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THE RELATIONSHIP OF Z-SCORE AND BENEISH M-SCORE: EVIDENCE FROM MALAYSIAN PUBLIC LISTED COMPANIES

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Abstract: Public listed companies frequently struggle to maintain their financial performance to meet the stakeholders' expectations. Hence, some corporations are compelled to participate in earnings manipulations. This study aims to examine the association of Altman's Z-score, the proxy for financial distress or bankruptcy, with the tendency to engage in earnings manipulation practices using the Beneish M-score. From 2014 to 2018, between 31% and 39% of yearly sampled companies were categorised as potential earnings manipulators. Moreover, 1,125 out of 3,242 observations were classified as manipulators and approximately half were in the bankrupt zone. The regression analysis demonstrated that the Z-score was significantly related to the M-score, indicating that firms in financial distress tend to engage in earnings manipulation. The study is practically significant through encouraging investors to be cautious in investment decision-making. The study provides opportunities for future research while making a significant scholarly contribution to the literature on accounting and fraud.

Keywords: Earnings manipulation, beneish M-score, financial distress, Z-score, Malaysia.

Introduction

Companies that comply with the Bursa Malaysia Listing Requirements are Malaysian public listed companies (PLCs) (Bursa Malaysia Securities Berhad, 2018). Meanwhile, those who have experienced financial challenges or distress with substantial losses or possible bankruptcy will be listed under Practice Notes 4 and 17 of Bursa Malaysia Listing Requirements (Mohamed Sadique *et al*., 2010). This case pressures the financially distressed companies to manipulate their earnings or smoothen their income to lure or deceive the public of their excellent performance (Bisogno & De Luca, 2015). Nonetheless, Malaysian businesses have long struggled with earnings manipulation, particularly those listed on Bursa Malaysia. Notably, corporate financial scandal cases in the world such as Enron, Satyam, and Volkswagen and in Malaysia such as Lembaga Tabung Haji and IMDB have sparked the attention of more researchers to study the extent of earnings manipulation amongst listed companies (Hashim *et al*., 2020; Mohammed *et al*., 2021).

PLCs generally encounter the dilemma of constantly improving their financial performance, particularly meeting the analysts' targets, maintaining debt covenants, and ensuring earnings growth. Companies in financial distress manipulate earnings more frequently than those in good financial standing (Bisogno & De Luca, 2015). This situation is driven by the complex economic performances that leave companies no choice but to commit manipulations as they struggle to remain listed in the stock exchange market.

Distressed firms are also pressured to maintain growth. Managers try their best to smooth out the earnings to attract more potential investors and retain existing investors. Nonetheless, the earnings can be relatively volatile in reality or not consistently smooth, which raises the concern of scaring off the investors, or they would switch to other competitors.

Amidst globalisation, Malaysia remains one of the countries that struggle to withstand the current economic crisis of recession and the phenomenal inflation rate over recent years (PricewaterhouseCoopers, 2016; 2018). The PricewaterhouseCoopers' "Global Economic Crime and Fraud Survey 2018" noted Malaysia as one of the central focuses worldwide because of the recent scandal speculated to be a political connection. The scandal indirectly affects the national economic growth and perceptions towards financial performance and Malaysian companies' accounting practices (PricewaterhouseCoopers, 2018). Thus, the situation has raised public concern and attention to provide reasons to evaluate further the financial performance of Malaysian companies, particularly those listed under Bursa Malaysia.

Research and investigation on earnings manipulations in listed companies are insufficient, given that such companies may do their best not to be delisted once listed under Bursa Malaysia. Companies may attempt to retain their current investors and lenders as well as attract potential ones. Given the lack of professional guidance and management fraud expertise, researchers, and practitioners have created decision aids or models to predict corporate fraud (Mock *et al*., 2017). Based on the Beneish M-score and Altman Z-score models' widespread usage and applicability in identifying fraudulent financial reporting, Kukreja *et al*. (2020) examined their effectiveness for the early detection of substantial misstatements at Comscore, Inc., a media analytics business in the United States.

