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AN INVESTIGATION INTO THE RELATIONSHIP BETWEEN COMPANY-SPECIFIC CHARACTERISTICS AND FINANCIAL MISREPRESENTATION USING THE BENEISH M-SCORE

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ABSTRACT

This study investigates the influence of firm-specific factors on the Beneish M-Score, a key indicator used to detect financial misreporting. The sample comprises 1,256 firm-year observations from manufacturing firms listed on Borsa Istanbul (BIST) between 2013 and 2023. Using a Panel Data Fixed Effect Model, this research explores the impact of firm size, Return on Assets (ROA), firm age, leverage, and net margin on the likelihood of financial misreporting. To determine the appropriate model specification, the study conducts several diagnostic tests, including the Hausman test, the Breusch-Pagan Lagrange Multiplier (LM) test, and assumption tests specific to fixed-effects modelling. The results reveal significant negative relationships between the Beneish M-Score and firm size, firm age, and net margin. These findings suggest that larger, older, and more profitable firms are less likely to engage in financial misreporting, potentially due to stronger governance structures and higher levels of external scrutiny. In contrast, no significant relationship is found between Beneish M-Score and ROA, indicating that efficiency, as measured by ROA, does not significantly affect financial misreporting likelihood. Additionally, the analysis identifies a significant positive relationship between the Beneish M-Score and leverage, indicating that firms with higher levels of debt are more likely to engage in financial misreporting.

***Anahtar Kelimeler**: Financial Accounting, Financial Misrepresentation, Beneish Score*

***Jel Kodları**: M10-M40-M49*

ŞİRKET ÖZGÜ ÖZELLİKLER İLE FİNANSAL YANLIŞ BEYAN ARASINDAKİ İLİŞKİNİN BENEİSH M-SKORU KULLANILARAK İNCELENMESİ

ÖZ

Bu çalışma, firma özelindeki faktörlerin finansal yanlış beyanları tespit etmek için kullanılan temel bir gösterge olan Beneish M-Score üzerindeki etkisini araştırmaktadır. Örneklem, 2013 ve 2023 yılları arasında Borsa İstanbul'da (BIST) işlem gören imalat firmalarından 1.256 firma-yıl gözleminden oluşmaktadır. Panel Veri Sabit Etki Modeli kullanılarak, bu araştırma, firma büyüklüğü, Aktif Karlılığı (ROA), firma yaşı, kaldıraç ve net marjın finansal yanlış beyan olasılığı üzerindeki etkisini incelemektedir. Uygun model yapısını belirlemek için çalışmada Hausman testi, Breusch-Pagan Lagrange Çarpanı (LM) testi ve sabit etkiler modeline özgü varsayım testleri gibi çeşitli tanısal testler uygulanmıştır. Sonuçlar, Beneish M-Score ile firma büyüklüğü, firma yaşı ve net marj arasında anlamlı negatif ilişkiler olduğunu ortaya koymaktadır. Bu bulgular, daha büyük, daha eski ve daha kârlı firmaların, daha güçlü yönetişim yapıları ve daha yüksek dış denetim seviyeleri nedeniyle finansal yanlış beyana daha az eğilimli olduğunu önermektedir. Buna karşın, Beneish M-Score ile ROA arasında anlamlı bir ilişki bulunmamış olup, ROA ile ölçülen etkinliğin finansal yanlış beyan olasılığını önemli ölçüde etkilemediği gözlemlenmiştir. Ayrıca, analiz, Beneish M-Score ile kaldıraç arasında anlamlı bir pozitif ilişki olduğunu göstermiş olup, daha yüksek borç seviyesine sahip firmaların finansal yanlış beyana daha yatkın olduğunu işaret etmektedir.

***Keywords:** Finansal Muhasebe, Finansal Yanlış Beyan, Beneish Skoru*

***Jel Codes:** M10-M40-M49*

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1.INTRODUCTION

The trueness and soundness of financial statments are essential for the proper functioning of capital markets. Financial misreporting, whether intentional or due to oversight, can distort market perceptions, leading to suboptimal investment decisions and a loss of confidence in financial institutions. To address this issue, various models have been developed to detect signs of financial manipulation. One such model is the Beneish M-Score, which has gained prominence as an indicator for identifying firms likely to engage in financial misreporting (Beneish, 1999). While the Beneish M-Score has been widely utilized, the factors that influence a firm's propensity to misreport remain underexplored, particularly in the context of emerging markets. This study is designed to fill this gap by scrutinizing how specific firm characteristics impact the Beneish M-Score among manufacturing firms listed on Borsa Istanbul (BIST) over a period from 2013 to 2023.

