999). Febrianti (2022) identified the indications of financial statement manipulation at PT Envy Technologies Indonesia Tbk. Hugo (2019) reported that the Beneish M-score achieved a classification accuracy of 86%. Sudradjat, Sudjali, and Marlina (2023) found indications of fraud in several observation periods in pharmaceutical companies. Zulzilawati and Wahyuni (2021) showed that the Beneish indices can classify companies as manipulators, non-manipulators, or grey companies. Larasati et al. (2024) focused on the factors affecting the timely filing of financial statements, where Pangestuti et al. (2020) examined the determinants of reporting timeliness in the transportation subsector. Thus, late financial reporting and financial statement manipulation have been studied separately.

This study addresses this gap through a sequential risk-based design. Unlike prior studies that only explain the determinants of reporting timeliness or apply the Beneish M-Score to general or sector-specific samples, this study first uses late filings to identify observations with higher information risk. The M-score is then used to assess whether accounting anomalies reinforce this signal. The objectives of this study are to analyze manipulation indications among companies that filed late with the IDX during 2021-2024, classify observations as potential manipulators or non-manipulators, and identify the Beneish ratios that most frequently exceeded their indicative thresholds. Accordingly, this study contributes a combined screening approach that can increase user vigilance and help regulators and auditors establish evidence-based monitoring priorities without considering late filing as proof of fraud.

2. LITERATURE REVIEW

2.1 Signaling Theory and Reporting Timeliness

Signaling theory explains that parties possessing more information can communicate observable signals to reduce the uncertainty of other parties (Spence, 1973). Connelly, Certo, Reutzel, DesJardine, and Zhou (2025) describe signaling theory as a communication and decision-making process in which a sender conveys observable signals to a receiver. In capital markets, financial statements and the timeliness of their publication function as signals used by investors and creditors to assess a company's condition, compliance, and the quality of its disclosures. Timeliness is an element of information quality because reports made available by the deadline remain relevant when decisions are made. Conversely, delays may increase uncertainty, although they do not necessarily indicate that manipulation has occurred. Ariani and Bawono (2018) show that firm size affects audit report lag, whereas firm age does not. Pangestuti et al. (2020) found that leverage and audit opinions affect reporting timeliness.

Videsia et al. (2022) showed that profitability, firm size, firm age, and audit opinions positively affect the timely filing of financial statements. Larasati et al. (2024) found that firm size, profitability, and firm age have negative effects, while audit opinion has a positive effect on financial reporting timeliness. Chudri, Elviza, Fitri, and Pristiwa (2026) found that solvency has a negative effect and firm size has a positive effect on the timeliness of reporting. These findings indicate that late reporting is a multidimensional phenomenon that should be analyzed alongside the company's financial condition and audit process.

2.2 Financial Statement Manipulation

Financial statement manipulation is the intentional act of altering, omitting, or presenting accounting information so that a company's condition appears different from its actual circumstances. Managers may exercise discretion in selecting accounting policies, estimates, and transaction-recognition methods to influence stakeholders' perceptions or contractual outcomes (Healy & Wahlen, 1999). Such manipulation may take the form of improper revenue recognition, deferred expense recognition, or asset overstatement (Salim, Reniati, & Sumiyati, 2025).

Manipulation risk is associated not only with financial figures but also with pressure, opportunity, rationalization, capability, arrogance, industry characteristics, and corporate governance. Apriliana (2017) showed that financial stability, external auditor quality, and the frequency with which the chief executive officer's photograph appears positively affect the predictions of fraudulent financial reporting. Setiawati and Baningrum (2018) found that financial targets are fraud pentagons that affect the detection of fraudulent financial reporting. Iswati, Nindito, and Zakaria (2017) found that internal financial indicators vary in their ability to explain the propensity for fraud.

Jati and Anisa'Setiyani (2023) showed that financial targets and industry characteristics have positive and significant effects on financial statement fraud. Suryandari and Januarti (2025) found that industry characteristics and auditor changes positively affect financial statement fraud, whereas financial stability strengthens these relationships. Tamaela, Zamzam, Hormati, and Zainuddin (2025) applied the Beneish M-Score with the fraud pentagon to assess financial statement fraud risk in the trading sector. Aprilia (2017) found that only financial stability significantly affects financial statement fraud, as proxied by the Beneish Model, whereas the other fraud pentagon proxies are not significant.