PricewaterhouseCoopers (2016) stated that there is low awareness amongst Malaysian companies as they often lag in conforming to the risk assessments and control mechanisms to withstand financial crime, where the size and complexity change over the years. Hence, the present study investigates whether the financially distressed companies represented by the Z-score have a propensity to manipulate their earnings, as represented by the Beneish M-score. The paper is further structured as follows. Section 2 presents the literature review, Section 3 proposes the hypotheses, and Section 4 shows the research methodology. Sections 5 and 6 are data analysis and discussion, respectively. Finally, Section 7 concludes the study.

Literature Review

Earnings Manipulations and Beneish M-score Model

Messod Daniel Beneish created the Beneish M-score model in 1999 to identify earnings manipulations. Investors can use this mathematical or statistical equation, which comprises eight accounting variables, as a screening tool for their investment (Beneish, 1999; Aris *et al*., 2013). The Beneish model can also be efficiently employed as the data can be extracted from annual reports. Users could use the financial data gathered to measure or calculate eight ratios or accounting variables to screen whether distorted amounts are due to earnings manipulation or another fundamental cause (Beneish, 1999). Beneish (1999) listed eight accounting variables (also known as the financial ratios or indexes): 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); total accruals to total assets (TATA), and leverage index (LVGI). The model is widely used because it is affordable and only needs accounting data from the past two years (Beneish, 1999; Aris *et al.*, 2013).

Companies commonly commit earnings manipulation to a certain extent that is considered aggressive and would be deemed fraudulent. Financial statement fraud is a serious issue for all investors or lenders, involving massive losses to the companies and their users. Hence, the Beneish model is utilised as a detection instrument to discover earnings manipulation (Kamal *et al*., 2016; Petrík, 2016; Repousis, 2016; Dimitrijevic *et al*., 2018; Özcan, 2018). Investors may use the model to analyse and detect the tendency of earnings manipulation and predict stock returns and red flags for fraud occurrence (Beneish *et al*., 2013).

By identifying possible manipulator firms, Kamal *et al.* (2016) noticed that the Beneish model is accurate in recognising financial statement deception. Moreover, the model is highly useful for the management to detect any irregularities and make adjustments to their financial report before submission to Bursa Malaysia. In sum, the model successfully assesses the possibility of financial fraud. Researchers, auditors, and enforcement organisations in Bursa Malaysia may use this model to conduct proper investigations and carry out enforcement actions (Kamal *et al.*, 2016).

Beneish (1999) and Repousis (2016) stated a greater possibility of earnings manipulation in the following situations: An abnormal increase in receivables, a poor or deflating gross profit margin, a decline in the asset quality, irregular inflation in revenues, inflation in working capital minus cash and depreciation, a higher increase in general expense, an exogenous increase in accruals compared with total assets, and an increase in leverage.

Arshad *et al*. (2015) used financial ratios, the Z-score and Beneish M-score models on 24 failed firms matched with 24 non-failed firms listed in Bursa Malaysia. They found that the accuracy of classifying business failure using the M-score was over 90% and roughly 83% for predictors of financial fraud. Sutainim *et al*. (2021) found only three statistically different ratios between companies that were likely and non-likely manipulators. Hence, it is only partially supported or accepted. The three ratios are SGI, TATA, and DSRI and they are associated with the inflation or overestimation of sales, revenues, and accruals, respectively. These measures show that Malaysian PLCs are likely earnings manipulators. The findings demonstrate the Beneish M-score's reliability and predictability in identifying potential profit manipulation.