Prior literature has extensively discussed the role of firm size, profitability, and financial health in influencing corporate behaviours, including the likelihood of misreporting. Larger firms, for instance, are generally thought to be less likely to manipulate financial reports due to higher levels of scrutiny from auditors, regulators, and the public (Dechow et al., 2011). Similarly, older firms with established reputations may be less incentivised to engage in risky financial behaviours to preserve their market position (Jensen & Meckling, 1976). Efficiency, often measured through ratios such as Return on Assets (ROA), has been discussed in mixed terms. While some studies suggest that highly efficienct firms have less reason to misreport (Rahman & Xion, 2021), others find no significant connection, indicating that efficiency alone may not deter fraudulent behaviour (Albrecht et al., 2018).

This study builds on these theoretical foundations by examining the relationship between Beneish M-Score and several key firm characteristics: firm size, ROA, firm age, leverage, and net margin. Using a Panel Data Fixed Effect Model, we test the significance of these variables in predicting the likelihood of financial misreporting. The outcomes reveal a significant negative association between Beneish M-Score and firm size, firm age, and net margin. These findings reveal that larger, older, and more profitable companies are less prone to financial manipulation, likely due to their more robust internal controls, established reputations, and financial health. Additionally, the analysis identifies a significant and positive relationship between Beneish M-Score and leverage, indicating that firms with higher levels of debt may be more likely to engage in financial misreporting. On the other hand, the lack of a significant relationship between Beneish M-Score and ROA suggests that efficiency, when measured in isolation, may not serve as a strong deterrent against financial misreporting.

There are important implications of this study. The findings highlight the importance of firm-specific factors, particularly size, age, leverage, and profitability margins, in shaping the likelihood of financial misreporting. This has practical relevance for regulators, auditors, and investors who rely on financial reports for decision-making. Understanding the characteristics of firms that are less likely to misreport can help these stakeholders allocate their resources more efficiently, targeting higher-risk firms for further scrutiny.

To sum up, this study provides valuable insights into the factors that influence financial misreporting, particularly in the context of an emerging market like Turkey. By identifying the features of companies less likely to involve in financial manipulation, this research contributes to both the theoretical literature on corporate governance and the practical efforts to enhance financial transparency.

2.LITERATURE REVIEW & HYPOTHESIS DEVELOPMENT

The Beneish M-Score was introduced by Beneish (1999) in his seminal paper "The Detection of Earnings Manipulation". This model was designed to detect companies that are likely engaging in financial manipulation by examining eight financial ratios derived from publicly available data. Beneish demonstrated that the model could correctly identify approximately 76% of manipulators, providing a valuable tool for auditors, analysts, and regulators. The model's success is grounded in its ability to highlight deviations in key financial indicators, such as days' trade in receivables, gross margin, and quality of assets, which often signal earnings manipulation.

Beneish's initial findings laid the groundwork for numerous subsequent studies, which have tested the M-Score in various markets and industries. One such study by Dechow, Ge, Larson, and Sloan (2011) attempted to generate an alternative model for prediction of financial manipulation, in which they assessed the performance of the Beneish model alongside other fraud detection models. The authors found that while the M-Score performed to some extent well in detecting material misstatements. Skousen, Stice, and Wright (2009) also referred Beneish Model in multiple occasion within the context of financial fraud detection.

In recent years, the Beneish M-Score model has been widely utilized to detect financial statement manipulation across various markets. A research conducted in Poland sought to assess the effectualness of the Beneish model in identifying manipulators among firms listed on the Warsaw Stock Exchange. The sample consisted of over 30 firms classified as manipulators and an equal number of firms considered non-manipulators. The findings revealed that the 8-factor model successfully detected manipulators with a hunder percent accuracy, while the 5-factor model showed considerably lower accuracy. The study concluded that the Beneish M-Score model is a reliable instrument for detecton of financial statement manipulation in the Polish market, consistent with results from similar studies in other countries (Holda, 2020).

