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FINANCIAL STATEMENT FRAUD DETECTION USING THE BENEISH M-SCORE AND ITS IMPLICATIONS FOR FIRM VALUE: A NARRATIVE LITERATURE REVIEW

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ABSTRACT

Financial statement fraud remains a major concern for investors, regulators, and researchers because it reduces the reliability of financial reporting and can lead to significant economic losses. Among the various approaches developed to detect such fraud, the Beneish M-Score has become one of the most widely used tools due to its practicality and reliance on publicly available financial data. This study aims to review the existing literature on the use of the Beneish M-Score in detecting financial statement fraud and to examine its implications for firm value. Using a narrative literature review approach, this article synthesizes prior theoretical and empirical studies related to fraud detection, earnings manipulation, and market responses to fraudulent financial reporting. The findings show that the Beneish M-Score is a useful initial screening tool for identifying potential earnings manipulation, although its effectiveness varies across countries, industries, and regulatory environments. The literature also indicates that financial statement fraud generally has a negative effect on firm value through declining investor confidence, falling stock prices, reputational damage, and higher costs of capital. Overall, this study highlights the importance of early fraud detection and emphasizes that the Beneish M-Score can provide meaningful insights when used alongside other analytical approaches and supported by strong corporate governance

Keywords: financial statement fraud; Beneish M-Score; firm value; earnings manipulation; narrative literature review

INTRODUCTION

Financial statement fraud remains one of the most serious challenges in modern financial reporting because it undermines the credibility of accounting information and weakens investor confidence in capital markets. Fraudulent reporting occurs when companies intentionally misstate or omit material financial information in order to present a more favorable picture of their financial condition and performance. Such practices may involve overstating revenues, understating expenses, manipulating accruals, or misrepresenting assets and liabilities. As a result, users of financial statements - including investors, creditors, auditors, and regulators - may make decisions based on distorted information, which can lead to significant financial losses and broader market inefficiency. Major corporate scandals such as Enron and WorldCom illustrate how financial statement manipulation can damage not only individual firms but also public trust in the financial reporting system.

From a theoretical perspective, financial statement fraud can be explained through agency theory proposed by Jensen and Meckling (1976). This theory suggests that conflicts of interest may arise between managers and shareholders when managers pursue personal objectives rather than the long-term interests of owners. In this context, managers may have incentives to manipulate accounting information in order to meet earnings targets, maintain stock prices, secure compensation, or avoid negative market reactions. In addition, signaling theory helps explain the role of financial reporting as a signal to the market. When the quality of reported information is compromised, the signal received by investors becomes misleading, which may ultimately distort market valuation.

The increasing complexity of business transactions and reporting practices has made the detection of financial statement fraud more difficult through conventional auditing procedures alone. This condition has encouraged researchers and practitioners to develop analytical tools capable of identifying unusual patterns in financial data that may indicate manipulation. Among the available models, the Beneish M-Score has become one of the most widely discussed and frequently applied approaches for detecting potential earnings manipulation. Developed by Beneish (1999), the model uses a set of financial ratios to assess whether a company is likely to have manipulated its earnings. One of its main strengths lies in its practical nature, as it relies on publicly available financial statement data and can therefore be used as an accessible initial screening tool by investors, auditors, analysts, and regulators.

Recent studies have further examined the effectiveness of the Beneish M-Score across different contexts. For example, several studies (e.g., Roxas, 2011; Skousen et al., 2009; and more recent empirical research) confirm that the model remains useful in identifying firms with a higher likelihood of earnings manipulation, although its predictive accuracy varies depending on institutional and industry-specific factors. Other recent studies also emphasize that combining financial ratios with governance and non-financial indicators can improve fraud detection performance.

More recent scholarship has reinforced and extended these findings in important ways. Kamal et al. (2020) demonstrated that the Beneish M-Score retains discriminatory power in emerging market contexts, particularly when applied alongside accrual-based earnings quality measures. Similarly, Omar et al. (2021) found that firms classified as potential manipulators by the M-Score exhibited significantly lower future return on assets, lending empirical support to the model's relevance for predicting operational deterioration. In the domain of fraud detection methodology, Perols et al. (2017) showed that machine learning classifiers can substantially outperform traditional ratio-based models when sufficient labeled data are available, though they also noted that hybrid approaches combining the Beneish variables with algorithmic features offer a practical middle ground for practitioners. With respect to firm value, Badertscher et al. (2022) documented that earnings restatements associated with accounting irregularities generate persistent declines in Tobin's Q, confirming that the market consequences of manipulation extend well beyond the initial disclosure event. Furthermore, Hribar and Yehuda (2015) provided evidence that accrual-based signals, including several components embedded in the Beneish model, are systematically priced by investors and thus linked to equity valuation. Taken together, these recent contributions highlight that the Beneish M-Score occupies an enduring but evolving role in the fraud detection landscape, and that its connection to firm value merits continued theoretical and empirical attention.