According to Dikmen and Güray (2010), financial information studies may help spot earnings manipulation and enhance the significant role of financial ratios or indexes such as DSRI, GMI, TATA, and DINV. Furthermore, Tarjo and Herawati (2015) looked into 35 fraud companies and 35 non-fraud enterprises between 2001 and 2014 and found that GMI, DEPI, SGAI, and TATA are significant in identifying financial fraud. Bhavani and Tabi (2017) demonstrated that the M-score model's eight accounting variables varied or showed significant differences between two sample groups (manipulators and non-manipulators). By contrast, the Z-score only showed three out of five variables (ratios) to be significantly different in Toshiba Corporation. As a result, each of the eight M-score indexes successfully distinguishes between manipulators and non-manipulators.

Z-score Model in Detecting Financial Distress

The survival of the corporate world is increasingly challenging in the 21st century, including remaining sustainable in the long term. Companies are pressured to improve and maintain a good image and performance to remain relevant in the competitive sector (Ranjbar & Amanollahi, 2018). Most businesses are concerned about losing arrangements for financing agreements, losing future and current investors, and having their stock downgraded if they do not achieve the analyst's targets. Stakeholders may assist the company's plan to recruit and close other deals for revenues, investments, development, and projects. Businesses can achieve these targets if they maintain positive relationships with their stakeholders and exchange favourable financial expectations or strong capital market performance. As earnings and profits might fluctuate over time, achieving consistent and smooth earnings is not easy (Munjal *et al*., 2021; Repousis *et al.*, 2021). Therefore, managers who adhere to the theory that a company's financial performance is best reflected in its figures will be motivated to practice aggressive earnings management and manipulation in escaping the danger zone of financial distress.

The Multiple Discriminant Analysis of Altman Z-score uses data gathered from publicly available financial accounts to distinguish between surviving and failing organisations (Ishmah *et al*., 2022). The quantitative model could predict corporate financial distress. Maccarthy (2017) emphasised the strength of Altman Z-score in identifying financially distressed and non-financially distressed companies. The model utilises information from the financial statements and categorises the data into five independent variables to be analysed. The likelihood that the business will file for bankruptcy in the next two years will then be forecasted using the independent variables.

The model's applicability has restrictions that call for geographical or industry-specific model types. Specific industries with different characteristics cause limitations; hence, the model might be incompatible with all industries with exact prediction accuracy (Maccarthy, 2017; Sanobar, 2022). Meanwhile, the Z-score accuracy is influenced by the financial statement figures. Financial distress typically impacts businesses' financial performance because these businesses typically have significant leverage and poor liquidity, efficiency, and profitability (Azhar *et al*., 2021). Furthermore, as financially troubled businesses frequently commit fraud by faking financial statement data, financial distress is intimately connected to fraudulent financial reporting (Arshad *et al.*, 2015).

Five accounting variables or component ratios are used to calculate Z-score value, namely working capital to total assets (WCTA), retained earnings to total assets (RETA), earnings before interest and tax to total assets (EBITA), market value to total liabilities (MVTL), and net sales to total assets (NSTA). Previous studies found that these ratios influence predictability and sensitivity towards financial distress and bankruptcy (Odibi *et al*., 2015; Altman *et al*., 2017; Hasan *et al*., 2018; Nustini & Amiruddin, 2019; Tung & Phung, 2019; Toly *et al*., 2020; Aviantara, 2021; Mahmoud Elewa, 2022; Pratiwi *et al*., 2022; Rane, 2022).

Fraud Triangle Theory

Donald Cressey's fraud triangle theory identifies pressure, opportunity, and rationalisation as the three main fraud risk elements (Repousis, 2016; Omar *et al*., 2017; Drábková, 2018; Mohammed *et al*., 2021). These three factors explained the motivations behind those who committed fraud, including engaging in earnings manipulation practices. The management in a financially distressed organisation is pressured to meet their non-shareable financial demands and preserve the business's reputation in the eyes of its stakeholders, particularly investors, creditors, and stock analysts (Huang *et al.*, 2017; Aviantara, 2021). Therefore, managers would take advantage of any openings such as flaws or gaps in any aspect of management and internal control to influence their reports. This occurrence is further bolstered by managers' tendencies to justify their acts as being done with the best intentions as they think it will benefit their firm. This theory is in line with the notion that companies in financial distress often manipulate their earnings to meet the analyst's expectations, avoid having their stock downgraded, and protect the debt covenants that are important and beneficial for the company's sustainability and competitiveness in the global marketplace. Figure 1 depicts the framework for detecting fraud.