In another international study, Hassan (2019) examined the use of the Beneish M-Score within the Pakistani stock market. Earnings management, where companies manipulate financial statements to obscure their true financial health, poses significant risks to investor decision-making in stock markets worldwide. A study focused on applying the Beneish M-Score model in order to capture earnings misrepresentation in two different sectors; namely sugar and cement, quoted on the Karachi Stock Exchange. The sample analysis revealed that around fifty-five percent of the companies were identified as misrepresentator, while the remaining forty-five percent were non-misrepresentator (Hassan, 2019).

A recent study carried out the Beneish M-Score model to investigate the likelihood of earnings management among Greek companies (Repousis, 2016). Using a sample size of 25,468 firms from 2011-2012 (excluding banks), the analysis found that thirt-three percent of the sample showed a Beneish M-Score higher than -2.2, indicating a tendency toward financial misrepresentation. Key variables such as the Days Sales in Receivables Index, Asset Quality Index, and Leverage Index were found to have a significant effects on the Beneish M-Score, with DSRI explaining 95.92% of the variation. The study's results are particularly relevant for the banking sector, as financial statement data significantly influence credit decisions, and the Beneish model offers an affordable and effective tool for detecting manipulation (Repousis, 2016).

Financial statement fraud remains a prevalent issue in modern financial systems, and early detection is crucial for preventing such frauds (Aghghaleh et al., 2016). A study comparing the effectiveness of the Beneish M-Score and Dechow F-Score models in determining FSF amongst Malaysian companies from 2001 to 2014 revealed that both models are effective, with average accuracy rates of 73.17% and 76.22%, respectively. The Dechow F-Score outperformed the Beneish model in predicting fraud cases with a sensitivity rate of 73.17% compared to 69.51%, and it also demonstrated a lower Type II error rate (26.83% vs. 30.49%). These results suggest that the Dechow F-Score model may be a more reliable tool for regulators in detecting FSF within Malaysian companies (Aghghaleh et al., 2016).

Akra and Chaya (2020) explored the application of the Altman and Beneish models in the Kuwaiti Stock Market, focusing on detecting financial distress and earnings manipulation, respectively. Excluding banking and insurance companies, the study found that the Altman model had limited predictive power, particularly for industrial and real estate firms. In contrast, the Beneish model exhibited strong predictive ability for uncovering potential earnings manipulation, supported by post-analysis reviews and news sources. The authors recommend recalibrating the Altman model to better suit specific industries and suggest that financial analysts should employ both models for comprehensive financial assessments (Akra & Chaya, 2020).

Following section review the relationship between firm-specific characteristics and financial misreporting

The association between firm-specific features and earnings manipulation has widely studied in the literature. Watt and Zimmerman (1990) argued that due to possible outcomes of political costs, firms with larger size are closely monitored. Moreover, they experience greater market scrutiny and thus have less motivation for applying earnings manipulation practices. Wuryani (2012) scrutinized the association between the firm-sizes and practices of earnings manipulation in the context of Indonesian listed companies for the time-span between 2004 and 2008. The researcher measured firm-size by the logarithm of total assets and found that there is a significantly negative association between firm-size and earnings manipulation. Das et al. (2018) analysed the relationship between several firm-specific characteristics and earnings management. They documented that there is a statistically strong and significant relationship between firm size and earnings management. Naz et al. (2011) investigated the listed Pakistani firms' earnings manipulation practices regarding their firm-sizes and they found no significant relationship between firm-size and earnings manipulation. Siekelova et al. (2020) investigated the relationship between firm-size and earnings manipulation practices. They found that 58.35% of "large firms" manipulate their earnings, while 36.98% SMEs manipulated their earnings. They also found that "large firms" significantly manipulated earnings more than SMEs.