Fathmaningrum and Anggarani (2021) showed that financial targets, financial stability, external auditor quality, external pressure, and industry characteristics affect fraudulent financial reporting, with different patterns of influence between Indonesian and Malaysian manufacturing firms. Lestari and Henny (2019) found that financial stability and ineffective monitoring are significant in detecting fraudulent financial statements in the banking sector, whereas the other four proxies are insignificant. Sasongko and Wijayantika (2019) showed that only changes in the board of directors affect fraudulent financial reporting, while the other seven proxies have no such effect.

Septriani and Handayani (2018) obtained sector-specific results for Indonesia. In manufacturing companies, financial stability, external pressure, auditor changes, and changes in the board of directors affect banking companies. Financial targets, financial stability, ineffective monitoring, and rationalization all have an effect. Noble (2019) found that financial targets and auditor changes affect financial statement fraud, whereas ineffective monitoring and changes in the board of directors do not affect it. Yesiariani and Rahayu (2017) show that external pressure and rationalization have significant positive effects, while financial stability and financial targets have significant negative effects, and the other proxies have no effect.

Rianggi (2023) found that financial stability, industry characteristics, total accruals to total assets, and dual positions affect financial statement fraud in construction companies, whereas changes in directors and collusion do not. Sagala and Siagian (2021) showed that financial targets and financial stability significantly affect fraudulent financial statements in the food and beverage subsector, whereas the other proxies are not significant. Overall, these findings indicate that fraud risk factors are context-dependent and should be interpreted according to the company, sector, and proxies.

2.3 Beneish M-Score

The Beneish M-Score was developed to identify the likelihood of earnings manipulation based on changes in accounting data between the reporting years. The eight-variable model uses the Days Sales in Receivables Index (DSRI), Gross Margin Index (GMI), Asset Quality Index (AQI), Sales Growth Index (SGI), Depreciation Index (DEPI), Sales, General and Administrative Expenses Index (SGAI), Leverage Index (LVGI), and Total Accruals to Total Assets (TATA) (Beneish, 1999). These eight indices capture changes in receivables, gross margin, asset quality, sales growth, depreciation, operating expenses, leverage, and accruals, which may provide early warning signs of irregularities in financial statements. The performance of the Beneish M-Score has been tested on companies with diverse characteristics. Hugo (2019) reported a classification accuracy of 86%. Zulzilawati and Wahyuni (2021) showed that the eight Beneish indices could categorize companies as manipulators, non-manipulators, or grey companies. Febrianti (2022) identified the indications of financial statement manipulation at PT Envy Technologies Indonesia Tbk.

Sudradjat et al. (2023) found indications of fraud in several observation periods for pharmaceutical companies. Pertiwi, Oktavia, and Amelia (2023) concluded that the Beneish M-Score is more capable of capturing year-to-year changes in financial statement components than other comparison models. Aprilia (2017) found that among the fraud pentagon proxies tested using the Beneish Model, only financial stability significantly affects financial statement fraud. Rianggi (2023) found that financial stability, industry characteristics, total accruals to total assets, and dual positions affect financial statement fraud, measured using the Beneish M-Score, whereas director changes and collusion do not.

Recent studies have also emphasized the importance of contextual interpretation. Savitri and Sinarwati (2025) applied the Beneish M-Score to PT Indofarma Tbk for 2021-2023. Sylwestrzak and Słomkowska (2025) evaluated modifications to the Beneish and Dechow models to improve the detection performance. Tamaela et al. (2025) combine the Beneish M-Score approach with the fraud pentagon in trading-sector companies. Overall, the M-Score is more appropriately used as an initial screening tool than as standalone evidence of fraud.

Synthesizing these literature streams produces sequential conceptual logic. Late filing is an externally observable but nonspecific information risk signal. In contrast, the Beneish indices provide accounting-based warning signs related to receivables, margins, asset quality, sales growth, depreciation, operating expenses, leverage, and accruals (Rabbani & Fadli, 2025). When both signals occur together, the basis for a follow-up examination becomes stronger, although neither proves fraud. Using the modified Beneish M-score, Ebaid (2023) found that the likelihood of financial statement fraud was significantly associated with board independence and board size, whereas board meeting frequency and gender diversity were not significant. These findings suggest that accounting-based fraud-risk indicators should be interpreted in conjunction with specific governance characteristics rather than as standalone signals. Thus, the unresolved issue is not whether every late-filing company manipulates its statements but whether the late-filing population contains a material concentration of accounting anomalies and which components most frequently generate warnings. This issue provides a conceptual basis for the present study.