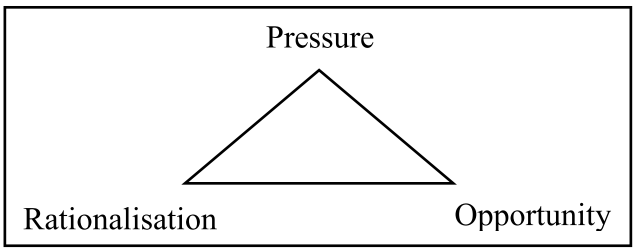
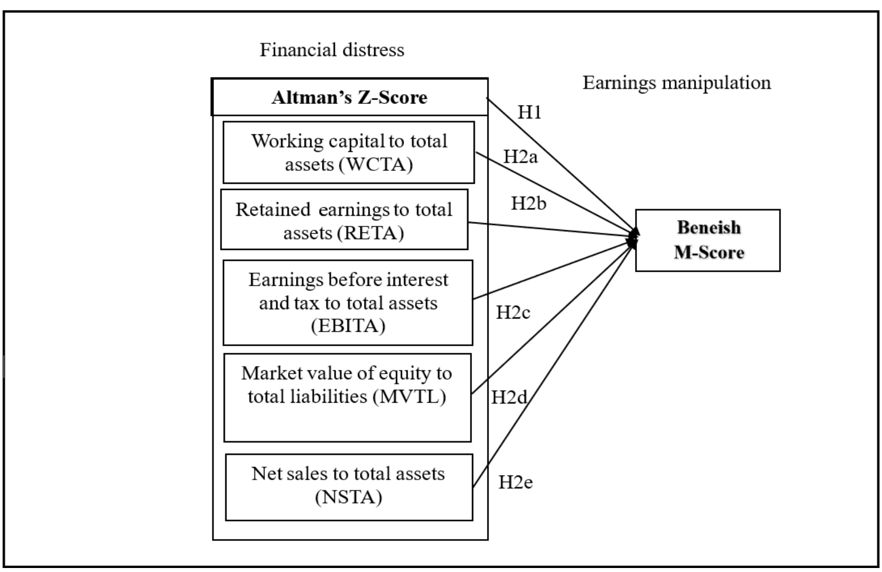


Figure 1: The Fraud Triangle by Donald Cressey in 1953

Framework and Constructs

Figure 2 shows the conceptual framework based on past studies. The independent variables of this study are Altman's Z-score model and the five accounting variables or ratios, which are the proxy for financial distress. The Beneish M-score model represents the dependent variable. Table 1 demonstrates the constructs tested in this study.