Along with other firm-specific characteristics, the relationship between firm-age and earnings manipulation has also been widely studied in the literature. Bassiouny et al. (2016) argued that as the firms getting older, they avoid earnings manipulation since they become more reputable. Moreover, their ethical codes & standards make these firms to aware adverse consequences of earnings manipulation. Hamzah et al. (2022) scrutinized the association between earnings management and its firm-specific determinants. They used 844 firm-year observations from listed firms on Indonesian Stock Exchange. They found statistically significant and negative association between earnings management and firm-age. Das et al. (2018) also analysed the relationship between particular comapany-specific characteristics and earnings management. They asserted that there is a statistically strong and significant relationship between firm size and earnings management. Gozali et al. (2021) analysed the listed Singaporean corporations' earnings management practices together with their firm-specific features, by using 852 firm-year observations. They documented a significant negative relationship between firm-age and earnings manipulation. Wijaya et al. (2020) scrutinized the relationship between earnings management and nine firm-specific features of firms, namely: firm-size, financial leverage, audit quality, directors' genders, firm-age, profitability, board-size, audit-committee-size and board meetings. They didn't find any statistically significant relationship between firm-age and earnings management.

Profit margin and its relationship with earnings manipulation is utilized as a new method to detect earnings manipulation (Jansen et al., 2012). The study reveals that simultaneous greater profit margin and lesser in asset turnover ratio are indicative of upward earnings management, while simultaneous decreases in profit margin and increases in asset turnover ratio suggest downward earnings management.

Profitability and earnings manipulation relationship is another area where researchers deeply anaylsed their association. Anjum et al. (2012) scrutinized the relationship between firms' profitability and earnings manipulation practices of Pakistani firms for the period between 2002 and 2006. Their results revealed that there is a negative and significant relationship between firm profitability and earnings manipulation amongst the sample firms. Khan (2022) found that there is a notable positive effect of earnings management on Return on Assets (ROA), indicating that companies that practice earnings management are likely to show enhanced profitability as reflected in their ROA. Conversely, the analysis interestingly shows no significant correlation between earnings management and Tobin's Q, which assesses firm value and market perception. Moreover, Ado et al. (2020) also found positive and significant relationship between earnings manipulation and profitability amongst Nigeran listed firms for the period between 2010 and 2018.

Studies have documented that leverage and debt level has also significant relationship with earnings manipulation. Tulcanaza-Prieto (2020) investigated the real earnings manipulation and leverage relationship for the Korean firms. They used total, short-term, and long-term debt ratios as leverage indicators and evaluates earnings manipulation using four different metrics. The findings reveal a strong positive association between leverage and earnings manipulation amongst listed Korean firms. Avabruth & Padhi (2023) explored the connection between earnings management and debt within the Indian context. The analysis is based on a substantial dataset, covering 16,629 firm-years over a nine-year period. The findings indicate that firms with higher-than-average debt levels tend to engage in greater earnings management practices. Suriyasarn (2023) examined how debt covenants influence accrual-based earnings management among firms listed on the Stock Exchange of Thailand. Using data from 1,772 companies between 2014 and 2018. The findings reveal a positive relationship between increasing debt covenants and accrual-based earnings management. Additionally, firms listed on the market-for-alternative-investments exhibit higher levels of accrual-based earnings management than other Thai-listed companies, driven by management's incentive to meet debt covenant requirements.

Based on the reviewed literature above, the following hypotheses are developed.

H1: There is a significant negative relationship between firm size and the Beneish M-Score.

H2: There is a significant negative relationship between firm age and the Beneish M-Score.

H3: There is a significant negative relationship between profit margin and the Beneish M-Score.

H4: There is a significant negative relationship between ROA and the Beneish M-Score.

H5: There is a significant positive relationship between leverage and the Beneish M-Score.

Following section explain the sample selection details and demonstrate the calculation of the Beneish model and related variables.

3.SAMPLE & METHODOLOGY

3.1. Sample

The sample for this study comprises 1,256 firm-year observations from manufacturing firms listed on Borsa Istanbul (BIST) over the period from 2013 to 2023. Manufacturing firms were selected due to their high relevance to financial reporting studies, as they typically involve more complex operations, which may increase the likelihood of financial misreporting. The inclusion criteria required that firms have consistent financial data available for the entire study period, resulting in an unbalanced panel dataset. Firms with incomplete financial information were excluded from the sample to avoid biased estimations. By focusing on the manufacturing sector within an emerging market context, this study adds to the growing body of literature exploring financial misreporting in less-studied markets. The use of firm-year observations over a ten-year period ensures that the study contains not only short term fluctuations but also long term trends in financial reporting behaviour.