3. METHODOLOGY

This study uses a descriptive quantitative design and the Beneish M-Score model to identify indications of financial statement manipulation among companies listed on the Indonesia Stock Exchange (IDX) that filed their financial statements late during 2021-2024. This study uses secondary data consisting of annual financial statements and IDX announcements concerning late financial statement filings (Sugiyono, 2017). The population comprises all companies listed on the Indonesia Stock Exchange (IDX) that filed their annual financial statements late between 2021 and 2024. Based on IDX announcements and Investor.id, the population consisted of 491 company-year observations. The sample was selected through purposive sampling based on specific inclusion criteria, including companies that operated in non-financial sectors and were listed on the Indonesia Stock Exchange, companies with complete annual financial statements and all data required to calculate the Beneish M-Score, and companies whose financial statements were presented in the Indonesian rupiah. The selection process was applied sequentially for each observation year. Each observation that failed to meet the criteria was recorded once under the first criterion that caused exclusion. The details of the sample-selection process are presented in Table 1.

Table 1. Research sample-selection process

No.	Description	2021	2022	2023	2024	Total
	Initial population	91	143	129	128	491
1	Companies operating in the financial sector and listed on the Indonesia Stock Exchange	(3)	(8)	(5)	(4)	(20)
2	Annual financial statements or data required to calculate the Beneish M-Score were not completely available	(45)	(51)	(59)	(64)	(219)
3	Financial statements were not presented in Indonesian rupiah	(7)	(13)	(10)	(9)	(39)
	Final sample, 2021-2024	36	71	55	51	213

Table 1 shows that 20 company-year observations were excluded because they belonged to the financial sector, 219 observations were excluded because the annual financial statements or data required to calculate the Beneish M-Score were incomplete, and 39 observations were excluded because the financial statements were not presented in Indonesian rupiah. Accordingly, the initial population of 491 observations produced a final sample of 213 company-year observations, comprising 36 observations in 2021, 71 in 2022, 55 in 2023, and 51 in 2024. Following the sample selection process, the analysis was conducted through the following steps:

1) The eight Beneish M-Score ratios are calculated using the data presented in the sampled companies' financial statements. The eight ratios were calculated using the Beneish M-Score formulas presented by Sudradjat et al. (2023) as follows:
   a. Days Sales in Receivables Index
      The Days Sales in Receivables Index (DSRI) assesses changes in the relationship between trade receivables and sales across two accounting periods. An abnormal increase may indicate a change in the revenue recognition policy or raise concerns about possible manipulation. The DSRI was calculated using the following formula:

$$DSRI = \frac{Account\ Receivables(t)\ /Sales(t)}{Account\ Receivables(t-1)\ /Sales(t-1)} \quad (1)$$

      Formula 1 calculates the days sales in receivables index, which measures the change in the ratio of accounts receivable to sales between the current and previous years. This ratio is used to identify unusual increases in receivables relative to sales, which may indicate potential revenue recognition issues or financial statement manipulation by the company.

   b. Gross Margin Index
      The Gross Margin Index (GMI) compares changes in the gross profit margin between the preceding and current periods. The GMI was calculated using the following formula:

$$GMI = \frac{Gross\ Profit(t\text{-}1)\ /\ Sales(t\text{-}1)}{Gross\ Profit(t1)\ /\ Sales(t1)} \quad (2)$$

Formula 2 calculates the gross margin index, which measures changes in gross profit margin between the previous and current periods. This ratio identifies whether a company experiences a decline in gross margin, as a higher GMI value may indicate increased pressure on management to manipulate financial statements to maintain the appearance of stable profitability.

c. Asset Quality Index
The Asset Quality Index (AQI) measures changes in a company's asset quality from one period to the next. The AQI was calculated using the following formula:

$$AQI=\frac{1-\frac{Current\ Assets(t)\ +\ Fixed\ Assets(t)}{Total\ Assets(t)}}{1-\frac{Current\ Assets(t-1)\ +\ Fixed\ Assets(t-1)}{Total\ Assets(t-1)}} \tag{3}$$