Previous studies have examined the effectiveness of the Beneish M-Score in different countries, industries, and regulatory settings. A number of studies report that the model is useful in identifying firms with a higher likelihood of manipulation, while others point out that its predictive ability is not equally strong in every context. These differences suggest that the performance of the Beneish M-Score may be influenced by factors such as accounting standards, enforcement quality, industry characteristics, and the overall reliability of financial reporting systems. Therefore, although the model is widely recognized as a valuable fraud detection tool, the literature also indicates that it should be interpreted carefully and, where possible, complemented by other indicators or governance-related variables.

Beyond the issue of detection, financial statement fraud is also closely related to firm value. Fraudulent reporting can initially create the appearance of strong performance, but once manipulation is revealed, the consequences are often severe. Firms may experience declining stock prices, reputational damage, legal sanctions, increased cost of capital, and reduced investor trust. In efficient capital market theory, Fama (1970) argues that market prices respond quickly to new information. Accordingly, the disclosure of fraud or earnings manipulation is generally expected to trigger a negative market reaction and a decline in firm value. This relationship makes the study of financial statement fraud important not only from an accounting and auditing perspective but also from the standpoint of financial economics and market behavior.

Although many studies have discussed fraud detection and market consequences separately, the relationship between Beneish M-Score-based fraud detection and firm value remains an area that deserves broader conceptual understanding. Existing studies often vary in their empirical setting, methodological approach, and interpretation of fraud-related outcomes. In addition, there is still a need to synthesize how the literature explains the usefulness of the Beneish M-Score, the limitations of the model, and the channels through which financial statement fraud influences firm value.

Based on this background, this article reviews the existing literature on financial statement fraud detection using the Beneish M-Score and examines its implications for firm value. Using a narrative literature review approach, this study synthesizes prior theoretical and empirical works in order to identify major findings, highlight important inconsistencies, and reveal research gaps for future studies. By doing so, the article seeks to provide a clearer understanding of the role of the Beneish M-Score in fraud detection and the broader economic consequences of fraudulent financial reporting.

RESEARCH METHODS

This study employs a narrative literature review approach. This method is appropriate for synthesizing and critically evaluating theoretical and empirical studies on a defined topic without the strict quantitative aggregation required by systematic or meta-analytic reviews. The narrative approach allows for a flexible, interpretive synthesis that identifies major themes, debates, and gaps in the existing body of knowledge (Baumeister & Leary, 1997).

Data Sources

Literature was sourced from peer-reviewed academic journals accessible

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through major academic databases including Scopus, Web of Science, Google Scholar, and JSTOR. Priority was given to Scopus-indexed journals to ensure quality and international recognition. Both theoretical foundational works and recent empirical studies were considered to provide a balanced synthesis of the field.

Inclusion Criteria

Studies were included based on the following criteria: (1) published in peer-reviewed academic journals; (2) published from 1990 to 2024, with an emphasis on studies from the last five years (2019–2024) for recent literature; (3) directly relevant to one or more of the following topics: financial statement fraud detection, the Beneish M-Score or related earnings manipulation models, firm value and market consequences of fraud, and earnings management; and (4) written in English. The primary search keywords used were: "Beneish M-Score," "financial statement fraud," "earnings manipulation," "fraud detection," "firm value," and "earnings management." Seminal theoretical works (e.g., Jensen & Meckling, 1976; Beneish, 1999; Fama, 1970) were retained regardless of publication year due to their foundational importance.

Analysis Technique

Selected studies were analyzed using a thematic literature synthesis approach. The analysis involved: (1) reading and summarizing the key arguments and findings of each study; (2) grouping studies by theme (fraud detection, Beneish M-Score applications, firm value implications); (3) identifying convergences and divergences across studies; and (4) developing an integrated narrative that highlights major insights, limitations, and research gaps. A conceptual framework was constructed to illustrate the theoretical relationships between financial statement manipulation, investor response, and firm value.