3.2. Methodology

This study employs a quantitative research approach, using a panel data model to analyse the relationship between firm-specific factors and the likelihood of financial misreporting, as measured by the Beneish M-Score. To ensure robust results, the study applies the Panel Data Fixed Effect Model, which controls for unobservable heterogeneity across firms. The choice of the fixed effect model is validated through the Hausman test, which tests for the correlation between individual firm effects and the regressors, and Breusch-Pagan Lagrange Multiplier (LM) Test. Moreover, the assumptions of panel data fixed-effect methodology are also tested via Breusch-Pagan Test for Heteroscedasticity, Wooldridge Test for Autocorrelation and Pesaran Test for Cross-sectional Dependence, to check whether these assumptions are violated or not. The results of these tests ensure that the fixed-effect model is appropriately specified and that assumptions of homoscedasticity, no serial correlation, and no cross-sectional dependence are met.

The following equation was developed by Beneish (1999). The model is a tool designed to identify the possibility of a firm engaging in earnings misrepresentation. It uses eight financial ratios to assess potential red flags in a company's financial statements. These ratios, which measure factors such as sales growth, gross margin, and accruals, are combined into a single score. If the M-Score is higher than a threshold of -2.22, it suggests that the company may be manipulating its earnings. The model is widely used by auditors, investors, and analysts for fraud detection purposes.

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

Days Sales in Receivables Index (DSRI): The index compares the proportion of receivables to sales over two periods. The higher DSRI suggests the company may be inflating revenues by increasing credit sales.

$$DSRI = (Receivables/Sales)_{i,t}/(Receivables/Sales)_{i,t-1} \quad \text{E-2}$$

Gross Margin Index (GMI): This index captures the difference gross margin between two periods. A declining gross margin could indicate that a company is under financial pressure, which might encourage manipulation.

$$GMI = ((Sales - COGS)/Sales)_{i,t-1}/((Sales - COGS)/Sales)_{i,t} \quad \text{E-3}$$

Asset Quality Index (AQI): AQI examines the proportion of non-current assets (excluding PPE) to total assets. A rising AQI suggests that the company may be shifting towards more intangible assets, which could mask manipulation.

$$AQI = [1 - (Current\ Assets + PPE)/Total\ Assets]_{i,t} / [1 - (Current\ Assets + PPE)/Total\ Assets]_{i,t-1} \quad \text{E-4}$$

Sales Growth Index (SGI): The index looks at the growth in sales from one period to the next. High sales growth can pressure companies to meet expectations, increasing the risk of earnings manipulation.

$$SGI = Sales_{i,t}/(Sales)_{i,t-1} \quad \text{E-5}$$

Depreciation Index (DEPI): This index compares the rate of depreciation between two periods. A decreasing depreciation rate may signal that the company is slowing its depreciation to artificially boost earnings.

$$DEPI = (Depreciation/PPE)_{i,t-1}/(Depreciation/PPE)_{i,t} \quad \text{E-6}$$

Sales, General, and Administrative Expenses Index (SGAI): The index captures changes in the ratio of SG&A expenses to sales. An increase might indicate that the company is struggling to control costs, leading to potential manipulation.

$$SGAI = (SG\&A\ Expenses/Sales)_{i,t}/(SG\&A\ Expenses/Sales)_{i,t-1} \quad \text{E-7}$$

Leverage Index (LVGI): LVGI tracks the trend of a company's leverage (debt-to-asset ratio) over time. Increased leverage could indicate financial stress, which may push a company towards manipulation.

$$LVGI = (Total\ Debt/Total\ Assets)_{i,t}/(Total\ Debt/Total\ Assets)_{i,t-1} \quad \text{E-8}$$

Total Accruals to Total Assets (TATA): TATA reflects the extent to which a company's earnings are driven by accruals rather than cash flow. Higher accruals relative to total assets can suggest aggressive accounting practices.

$$TATA = (Income\ from\ Operations - Cash\ Flow\ from\ Operations)_{i,t} /Total\ Assets_{i,t} \quad \text{E-9}$$

The calculated M-Scores of each observation is utilized as dependent variable in Equation-10, where M-Scores are run on firm size, return-on-assets, firm-age, leverage and net profit margins of the observations.

$$M - Score_{i,t} = \alpha + \beta_1 Size_{i,t} + \beta_2 ROA_{i,t} + \beta_3 AGE_{i,t} + \beta_4 NMarg_{i,t} + \beta_5 LEV_{i,t} + \varepsilon_{i,t} \quad \text{E-10}$$

Where;

M – Score : Value for each observation obtained via Equation-1 for firm i, in year t,

Size : Natural log of total assets for firm i, in year t,

ROA : Return-on-Assets for firm i, in year t,

AGE : Age of firm,

LEV : Total debt of the firm scaled by total equity of for firm i, in year t,

Nmarg: : Net profit margin for firm i, in year t, Coefficients of β_1, β_2, β_3, β_4 and $\beta_5$will show the relationship between M-Score and size, return-on-assets, firm-age, net profit margins and leverage of the observations repectively.