Formula 3 calculates the asset quality index, which measures changes in the proportion of non-current and less tangible assets relative to total assets between the current and previous periods, a higher AQI indicates a potential increase in asset-related uncertainty or a shift toward less verifiable assets, which may signal a higher likelihood of financial statement manipulation.

d. Sales Growth Index
The Sales Growth Index (SGI) compares current period sales with prior period sales. The SGI was calculated using the following formula:

$$SGI=\frac{Sales(t)}{Sales(t-1)} \tag{4}$$

Formula 4 calculates the sales growth index, which measures the growth rate of sales between the current and previous periods. A higher SGI value indicates significant sales growth, which may create incentives or pressure for management to manipulate financial statements to maintain the appearance of improved performance.

e. Depreciation Index
The Depreciation Index (DEPI) compares the depreciation rate of fixed assets in the preceding period with that in the current period. The DEPI was calculated using the following formula:

$$DEPI=\frac{\frac{Depreciation(t-1)}{Depreciation(t-1)\ +\ Fixed\ Assets(t-1)}}{\frac{Depreciation(t)}{Depreciation(t)\ +\ Fixed\ Assets(t)}} \tag{5}$$

Formula 5 calculates the depreciation index, which measures the changes in the depreciation rate of fixed assets between the previous and current periods. A higher DEPI value indicates a potential decrease in depreciation expenses relative to fixed assets, which may suggest changes in depreciation policies or the possible manipulation of asset values and reported earnings.

f. Sales, General and Administrative Expenses Index
The Sales, General and Administrative Expenses Index (SGAI) compares selling, general, and administrative expenses as a proportion of sales across two periods. The SGAI is calculated using the following formula:

$$SGAI = \frac{SG\&A\ Expenses(t)\ /\ Sales(t)}{SG\&A\ Expenses(t-1)\ /\ Sales(t-1)} \tag{6}$$

Formula 6 calculates the sales, general, and administrative expenses index, which measures changes in selling, general, and administrative expenses relative to sales between the current and previous periods. A higher SGAI value indicates that operating expenses are increasing faster than sales, which may pressure management to manipulate financial statements to maintain the appearance of stable profitability.

g. Leverage Index
The Leverage Index (LVGI) measures changes in a company's use of debt between the preceding and current periods. The LVGI was calculated using the following formula:

$$LVGI = \frac{Total\ Liabilities(t)\ /\ Total\ Assets(t)}{Total\ Liabilities(t-1)\ /\ Total\ Assets(t-1)} \tag{7}$$

Formula 7 calculates the leverage index, which measures the change in the ratio of total liabilities to total assets between the current and previous periods. A higher LVGI value indicates an increase in financial leverage, which may reflect greater debt pressure and create incentives for management to manipulate financial statements to meet debt-related expectations or to maintain investor confidence.

h. Total Accruals to Total Assets
Total Accruals to Total Assets (TATA) measure the magnitude of accrual components relative to a company's total assets. TATA is calculated using the following equation:

$$TATA = \frac{Operating\ Income(t)\ -\ Cash\ Flow\ from\ Operating\ Activities(t)}{Total\ Assets(t)} \tag{8}$$

Formula 8 calculates the total accruals to total assets index, which measures the proportion of accrual components relative to total assets by comparing operating income with cash flow from operating activities. A higher TATA value indicates a greater reliance on accrual-based earnings rather than cash-based performance, which may signal a higher possibility of earnings management or financial statement manipulation by the firm.

2) The M-Score is calculated from the eight indices using the equation developed by Beneish (1999) as follows:

$$\begin{aligned} M-Score \ = \ & -4.84 + (0.920\ x\ DSRI) + (0.528\ x\ GMI) + (0.404\ x\ AQI) \\ & + (0.892\ x\ SGI) + (0.115\ x\ DEPI) - (0.172\ x\ SGAI) \\ & + (4.679\ x\ TATA) - (0.327\ x\ LVGI) \end{aligned} \tag{9}$$

Formula 9 calculates the Beneish M-score, which combines eight financial indicators to assess the likelihood of financial statement manipulation. The model integrates the DSRI, GMI, AQI, SGI, DEPI, SGAI, TATA, and LVGI to capture abnormal changes in revenue quality, asset composition, sales growth, expense structure, depreciation policies, leverage, and accrual-based earnings. An M-score value greater than −2.22 indicates a higher probability of manipulation, whereas a value below −2.22 indicates a lower probability of manipulation. This score is used as an initial screening tool rather than as definitive evidence of fraudulent reporting.