Research Flowchart

The research process followed the sequential steps illustrated below (Figure 1):

[Step 1] Topic Identification
(Define research objectives and key themes: Beneish M-Score, fraud detection, firm value)
↓
[Step 2] Literature Search
(Search in Scopus, Web of Science, Google Scholar, JSTOR using defined keywords)
↓
[Step 3] Screening
(Review title and abstract; exclude studies outside the topic scope)
↓
[Step 4] Eligibility Assessment
(Apply full-text inclusion criteria: peer-reviewed, relevant topic, English language, 1990–2024)
↓
[Step 5] Data Extraction and Thematic Analysis
(Extract key findings; group by theme: detection, M-Score applications, firm value)
↓
[Step 6] Narrative Synthesis

(Integrate findings; identify convergences, contradictions, and gaps)
↓
[Step 7] Conclusion and Research Gap Identification
(Draw conclusions; propose directions for future research)

Figure 1. Research Flowchart of the Narrative Literature Review Process

Financial statement fraud and its conceptual foundations

Financial statement fraud refers to the intentional misrepresentation of a company's financial information to mislead users of financial reports. This type of fraud usually involves manipulating revenues, expenses, assets, or liabilities to present a stronger financial position. According to Healy and Wahlen (1999), earnings management becomes fraud when managers use judgment to mislead stakeholders about the true economic performance of the firm.

Fraud in financial statements is often explained by the fraud triangle theory, developed by Donald Cressey. This theory suggests that fraud occurs when three factors are present: pressure, opportunity, and rationalization. Managers may feel pressure to meet financial targets, find opportunities due to weak internal controls, and justify their actions for personal or organizational reasons. This perspective is consistent with positive accounting theory, which suggests that managers make accounting choices strategically based on self-interest and economic incentives (Watts & Zimmerman, 1986).

Previous studies show that financial statement fraud can have serious consequences. It reduces the reliability of financial reporting and damages investor confidence. Large corporate scandals such as Enron and WorldCom have increased the need for better fraud detection tools and stronger corporate governance.

Researchers have also found that fraudulent firms often show unusual financial patterns before fraud is discovered. These patterns can include rapid revenue growth, increasing accruals, and declining cash flows. Therefore, analyzing financial ratios has become a common method for detecting potential fraud.

The Beneish M-Score as a fraud detection tool

The Beneish M-Score is one of the most widely used models for detecting financial statement fraud. It was developed by Beneish in 1999. The model uses a set of financial ratios to identify whether a company is likely manipulating its earnings.

The M-Score is calculated using eight variables, including 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). These variables capture different aspects of financial performance and potential manipulation. A higher M-Score indicates a higher probability of earnings manipulation (Beneish, 1999).

Many studies have tested the effectiveness of the Beneish model in different contexts. For example, Roxas (2011) found that the model can successfully detect manipulation in developing countries, although with some limitations. Similarly, Aghghaleh et al. (2016) demonstrated that the model performs well in identifying firms with a higher likelihood of manipulation, achieving a detection accuracy of 73.17% in the Malaysian context. However, some researchers argue that the model is not always accurate in all situations. Its effectiveness may depend on the country, industry, and accounting standards used. For instance, differences in financial reporting systems can influence how the variables are interpreted and, consequently, how accurately the model indicates fraud.

Despite its limitations, the Beneish M-Score remains a popular tool because it is simple, cost-effective, and based on publicly available data. It is widely used by investors, auditors, and regulators as a first-level screening mechanism.

Financial statement fraud and firm value

Firm value represents the overall worth of a company as perceived by investors. It is often measured using market-based indicators such as stock price, market capitalization, or financial ratios like Tobin's Q. Firms with strong and transparent financial reporting are more likely to enjoy investor trust and stable market valuation.

In addition, signaling theory introduced by Spence (1973) explains that financial reports act as signals to investors. When manipulation is detected, the signal becomes negative, leading to a decline in investor confidence and market value.

Financial statement fraud has a significant negative impact on firm value. When fraud is detected, investors usually react quickly by selling their shares, which leads to a decline in stock prices. According to Fama's efficient market hypothesis, markets respond rapidly to new information, meaning that news about fraudulent reporting can trigger a direct market penalty.

Empirical studies support this idea. Karpoff et al. (2008) found that firms involved in fraud experience not only financial penalties but also reputational losses, which can have long-term effects on future performance. These effects can result from shareholder lawsuits, loss of business relationships, or stricter regulatory oversight.

In addition, fraud can increase the cost of capital and reduce future investment opportunities. Investors may demand higher returns to compensate for the increased risk, and lenders may be less willing to provide financing. This can limit the company's ability to grow and compete in the market.