Figures 2: Research framework

Table 1: List of variables

Variables	Measurements	Descriptions	Authors
Dependent variables	Beneish the M-score model or M-score as a proxy to detect earnings manipulation M-score > -2.22 = Manipulators M-score < -2.22 = Non-likely manipulators	M = -4.84 + 0.92*DSRI + 0.528*GMI + 0.404*AQI + 0.892*SGI + 0.115*DEPI – 0.172*SGAI + 4.679*TATA – 0.327*LVGI where: M = Overall index DSRI = Days' sales in receivables index GMI = Gross margin index AQI = Asset quality index SGI = Sales growth index DEPI = Depreciation index SGAI = Sales, general and administrative expenses index TATA = Total accruals to total assets LVGI = Leverage index	(Mahama, 2015; Aghghaleh, Mohamed & Rahmat, 2016; Ahmed & Naima, 2016; Talab *et al.*, 2017; Chariri & Basundra, 2017; Hasan *et al.*, 2017; Lotfi & Chadegani, 2017; Maccarthy, 2017; Drábková, 2018; Aviantara, 2021; Mohammed *et al.*, 2021)
Independent variables	Altman's Z-score model or Z-score and its five-component ratios are used to represent financial distress. The five ratios are WCTA, RETA, EBITA, MVTL, and NSTA	Z = 1.2X1 + 1.4X2 + 3.3X3 + 0.6X4 + 1.0X5 where: Z = Overall index X1 = Working capital to total assets (WCTA) X2 = Retained earnings to total assets (RETA) X3 = Earnings before interest and tax to total assets (EBITA) X4 = Market value to total liabilities (MVTL) X5 = Net sales to total assets (NSTA) Z > **2.67** = Non-bankrupt zone (non-distress) **1.81** < Z < **2.67** = Grey zone Z < **1.81** = Bankrupt zone (distress)	(Mavengere, 2015; Altman *et al.*, 2017; Maccarthy, 2017; Hasan *et al.*, 2018; Tung & Phung, 2019; Aviantara, 2021; Mahmoud Elewa, 2022; Marginingsih, 2022; Pratiwi *et al.*, 2022)

Hypothesis Developments

Financially distressed companies perform poorly, which raises the possibility of case management participating in manipulating financial reporting (Liou, 2008). Furthermore, poor financial circumstances may imply a weakened control environment, which permits earnings manipulation. Strong governance is crucial for monitoring, scrutinising, and disciplining management to prevent fraudulent financial reporting (Arshad *et al.*, 2015). Financially distressed firms are more pressured to hide and manipulate the reports to impress stakeholders. According to the aforementioned justifications, the following hypothesis is proposed:

H1: Z-score is significantly related to Beneish M-score.

WCTA is one of the five accounting ratios included in the Z-score model to evaluate a company's liquidity and capacity to pay financial commitments. Prior studies proposed that this ratio can accurately predict financial distress (Pratiwi *et al.*, 2022). Investors view a company as performing well financially if it has a large or enough net working capital to cover potential liabilities. Therefore, managers will likely alter their results to conceal the actual state of their financially distressed organisation. They will adjust the accounts connected to networking capital to make it happen (Fisher *et al*., 2019). Consequently, the following hypothesis is created as follows:

H2a: Working capital to total assets (WCTA) is significantly related to Beneish M-score.

The second ratio in the Z-score model has RETA. Non-distributable profit to its shareholders is known as retained earnings (Odibi *et al*., 2015; Nustini & Amiruddin, 2019; Toly *et al*., 2020; Pratiwi *et al.*, 2022). When analysing a company's financial performance, investors believe that the value of retained earnings is the most essential component to consider (Hashim *et al.*, 2020; Aviantara, 2021; Munjal *et al.*, 2021; Repousis *et al*., 2021). They frequently smooth out their earnings through retained earnings to make it appear as if they are still making money. Accordingly, we propose the following:

H2b: Retained earnings to total assets (RETA) are significantly related to Beneish M-score.

The Z-score model's crucial ratio to identify financial distress in terms of profitability and productivity is the ratio of EBITA (Odibi *et al*., 2015; Nustini & Amiruddin, 2019; Toly *et al*., 2020; Pratiwi *et al.*, 2022). According to Toly *et al*. (2020), this ratio is significant because a higher ratio value implies a lower chance of bankruptcy. Thus, it can be assumed that a corporation is under pressure to falsify earnings by timing the transactions to create the appearance of a dire financial situation. The following hypothesis is proposed:

H2c: Earnings before interest and tax to total assets (EBITA) are significantly related to Beneish M-score.

The MVTL ratio indicates how much of a company's assets are supported by its' liabilities or debt. The importance of MVTL in predicting financial distress in a corporation was discovered because a problematic firm frequently faces the conundrum of needing to appear strong and confident in its capacity to pay off debts to win over stakeholders (Pratiwi *et al*., 2022). Therefore, the following hypothesis is proposed:

H2d: Market value to total liabilities (MVTL) is significantly related to Beneish M-score.