3) The companies are classified as potential manipulators or non-manipulators, and the indices that most frequently exceed their indicative thresholds within the potential-manipulator group are identified. The assessment uses a threshold for each index, as presented below:

Table 2. Index Threshold Values

No.	Ratio	Potential Manipulator Threshold
1	DSRI	≥ 1.465
2	GMI	≥ 1.193
3	AQI	≥ 1.254
4	SGI	≥ 1.607
5	DEPI	≥ 1.077
6	SGAI	≥ 1.041
7	LVGI	≥ 1.111
8	TATA	≥ 0.031

Table 2 shows the indicative threshold values for each Beneish M-score ratio used to identify potential financial statement manipulation. Observations exceeding these threshold values are considered to have higher manipulation risk signals because they indicate abnormal changes in specific financial characteristics such as revenue quality, asset composition, sales growth, expense patterns, leverage, and accrual-based earnings. These thresholds serve as supporting indicators in the screening process, while the final classification of potential manipulators is based on the overall Beneish M-Score value.

4. RESULTS AND DISCUSSION

4.1 Descriptive Statistics of the Beneish M-Score

A total of 213 company-year observations were analyzed, comprising 36 observations in 2021, 71 in 2022, 55 in 2023, and 51 in 2024. The number of observations differs across years because not all companies that filed late met the sample selection criteria. Table 3 presents the descriptive statistics for the M-score.

Table 3. Descriptive statistics of the Beneish M-Score

Year	Sample Size	Minimum	Maximum	Mean	Median
2021	36	-21.002	162.836	3.736	-2.468
2022	71	-18.167	5.185	-2.245	-2.299
2023	55	-7.215	13.925	-1.377	-2.062
2024	51	-9.995	294.706	4.512	-2.389

Table 3 shows the exceptionally high maximum values in 2021 and 2024, with means of 3.736 and 4.512, respectively, while the medians remained below the -2.22 threshold. This pattern indicates that several outliers increased the mean, making the median more representative of central tendency. In 2022, the mean was -2.245, and the median was -2.299, both slightly below the threshold. In 2023, the mean of -1.377 and median of -2.062 were above the threshold, indicating that the tendency toward manipulation in that year was not attributable to a single extreme observation. The highest annual M-Scores were recorded by PT Borneo Olah Sarana Sukses Tbk (BOSS), at 162.836 in 2021, PT Dua Putra Utama Makmur Tbk (DPUM), at 5.185 in 2022, PT Koka Indonesia Tbk (KOKA), at 13.925 in 2023, and PT LCK Global Kedaton Tbk (LCKM), at 294.706 in 2024. These exceptionally high values indicate that one or more component ratios changed substantially and should be prioritized for further investigations. However, these values cannot be regarded as conclusive evidence of manipulation.

4.2 Classification of Potential Manipulators and Non-Manipulators

Table 4. Number and percentage of Beneish M-Score categories

Year	Observations	Potential Manipulators	Percentage (%)	Non-Manipulators	Percentage (%)
2021	36	14	38.89	22	61.11
2022	71	32	45.07	39	54.93
2023	55	30	54.55	25	45.45
2024	51	22	43.14	29	56.86
Total	213	98	46.01	115	53.99

Table 4 shows that of the 213 observations, 98 observations (46.01 %) were classified as potential manipulators, whereas 115 observations (53.99 %) were classified as non-manipulators. Overall, non-manipulator observations were more prevalent. This finding indicates that late filings are not synonymous with manipulation. Nevertheless, the proportion of observations classified as potential manipulators was substantial and should be treated as a risk signal requiring further examination.