Synthesis of prior studies

This section provides a broader overview of previous studies on financial statement fraud detection and its impact on firm value. By comparing different studies, it becomes easier to understand the strengths and limitations of various methods, especially the Beneish M-Score model.

The early work of Summers and Sweeney (1998) showed that companies involved in fraud often have abnormal financial ratios before the fraud is revealed. This finding supports the idea that financial data can be used as an early warning signal.

The model developed by Beneish (1999) is one of the most influential contributions in this field. It introduced the M-Score, which remains widely used due to its simplicity and practical application. Subsequent studies, such as Aghghaleh et al. (2016), confirmed that the model is effective in detecting firms that engage in fraudulent financial reporting, with both the Beneish M-Score and Dechow F-Score showing reliable predictive performance.

Table 1. Selected literature on Beneish M-Score and firm value

Author	**Country/Context**	**Method**	**Main finding**
Beneish (1999)	USA	M-Score	Effective in detecting earnings manipulation.
Summers & Sweeney (1998)	USA	Financial ratios	Fraud firms tend to display unusual ratio patterns before disclosure.
Roxas (2011)	Asia	M-Score	Model is useful but only moderately accurate in some developing-market settings.
Aghghaleh et al. (2016)	Malaysia	M-Score	Both Beneish M-Score and Dechow F-Score are effective; M-Score accuracy at 73.17%, F-Score at 76.22%.
Dechow et al. (2011)	USA	Fraud prediction model	More comprehensive models can improve detection accuracy.
Tarjo & Herawati (2015)	Indonesia	M-Score + other indicators	Combined approaches may yield better results in developing countries.
Karpoff et al. (2008)	USA	Market analysis	Fraud significantly reduces firm value through market and reputational penalties.
Skousen et al. (2009)	USA	Fraud triangle	Pressure and weak controls increase fraud risk.

Source: Processed Data (2026)

Research conducted in different regions shows that the effectiveness of the M-Score may vary. Roxas (2011) found that the model is moderately accurate in Asian countries. Similarly, Tarjo and Herawati (2015) suggested that combining the Beneish model with other techniques can improve detection accuracy, especially in developing countries such as Indonesia.

Dechow et al. (2011) proposed a more advanced fraud detection model that includes additional variables beyond financial ratios. Their results indicate that a more comprehensive approach can provide better accuracy compared to relying on a single model.

In addition, studies such as Karpoff et al. (2008) focused on the consequences of fraud and found that it has a strong negative impact on firm value. Companies involved in fraud often experience a decline in stock prices and long-term reputational damage. This supports market-based arguments that investors react quickly to negative information.

Skousen et al. (2009) also contributed to the literature by applying the fraud triangle theory, originally developed by Donald Cressey. Their findings show that factors such as financial pressure and weak internal controls increase the likelihood of fraud.

Overall, the literature mapping shows that while many models exist, no single method can perfectly detect financial statement fraud. The Beneish M-Score remains a valuable tool, especially when used together with other models and supported by strong corporate governance practices.

Critical synthesis

The existing literature suggests that the Beneish M-Score is a useful and widely applied tool for detecting potential earnings manipulation, yet its effectiveness is not uniform across all contexts. While a number of studies support its ability to identify firms with a higher likelihood of fraudulent reporting, other studies show that its predictive power is only moderate and may vary depending on contextual and methodological factors. This indicates that the Beneish M-Score should be understood not as a definitive fraud detection instrument, but rather as an initial screening tool whose results require careful interpretation.

One important issue emerging from the literature is that the performance of the Beneish M-Score is highly influenced by differences in institutional settings. Studies conducted in countries with stronger regulatory enforcement, higher audit quality, and more mature capital markets tend to report more consistent findings. In contrast, research in developing or emerging markets often reveals more varied results. This may be caused by differences in accounting standards, reporting quality, legal enforcement, and the general reliability of published financial statements. As a consequence, ratios used in the Beneish M-Score may not always capture manipulation with the same level of accuracy across countries.

Another important concern relates to industry characteristics. The Beneish M-Score applies a common set of financial indicators to firms that may operate under very different business conditions. High-growth industries, for example, may naturally show rapid increases in sales, receivables, and asset expansion, which can resemble signals of earnings manipulation even when no fraud is present. This creates the possibility of false positive results. On the other hand, in industries with more stable reporting patterns, unusual ratio movements may be easier to interpret as warning signs. Therefore, the literature implies that industry context is essential in evaluating the reliability of Beneish M-Score outcomes.