3.RESULTS & DISCUSSION:

Table 1 presents the descriptive statistics for the variables used in the analysis, which include the Beneish M-Score, firm size (log of total assets), firm age, return on assets (ROA), net margin, and leverage (total debt to equity). The Beneish M-Score has a mean of -2.2751, with a standard deviation of 1.7058. The wide range of values, from -9.3075 to 15.5778, suggests significant variation in the likelihood of earnings manipulation across firms. Firm size, measured as the logarithm of total assets, has a mean of 13.3529 and a standard deviation of 1.8647, indicating a moderately dispersed firm size distribution with values ranging from 8.1825 to 18.9054.

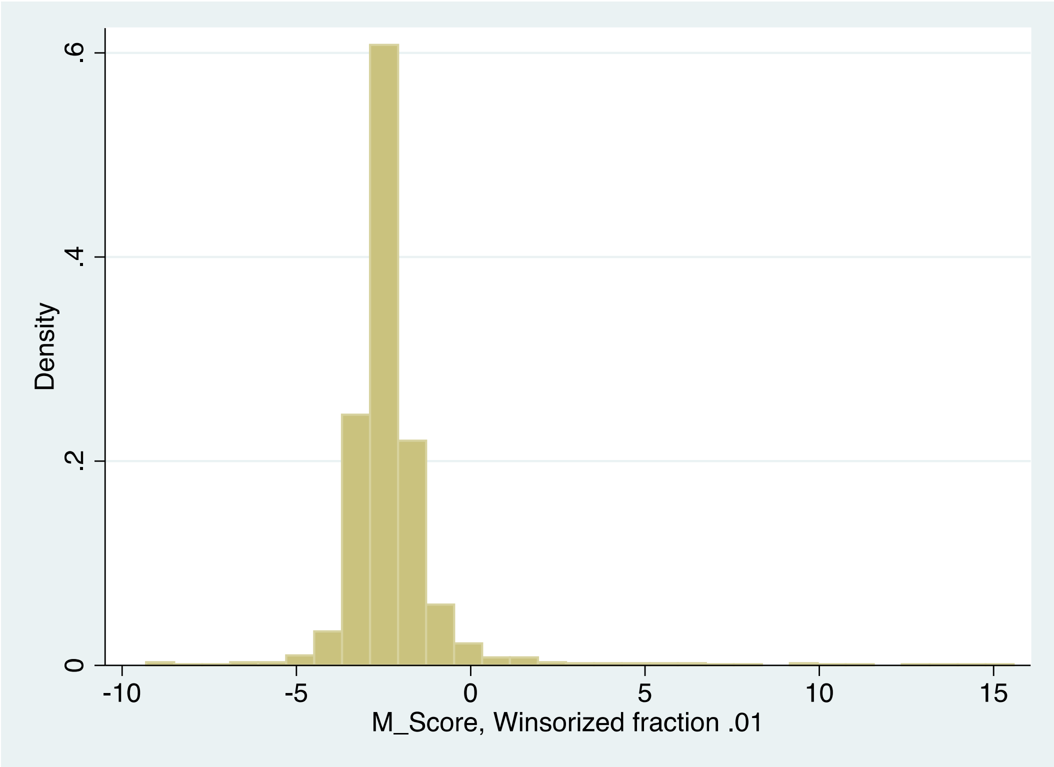
Table 1. Descriptive Statistics of Key Variables

Variables	Mean	Std. Dev.	Min	Median	Maximum
M - Score	-2.2751	1.7058	-9.3075	-2.5016	15.5778
SIZE	13.3529	1.8647	8.1825	13.2593	18.9054
AGE	18.6082	9.7544	0	21	34
ROA	7.7012	9.5612	-26.43	7.0950	44.2500
NMarg	4.4928	15.4123	-68.6000	4.9000	50.2800
LEV	127.6714	210.7227	2.02	71.1900	1467.320