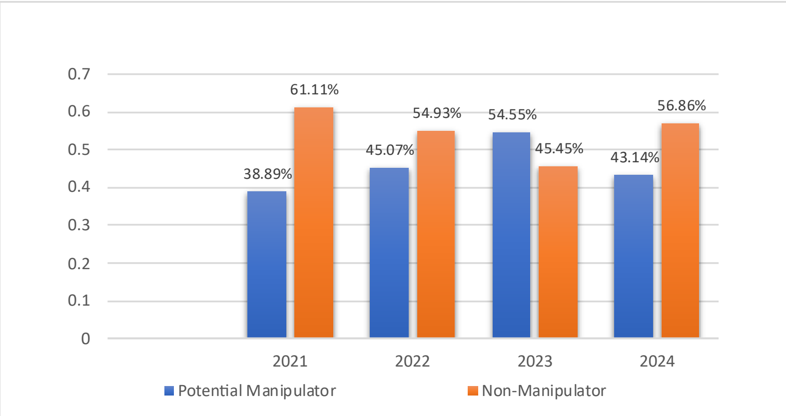

Figure 1. Annual percentages of Beneish M-Score categories

Figure 1 shows that the highest proportion of observations classified as potential manipulators occurred in 2023, reaching 54.55%, whereas the lowest proportion was recorded in 2021 at 38.89%. These variations indicate that the indications of financial statement manipulation did not follow a consistent upward or downward trend over the observation period. Instead, the changes reflect differences in company-specific financial conditions, reporting pressures, and operational circumstances over the years. The increase observed in certain periods suggests that some companies may have faced greater incentives or opportunities to present more favorable financial performance, whereas the decline in other periods indicates variations in the level of financial reporting risk among late filing companies.

4.3 Repeated Indications among Potential Manipulators

An additional analysis was conducted to identify companies with M-scores above -2.22 for more than one year. Twenty-one companies exhibited repeated indications: four were classified as potential manipulators for three years, and 17 for two years. Table 5 presents the companies with the highest frequency.

Table 5. Companies classified as potential manipulators in three years

Code	Company Name	2021	2022	2023	2024	Frequency
HOTL	PT Saraswati Griya Lestari Tbk	M	M	M	-	3
MPRO	PT Maha Properti Indonesia Tbk	M	M	M	-	3

RAFI	PT Sari Kreasi Boga Tbk	-	M	M	M	3
WMUU	PT Widodo Makmur Unggas Tbk	-	M	M	M	3

Note: M = potential manipulator; - = not included in the sample for that year.

Table 5 shows HOTL was classified as a potential manipulator during 2021-2023, with M-Scores of -2.011, 1.381, and 0.502, respectively. MPRO recorded M-scores of -1.840, -0.176, and 1.049 over the same period. RAFI was classified as a potential manipulator during 2022-2024, with M-Scores of 1.020, -1.236, and -1.727, while WMUU recorded M-Scores of -2.201, -1.537, and -1.731 over the same period. These frequencies do not imply that manipulation occurred three times. However, the repeated pattern signals a consistent warning that should be prioritized for more in-depth analysis.

4.4 Ratios Most Frequently Exceeding the Indicative Threshold

The most prevalent ratios were identified based on the frequency with which each index exceeded its indicative threshold among the 98 observations classified as potential manipulators. This approach does not assess the magnitude of the coefficients in the M-Score equation; rather, it identifies the characteristics most frequently observed in the higher-risk group.

Table 6. Ratios most frequently exceeding indicative thresholds among potential-manipulator observations

Ratio	Indicative Threshold	Number Exceeding Threshold	Percentage (%)	Rank
SGAI	1.041	44	44.90	1
GMI	1.193	41	41.84	2
DSRI	1.465	40	40.82	3
TATA	0.031	37	37.76	4
DEPI	1.077	33	33.67	5
LVGI	1.111	26	26.53	6
SGI	1.607	23	23.47	7
AQI	1.254	21	21.43	8

Table 6 shows that SGAI was the most prevalent ratio, exceeding its threshold in 44 observations (44.90%), followed by GMI in 41 observations (41.84%), and DSRI in 40 observations (40.82%). The most prevalent ratio differed by year, such as SGAI in 2021 (71.43%), GMI in 2022 (46.88%), DSRI in 2023 (50.00%), and DEPI in 2024 (40.91%). These changes indicate that the characteristics associated with manipulation indications are dynamic and cannot be linked to the same accounts every year. The prevalence of SGAI reflects an increase in selling, general, and administrative expenses relative to sales among many higher-risk observations. However, the SGAI coefficient in the Beneish equation is negative (-0.172), therefore, its frequent occurrence does not mean that SGAI makes the largest positive contribution to the M-Score. A high GMI reflects a decline in the gross margin, whereas a high DSRI indicates that receivables are growing faster than sales. These conditions may increase the pressure to maintain perceived performance and should be examined by reviewing credit policies, revenue-recognition practices, and cost structures (Beneish, 1999).