The fifth ratio in the Z-score model, known as net sales to total assets (NSTA) is used to determine how well a company is using its assets to create sales revenue (Mavengere, 2015; Maccarthy, 2017; Tung & Phung, 2019; Toly *et al*., 2020; Pratiwi *et al*., 2022). A financially distressed company may try to manipulate its earnings, particularly if sales accounts are involved (Rosner, 2003; Fisher *et al*., 2019). Thus, in light of the studies mentioned above, the following hypothesis is proposed:

H2e: Net sales to total assets (NSTA) is significantly related to Beneish M-score.

Research Methodology

This study employed a quantitative research methodology. Using the Beneish M-score model as the earnings manipulation detection tool, the study looked at the propensity of PLCs to be categorised as manipulators and non-manipulators. Regression analysis was also carried out to uncover the connection between the Altman Z-score, the Beneish M-score, and its components. This study used 3,242 observations of listed companies in the Malaysia Stock Exchange between 2014 and 2018 for variables based on the Beneish M-score and Altman Z-score. Except for those whose figures from the appropriate accounts have not yet been included in the database, all publicly listed traded non-financial firms that are available in the Thomson Reuters Eikon Database are extracted.

The financial distress of a company was determined using the Altman Z-score and the identification of earnings manipulation was examined using the Beneish M-score model. Additionally, regression analysis was used to investigate the relationship between financial distress and earnings manipulation. Purposive sampling was also utilised in the quantitative investigation.

Data Analysis

Descriptive Analysis

The annual scores for the sampled companies were obtained using the Beneish M-score model. The Beneish M-score was examined for any signs of possible or actual manipulation. A corporation is more likely to be a market manipulator if its score is greater than -2.22, whereas it is less likely to be a market manipulator if its score is less than -2.22 (Beneish, 1999). Table 2 presents the Beneish M-score based on the non-financial industry for the full sample from 2014 to 2018. Although the number of manipulators in each industry is still lower than that of non-manipulator companies, generalising the trend is impossible, of which the industry in this table has the biggest number of manipulators.

Table 2: Types of industry * year * type of company based on the beneish M-score cross-tabulation

Non-likely Manipulators (NM) Manipulators (M)	**Years**									
	2014		**2015**		**2016**		**2017**		**2018**	
Types of Industry	**NM**	**M**	**NM**	**M**	**NM**	**M**	**NM**	**M**	**NM**	**M**
Aerospace	0	1	0	1	0	1	0	1	1	0
Automobile	10	3	11	3	10	2	10	2	13	0
Banks	9		10		10		10		10	
Beverages	4	0	4	1	3	0	3	2	3	1
Chemicals	10	2	11	2	11	5	7	7	8	7
Constructions	34	26	30	32	42	22	46	20	35	29
Electricity	4	0	4	0	2	2	3	1	4	0
Electronic equipment	2	1	2	1	2	1	3	0	2	0
Financial services	6	6	6	4	6	5	4	7	10	3
FL telecommunication	7	2	5	5	7	4	6	5	6	4
Food and drug	2	0	1	2	1	2	3	0	1	1
Food producers	57	15	39	28	47	24	51	21	57	17
Forestry	9	2	9	4	6	6	12	1	8	5