The average firm age in the sample is 18.6082 years, with a standard deviation of 9.7544, suggesting a mix of both younger and older firms, with ages ranging from newly established firms to as old as 34 years. In terms of efficiency, firms have an average ROA of 7.7012%, but the large standard deviation of 9.5612, along with the range from -26.43% to 44.25%, points to considerable heterogeneity in financial performance. Net margin, which averages 4.4928%, also exhibits substantial variability, with a standard deviation of 15.4123 and values spanning from -68.60% to 50.28%. Finally, leverage, measured as the ratio of total debt to total equity, shows the highest level of variability among all variables. The mean leverage is 127.6714%, with an exceptionally large standard deviation of 210.7227, and ranges from 2.02% to as high as 1467.32%. This suggests that some firms are highly leveraged, while others maintain lower levels of debt relative to equity.

Figure-1 presents the distribution of M-Scores of the each firm-year in the sample. As this histogram visualises the distribution of the Beneish M-Score, where a winsorisation (at 0.01) has been applied. The X-axis (M_Score, Winsorised fraction .01) of the grapg represents the Beneish M-Score values, with a range approximately from -10 to +15. Winsorisation at 0.01 implies that extreme values have been adjusted to limit outliers' influence, and Y-axis shows the relative frequency of observations for each M-Score range, with the peak reaching around 0.6. The histogram is highly skewed to the right, with the majority of the M-Score values clustering around -3 to 0. The large peak around -3 suggests that most observations have an M-Score around this value. There are fewer occurrences of M-Scores on the right side of the distribution (positive values), indicating that extreme positive values of M-Score are rare.

Figure.1 Distribution of M-Scores



Source: Generated by the author.

This could imply that most of the firms in the sample exhibit financial characteristics that suggest lower likelihoods of financial manipulation, but there are some firms with extremely positive M-Scores, which could be candidates for higher risk of fraudulent behaviour.

Table-2 below presents the correlation matrix for the key variables in the analysis. The Beneish M-Score is negatively correlated with firm size and firm age, with significant coefficients of -0.1434 and -0.1465, respectively, suggesting that larger and older firms are less likely to engage in earnings manipulation. Return on assets and net margin also exhibit negative correlations with the M-Score, though only the correlation with net margin is significant (-0.1165), indicating that more profitable firms may engage in less manipulation.

Table 2. Correlation Matrix

	M - Score	SIZE	AGE	ROA	NMarg	LEV
M - Score	1.000					
SIZE	-0.1434*	1.000				
AGE	-0.1465*	0.4821*	1.000			
ROA	-0.0700	0.2623*	0.1189*	1.000		
NMarg	-0.1165*	0.2808*	0.1222*	0.8024*	1.000	
LEV	0.0812*	0.0064	0.0647	-0.2824*	-0.3352*	1.000

Firm size is significantly positively correlated with firm age (0.4821), ROA (0.2623), and net margin (0.2808), implying that larger firms tend to be older and more profitable. Additionally, ROA and net margin are highly correlated (0.8024), which is expected as both use profit figures as numerator and related with profitability. Leverage, on the other hand, shows a significant negative correlation with ROA (-0.2824) and net margin (-0.3352), indicating that firms with higher debt tend to be less profitable. Interestingly, leverage has a small but significant positive correlation with the Beneish M-Score (0.0812), suggesting that more leveraged firms may have a slightly higher likelihood of earnings manipulation.

Table 3. Regression Results

Variables	Coeff.	p-values
SIZE	-0.0768***	0.005
AGE	-0.0186***	0.001
ROA	0.0148	0.233
NMarg	-0.0137*	0.073
LEV	0.0051**	0.040
Adj-R Square	0.1417	
Obs.	1,256	