4.5 Discussion

The results show that 46.01% of the observations involving companies that filed their financial statements late were classified as potential manipulators based on the Beneish M-Score. The remaining 53.99% were classified as non-manipulators of the environment. This finding indicates that late financial statement filings should not be treated as direct evidence of manipulation. This is an initial signal that warrants attention, particularly when accompanied by an M-score above the -2.22 threshold. The findings can be explained through the signaling theory. Spence (1973) explains that information communicated by a better-informed party can influence the assessments of other parties. In capital markets, timely financial statement filing signals corporate compliance and transparency. When financial statements are filed late, investors, creditors, auditors, and regulators face greater uncertainty. This uncertainty becomes more pronounced when the Beneish M-Score indicates potential manipulation.

However, late filing may result from various factors that are not necessarily related to financial statement manipulation. Complex audit processes, limited audit evidence, financial conditions, firm size, leverage, and audit opinions may extend the time required to complete reports. Ariani and Bawono (2018) show that firm size affects audit report lags. Pangestuti et al. (2020) found that leverage and audit opinions affect reporting timeliness. Larasati et al. (2024) also show that firm size, profitability, firm age, and audit opinion are associated with timely financial statement filing. Therefore, late filing should be analyzed in conjunction with a company's conditions and characteristics.

The highest percentage of potential manipulator observations occurred in 2023. This result is supported by the 2023 median M-Score of -2.062, which was above the -2.22 threshold. This indicates that the 2023 pattern was not driven solely by a single observation with an exceptionally high value but was also reflected in the overall data distribution. By contrast, the mean M-Scores in 2021 and 2024 were influenced by several extreme values. Therefore, the mean should be interpreted alongside the median to prevent outliers from disproportionately affecting the interpretation. The study also found that several companies were repeatedly classified as potential manipulators during two or three years of observation. Repeated indications do not prove that manipulation occurred each year. However, this pattern indicates a consistent risk signal. Companies with repeated indications warrant further attention through reviews of revenue recognition, changes in receivables, asset quality, depreciation methods, accrual values, and notes to financial statements.

Based on the Beneish M-Score components, SGAI, GMI, and DSRI were the ratios that most frequently exceeded their indicative thresholds. The SGAI captures selling, general, and administrative expenses relative to sales. The prevalence of SGAI may reflect rising costs, operating disruptions, or expansion costs among late-filing companies. However, the SGAI coefficient in the M-Score equation is negative (-0.172) therefore, its frequent threshold exceedance does not mean that it makes the largest positive contribution to the final score. The GMI has a positive coefficient and indicates a decline in gross margin, which may increase the pressure to maintain reported performance when costs rise faster than selling prices. The DSRI also has a positive coefficient and indicates that receivables are growing faster than sales, which may reflect weaker collection, extended credit terms, or potentially aggressive revenue recognition. These interpretations identify accounts that require examination rather than causal evidence of manipulation.

The prevalence of these ratios should be interpreted in the context of sample characteristics. Beneish (1999) treats an increase in DSRI and GMI as warning signs because unusual receivables growth and declining margins may be associated with performance pressure. Using the modified Beneish M-score, Ebaid (2023) found significant associations between the likelihood of financial statement fraud and two specific board characteristics: board independence and board size. Accordingly, the SGAI, GMI, and DSRI should be examined together with credit policies, revenue cut-offs, cost structures, internal controls, and relevant governance conditions. Prior studies have also shown that the factors associated with financial statement fraud vary across companies and sectors. Aprilia (2017) found that financial stability affects financial statement fraud. Sagala and Siagian (2021) identified the effects of financial targets and stability. Rianggi (2023) found the effects of financial stability, industry characteristics, total accruals to total assets, and dual positions. These differences indicate that no single factor explains all the indications of financial statement manipulation.