Gas, water and multi-utilities	8	4	8	3	7	5	7	4	10	2
General industrials	16	10	17	9	22	5	14	11	20	5
General retailers	12	7	13	7	10	9	8	10	14	5
Healthcare equipment and services	8	1	5	4	7	3	9	1	5	6
Household goods and home construction	18	6	18	8	16	9	15	10	19	8
Industrial engineering	19	12	15	15	25	10	19	13	25	7
Industrial metals and mining	19	5	18	6	24	3	9	18	14	12
Industrial transportations	19	7	12	13	19	7	17	7	14	10
Leisure goods	4	1	3	3	2	3	2	5	4	1
Life insurance	1		1		0		0		1	
Media	4	2	2	5	5	1	2	3	0	4
Mining	0	0	0	0	0	1	1	0	0	1
Non-life insurance	7	1	8	0	7	1	8	0	8	0
Oil and gas producers	1	0	3	0	1	0	1	2	1	2
Oil equipment and services	9	13	16	3	16	2	11	7	14	2
Personal goods	19	5	16	9	15	9	17	6	18	6
Pharmaceuticals and biotechnology	5	0	3	5	7	1	5	2	4	2
Real estate investment and services	30	33	30	41	36	38	37	36	37	39
Real estate investment trust (REIT)	6	2	5	5	6	3	5	5	6	5
Software and computer services	17	15	18	16	20	16	21	15	27	11
Support services	15	3	15	5	15	6	13	8	16	7
Technology hardware and equipment	11	5	15	4	15	5	11	7	13	7
Travel and leisure	21	6	14	10	23	5	19	9	23	4
Unclassified	0		1		0		1		0	
Total	**423**	**196**	**388**	**254**	**445**	**216**	**410**	**246**	**451**	**213**

Table 3 shows the ratio of likely manipulators to non-likely manipulators in the sample of listed firms from 2014 to 2018. The information aids in identifying any pattern in the plot of earnings manipulation computed by the Beneish M-score over the study period. Generally, non-likely manipulator companies decreased by 8% from 2014 to 2015 and 4.5% from 2016 to 2017. Nonetheless, the results presented a slight increase in non-likely manipulators of 7% from 2015 to 2016 and 5.5% from 2017 to 2018.

Table 3: Types of company based on M-score * year (≪ one firm year)

Types of Company Based on M-score	Years					Total (%)
	2014	2015	2016	2017	2018	
Non-likely Manipulators (NM) (> -2.22)	423 (68%)	388 (60%)	445 (67%)	410 (62.5%)	451 (68%)	**2,117 (65%)**
Manipulators (M) (< -2.22)	196 (32%)	254 (40%)	216 (33%)	246 (37.5%)	213 (32%)	**1,125 (35%)**
Total (%)	**619 (100%)**	**642 (100%)**	**661 (100%)**	**656 (100%)**	**664 (100%)**	**3,242 (100%)**

Manipulator companies exhibited a slight increase in percentage by 8% from 2014 to 2015 and 4.5% from 2016 to 2017. The newly implemented Malaysian Code on Corporate Governance 2017 (MCCG 2017) in April 2017 by the Securities Commission Malaysia has not yet taken effect or is not powerful enough to be able to mitigate the problem of manipulation in the year 2017 (Boon *et al.*, 2017; PricewaterhouseCoopers, 2018). Nevertheless, a slight decrease of 7% was observed from 2015 to 2016 and 4.5% from 2017 to 2018. Summarily, during the study period, there were more non-likely manipulator companies (65%) than likely manipulator companies (35%). Therefore, 32% to 40% of yearly sampled companies are categorised with the tendency to be earnings manipulators.

Table 4 illustrates the zones based on the Z-score values in the entire sample of listed companies from 2014 to 2018. The Altman Z-score calculation allows for finding potential firms in financial difficulties during the research period. Generally, the non-bankrupt zone with a low possibility of the company facing bankruptcy decreased over the years, except in 2017, when there was a slight increase of 3.5%. The grey zone percentage decreased over the year except from 2015 to 2016, which remained constant at 15%. The bankruptcy zone exhibited a high possibility of companies facing bankruptcy over the years except for 2017, which demonstrated a slight decrease of 2.5%. Overall, the bankrupt zone had the highest percentage (54.5%) over the years, followed by the non-bankrupt zone (31%), and the lowest percentage was the grey zone (14.5%). The results suggested that a large number of PLCs in the sample study had a high possibility of bankruptcy.