Table-3 presents the results of the regression analysis examining the relationship between various firm-specific variables and the Beneish M-Score, a key indicator of financial misreporting. The analysis includes five independent variables: firm size (SIZE), firm age (AGE), Return on Assets (ROA), net margin (Nmarg), and leverage (LEV), with their corresponding coefficients and p-values. The significance of the coefficients is denoted by asterisks, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The regression results indicate that firm size (SIZE) has a negative coefficient of -0.0768, which is statistically significant at the 1% level (p-value = 0.005). This finding suggests that larger firms are less likely to engage in financial misreporting, as reflected by a lower Beneish M-Score. The negative relationship may be attributed to the higher scrutiny and accountability that larger firms face from auditors, regulators, and the public. Thus, the results align with the notion that increased external oversight diminishes the likelihood of fraudulent reporting. Similarly, the coefficient for firm age (AGE) is -0.0186, also statistically significant at the 1% level (p-value = 0.001). This negative relationship indicates that older firms tend to have lower Beneish M-Scores, suggesting that established firms may possess stronger governance structures and reputational incentives that deter financial misreporting. As firms age, their commitment to maintaining a good standing in the market becomes more pronounced, thereby reducing the temptation to manipulate earnings. In contrast, the coefficient for Return on Assets (ROA) is 0.0148, with a p-value of 0.233, indicating that this variable does not have a statistically significant impact on the Beneish M-Score. The lack of significance suggests that profitability, when measured solely by ROA, does not serve as a reliable indicator of financial reporting quality or the propensity for misreporting. This finding highlights the complexity of the relationship between profitability and financial manipulation, suggesting that additional factors may play a more pivotal role in influencing reporting behaviour. The variable net margin (Nmarg) has a coefficient of -0.0137, with a p-value of 0.073, indicating a marginally significant negative relationship at the 10% level. This suggests that higher net margins are associated with lower Beneish M-Scores, implying that more profitable firms are less inclined to engage in earnings manipulation. While the evidence is not as robust as for SIZE and AGE, it nonetheless points to the notion that financial health may provide firms with less incentive to resort to fraudulent reporting practices. Finally, leverage (LEV) exhibits a positive coefficient of 0.0005, which is statistically significant at the 5% level (p-value = 0.040). This finding indicates that higher leverage is associated with an increased likelihood of financial misreporting, suggesting that firms under financial distress may engage in earnings manipulation to mask their true financial condition. The pressure associated with high levels of debt can lead management to adopt aggressive accounting practices to present a more favourable image to investors and creditors.

The adjusted R-squared value of 0.1417 indicates that approximately 14.17% of the variance in the Beneish M-Score can be explained by the independent variables in the model. While this suggests that there are additional factors influencing the likelihood of financial misreporting, the significant relationships identified in this analysis underscore the importance of firm-specific characteristics in assessing financial reporting integrity. Overall, these results contribute valuable insights into the determinants of financial misreporting, highlighting the critical role of firm size, age, net margin, and leverage in shaping corporate behaviour in financial reporting contexts.

CONCLUSION

This study set out to examine the relationship between firm-specific factors and financial misreporting, as measured by the Beneish M-Score, using a sample of manufacturing firms listed on Borsa Istanbul (BIST) from 2013 to 2023. By employing a Panel Data Fixed Effect Model, the analysis uncovered significant negative relationships between Beneish M-Score and firm size, firm age, and net margin. These findings indicate that larger, older, and more profitable firms are less likely to engage in financial misreporting. This aligns with the broader literature suggesting that firms with greater resources, more established reputations, and higher profitability are subject to greater scrutiny and have stronger internal controls in place, which reduces the likelihood of fraudulent reporting. Interestingly, the study found no significant relationship between Beneish M-Score and Return on Assets (ROA), suggesting that efficiency alone may not be a sufficient deterrent against financial manipulation. This result reinforces the view that while efficiency is an important factor, it must be considered alongside other characteristics to fully understand the drivers of financial misreporting. The implications of these findings are twofold. First, for regulators and auditors, firm size, age, and profitability margins can serve as useful indicators for identifying firms less likely to manipulate their financial reports, allowing them to focus on firms that present higher risks. Second, the results contribute to the academic debate on the role of efficiency in financial fraud detection, providing further evidence that efficiency measures like ROA may not always be reliable indicators of misreporting. In conclusion, this study contributes to the understanding of firm-specific factors that influence financial reporting practices in the context of an emerging market. Future research could extend these findings by incorporating additional firm characteristics or by exploring different industry sectors to assess the generalisability of the results. Additionally, examining the role of governance mechanisms and external monitoring in deterring financial misreporting could provide deeper insights into preventing fraudulent behaviour across firms.

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