The literature also shows that many studies focus primarily on financial statement ratios while giving less attention to non-financial factors that may shape fraud risk. Variables such as board effectiveness, ownership structure, audit committee quality, internal control strength, and external audit credibility are often discussed as important determinants of fraudulent behavior, yet they are not directly incorporated into the original Beneish model. This limitation suggests that relying solely on financial ratios may oversimplify the complexity of fraud. In practice, fraudulent reporting is often driven by organizational incentives, governance weaknesses, and managerial pressure, which cannot always be fully captured by numerical indicators alone.

In addition, differences in methodological design across studies also contribute to inconsistent conclusions. Some studies use confirmed fraud cases, while others use earnings manipulation proxies or financial distress indicators as substitutes for actual fraud. These differences affect how the effectiveness of the Beneish M-Score is evaluated. In other words, the model may appear more or less accurate depending on how fraud itself is defined in each study. This issue is important because it shows that inconsistent empirical findings may not only result from weaknesses in the model, but also from variation in research design.

With regard to firm value, the literature consistently suggests that financial statement fraud tends to generate negative market consequences, although the magnitude and timing of those consequences are not always identical. In many cases, fraud revelation is followed by a decline in stock prices, reputational losses, and reduced investor trust. However, the severity of the impact depends on several conditions, including the scale of the fraud, the firm's prior reputation, the transparency of the disclosure process, and prevailing market sentiment. This means that the relationship between fraud and firm value is not entirely mechanical. Market reactions may be immediate and severe in some cases, but more gradual or limited in others.

Overall, the critical review of prior studies shows that the Beneish M-Score remains valuable because of its simplicity, practicality, and accessibility. However, its usefulness is conditional rather than universal. The model performs best when applied with contextual awareness and when complemented by other indicators, particularly governance-related and non-financial variables. Likewise, the effect of fraud on firm value is generally negative, but the strength of that effect depends on institutional context, investor perception, and the nature of the fraud itself.

Research gaps and future directions

Despite the growing body of literature on financial statement fraud detection and the use of the Beneish M-Score, several important gaps remain in the existing research.

First, prior studies have not yet provided a sufficiently integrated understanding of how the Beneish M-Score relates to firm value. Most studies tend to focus on one of two separate areas: either the effectiveness of the Beneish M-Score in identifying potential earnings manipulation or the market consequences of fraudulent reporting. As a result, the connection between fraud detection indicators and firm value implications is still fragmented in the literature. More comprehensive discussion is needed to explain how the identification of manipulation risk through the Beneish M-Score can be linked conceptually to investor response and market valuation.

Second, the literature shows inconsistent findings regarding the effectiveness of the Beneish M-Score across different countries and institutional settings. While some studies report that the model performs well as an initial screening tool, others find only moderate or context-dependent accuracy. This suggests that cross-country differences in accounting standards, enforcement quality, audit practices, and financial reporting systems may influence the model's predictive ability.

Third, there is still limited discussion of how industry characteristics shape the interpretation of Beneish M-Score signals. Many studies apply the model across firms without giving sufficient attention to sector-specific financial patterns. In reality, companies in high-growth or asset-intensive industries may naturally exhibit ratio movements that resemble manipulation indicators, even when fraudulent behavior is absent. This creates the possibility of misclassification and indicates a need for deeper conceptual and comparative analysis across industries.

Fourth, previous studies largely emphasize financial ratios while giving less attention to non-financial determinants of fraud. Factors such as corporate governance quality, board effectiveness, ownership structure, audit committee oversight, and internal control strength are frequently acknowledged as relevant to fraud risk, yet they are often treated separately from Beneish M-Score analysis. This creates a gap in the literature, as fraud detection may be better understood through a more integrated perspective that combines financial indicators with governance-related and organizational variables.

Fifth, although many studies agree that financial statement fraud negatively affects firm value, there is still limited conceptual clarity regarding the mechanism through which this effect occurs. The literature often reports stock price decline, reputational loss, or reduced investor confidence as consequences of fraud, but fewer studies synthesize how these factors interact in influencing firm value. This indicates a need for a clearer conceptual explanation linking financial manipulation, information quality, investor trust, and market valuation.

Finally, recent developments in data analytics, machine learning, and artificial intelligence suggest that fraud detection research is moving beyond traditional ratio-based models. However, the role of the Beneish M-Score within this evolving landscape remains underexplored. There is still limited literature that discusses whether the Beneish M-Score should be viewed as a standalone detection tool, a complementary screening model, or part of a broader hybrid fraud detection framework.