The finding that 46.01% of late-filing observations were classified as potential manipulators indicates a substantial but non-universal risk concentration. Febrianti (2022) showed that the Beneish model can flag particular entities for further review. Sudradjat et al. (2023) likewise found that indications may arise only during certain observation periods. The repeated indications found for several companies in this study are consistent with those of Pertiwi et al. (2023), who emphasized the model's ability to capture year-to-year changes in financial statement components. In the international context, Ebaid (2023) found that the likelihood of financial statement fraud, measured using the modified Beneish M-Score, was significantly associated with board independence and board size, while the other board characteristics examined were not significant. Sylwestrzak and Słomkowska (2025) show that model performance may change when the specification is modified. Therefore, the present findings complement, rather than merely replicate, previous evidence by applying the M-Score specifically to a population of late-filing companies.

Based on the overall findings, the Beneish M-score is more appropriately used as an initial screening tool than as a standalone proof of manipulation. Companies that file late, have an M-score above -2.22, or exhibit repeated indications should be prioritized for further examination. Tümmler and Quick (2026) show that interventions that increase auditors' attention to fraud cues can improve fraud brainstorming, risk assessment, and evaluation of audit evidence. Therefore, ratio-based screening should be supplemented by professional skepticism, internal control evaluation, analytical procedures, and substantive audit evidence. The examination should cover financial statements, notes to the financial statements, independent auditors' reports, transaction evidence, industry conditions, and corporate governance to support a more accurate conclusion.

5. CONCLUSIONS

5.1 Conclusion

This study concludes that late financial statement filing can be used as an initial screening criterion to focus on monitoring, but it cannot serve as standalone evidence of manipulation. The Beneish M-Score distinguishes observations classified as potential manipulators from those classified as non-manipulators and shows that the risk signal becomes stronger when the M-score repeatedly exceeds the threshold. Theoretically, this study extends the application of signaling theory by demonstrating that the reporting-timeliness signal becomes more informative when it occurs with accounting-based anomaly signals. Empirically, the two-stage integration of late filing and the Beneish M-Score provides a transparent financial reporting risk-assessment framework by identifying 98 of 213 late-filing observations for prioritized follow-up examination without making causal claims or confirming fraud. SGAI, GMI, and DSRI were the most frequently observed characteristics among potential manipulators. These findings indicate that changes in selling, general, and administrative expenses, declining gross margins, and receivables growing faster than sales warrant attention when reviewing the financial statements. Thus, the Beneish M-Score is appropriate as an early detection tool and as a basis for prioritizing examinations, whereas establishing that manipulation has occurred still requires audit evidence and substantive procedures.

5.2 Research Limitations

This study had several limitations. First, the analysis uses only the Beneish M-Score; therefore, the results depend on the sensitivity and assumptions of a single model. Second, the data were obtained from financial statements and public announcements; therefore, the study had no access to audit evidence, transaction documents, or internal company information. Third, the sample was limited to non-financial companies reporting in Indonesian rupiah, while the descriptive research design did not test the causal relationship between late filing and manipulation. Fourth, extreme values in several ratios reduced the stability of the mean, requiring the results to be interpreted alongside the median and the context of each firm.

5.3 Suggestions and Directions for Future Research

Investors, creditors, auditors, and regulators are advised to use late filing together with the M-score as a risk-screening mechanism rather than as the sole basis for alleging manipulation. From a managerial perspective, companies should establish a monitored financial close calendar, escalate unresolved reporting issues before the deadline, reconcile revenue and receivables before closing, independently review material estimates and accruals, and require the audit committee to monitor recurring trends in the SGAI, GMI, DSRI, and M-score. Internal audit or financial control functions should use exception-based analytics to investigate unusual changes, document legitimate business explanations, and monitor corrective actions. A formal root-cause review of every delay, covering systems, personnel, internal controls, transaction complexity, and coordination with auditors, can improve reporting quality and reduce the recurrence of conditions associated with manipulation risk.

Future studies may extend the observation period and sectoral coverage, compare the Beneish M-Score with the F-Score, Dechow model, or other fraud-detection approaches, and incorporate variables such as corporate governance, auditor changes, audit opinion, audit report lag, financial stability, and industry characteristics. Panel data regression, logistic regression, or predictive research designs may also help identify factors associated with manipulation indications and improve the external validity of the findings.

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