Based on these gaps, this article seeks to provide a narrative synthesis of prior literature on financial statement fraud detection using the Beneish M-Score and its implications for firm value. By integrating findings from different studies and contexts, the article aims to offer a clearer understanding of the model's usefulness, limitations, and broader relevance for financial reporting and market valuation research.

Conceptual framework

This study is based on a conceptual framework that explains the relationship between financial statement manipulation and firm value through several intermediate factors. The framework focuses on how the quality of financial information and investor perception play a key role in this process.

Financial statement manipulation occurs when managers intentionally distort financial data to present a more favorable view of the company's performance. This behavior reduces the quality, reliability, and transparency of financial information. When financial reports do not reflect the true economic condition of a firm, users of this information are more likely to make incorrect decisions. This situation creates information asymmetry, where managers have more accurate knowledge than investors and other stakeholders.

Reduced information quality has a direct impact on investor trust. Investors depend heavily on financial statements to evaluate risk and return. When there is a suspicion or evidence of manipulation, confidence in the company decreases. As trust declines, investors may become more cautious or even withdraw their investments. According to Fama (1970), financial markets are sensitive to new information, and negative signals such as fraud or manipulation can quickly influence investor behavior.

In addition, the reaction of investors is not always the same in every situation. It may depend on factors such as the severity of manipulation, the reputation of the firm, and overall market conditions. In some cases, investors may react strongly and immediately, while in others the reaction may be slower or less intense. Nevertheless, the general outcome is a decrease in investor confidence.

Conceptual relationship

Financial statement manipulation => reduced information quality => lower investor trust => lower firm value

Lower investor trust leads to reduced demand for the company's shares, which causes a decline in stock prices. This directly reduces the market value of the firm. Furthermore, companies with lower trust levels may face higher costs of capital, as investors require higher returns to compensate for the increased risk. This can limit the company's ability to invest, expand, and compete in the market.

However, this relationship is not always linear and can be influenced by several moderating factors. For example, strong corporate governance, effective internal controls, and high-quality audits can reduce the negative impact of manipulation. Conversely, weak governance systems can make the situation worse by allowing manipulation to continue undetected.

Moreover, external factors such as economic conditions and market sentiment also play an important role. During periods of economic stability, investors may respond more rationally, while in times of uncertainty, reactions may be stronger and more volatile.

The framework also highlights the importance of early fraud detection. Tools such as the Beneish M-Score, developed by Beneish (1999), can help identify potential manipulation before it causes serious damage. Early detection allows investors, auditors, and regulators to take preventive actions and reduce the negative impact on firm value.

Overall, this conceptual framework provides a clear explanation of how financial statement manipulation affects firm value through multiple channels. It also emphasizes that improving transparency, strengthening governance, and applying effective detection tools are essential for maintaining investor trust and ensuring stable financial markets.

CONCLUSION

This study set out to review the existing literature on financial statement fraud detection using the Beneish M-Score and to examine its implications for firm value. The findings directly address both objectives. With respect to the first objective, the literature confirms that the Beneish M-Score is a practical and widely recognized initial screening tool for identifying potential earnings manipulation. Its reliance on publicly available financial data makes it accessible to investors, auditors, analysts, and regulators across various institutional contexts. However, the review also consistently shows that the model's predictive accuracy is not uniform: its effectiveness varies across countries, industries, and governance environments, and it performs best when complemented by governance-related and non-financial indicators rather than being applied in isolation.

With respect to the second objective — the implications of Beneish M-Score-based fraud detection for firm value — the reviewed literature consistently indicates that financial statement fraud generates negative market consequences. Once manipulation is disclosed, firms typically experience declining stock prices, reputational damage, reduced investor trust, higher costs of capital, and diminished competitiveness. These effects are generally mediated through information quality: fraud reduces the transparency and reliability of financial reporting, which in turn weakens investor confidence and lowers market valuation. The severity of this impact, however, is influenced by the scale of the fraud, the strength of corporate governance, and prevailing market conditions.

In conclusion, the Beneish M-Score remains a meaningful contribution to fraud detection practice, but its usefulness is conditional rather than universal. Effective fraud detection and its positive contribution to preserving firm value require an integrated approach that combines the M-Score with other financial, governance, and non-financial indicators. Future research is encouraged to pursue cross-country comparisons, industry-specific analyses, and hybrid frameworks that integrate traditional ratio-based models with advances in data analytics and machine learning, thereby offering a more comprehensive understanding of fraud and its firm value implications in increasingly complex financial environments.

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