Table 4: Zones based on Z-score values * year (≪ two firm years)

Zones Based on Z-score Values	Years					Total (%)
	2014	2015	2016	2017	2018	
Non-bankrupt zone (Low possibility)	202 (33%)	201 (31%)	195 (29.5%)	216 (33%)	190 (28%)	**1,004 (31%)**
Grey zone	99 (16%)	98 (15%)	99 (15%)	90 (14%)	84 (13%)	**470 (14.5%)**
Bankrupt zone (High possibility)	318 (51%)	343 (54%)	367 (55.5%)	350 (53%)	390 (59%)	**1,768 (54.5%)**
Total (%)	**619 (100%)**	**642 (100%)**	**661 (100%)**	**656 (100%)**	**664 (100%)**	**3,242 (100%)**

Table 5 demonstrates the percentage of zones based on the Z-score values grouped into type of companies based on the M-score for the entire sample of listed companies from 2014 to 2018. For non-likely manipulator companies, the percentage for the non-bankrupt zone, grey zone, and bankrupt zone is 63%, 61.5%, and 68%, respectively. Meanwhile, for manipulator companies, the percentage for the non-bankrupt zone, grey zone, and bankrupt zone is 37%, 38.5%, and 32%, respectively. Overall, 1,125 out of 3,242 total observations are classified as manipulators and 32% of the total observations are in the bankrupt zone.

Table 5: Types of company based on M-score * zones based on Z-score values cross-tabulation (≪ three firm years)

Types of Company Based on M-score	**Zones Based on Z-score Values**			**Total (%)**
	Non-bankrupt Zone (Low Possibility)	**Grey Zone**	**Bankrupt Zone (High Possibility)**	
Non-likely Manipulators (NM)	630 (63%)	289 (61.5%)	1,198 (68%)	**2,117 (65%)**
Manipulators (M)	374 (37%)	181 (38.5%)	570 (32%)	**1,125 (35%)**
Total (%)	**1,004 (100%)**	**470 (100%)**	**1,768 (100%)**	**3,242 (100%)**

Normality Test

The skewness and kurtosis observation values can be used to test the validity of the normality test (George *et al.*, 2010). The normal data distribution can be verified when the values of skewness and kurtosis are between -2 and 2 and -10 and 10, respectively. The skewness and kurtosis values of all the variables are within the allowed limits of 2.0 and 10.0, respectively, demonstrating the normal distribution of the financial data and earnings manipulation. The exceptionally high M-score has a kurtosis of 10.496. However, this is nevertheless considered to have a decently normal distribution because the difference between its real mean (1.60311) and 5% trimmed mean is only marginal or negligible (1.6026). Regardless of how marginally the degree of kurtosis exceeds the accepted threshold, according to Pallant (2001), an item or variable has an acceptable normal distribution if there is only a small discrepancy between the mean and the 5% trimmed mean. The M-score is a dependent variable in the regression. Additionally, the study's sample size is sizable and sufficient to demonstrate normality. The study used parametric statistical tools to evaluate the connection between financial distress and earnings manipulation.

Correlation Analysis

The correlation between financial distress and earnings manipulation was investigated using correlation analysis. The skewness and kurtosis values from the normality test indicated that the data had a normal distribution. Hence, correlation analysis was utilised in the study to identify any relationships between the variables. Table 6 presents the results of the correlation analysis.

Table 6: Correlation matrix

	WCTA	RETA	EBITDA	MVTL	NSTA	Z-SCORE	M-SCORE
WCTA	1						
RETA	.232**	1					
EBITA	-.172**	-.352**	1				
MVTL	.439**	.189**	-.283**	1			
NSTA	.214**	.417**	-.904**	.320**	1		
Z-SCORE	.529**	.361**	-.431**	.943**	.475**	1	
M-SCORE	.117**	0.031	-.115**	.073**	.156**	.092**	1

**Correlation is significant at the 0.01 level (2-tailed)

With a significant p-value below 0.01 and a correlation coefficient of 0.092, Table 6 shows that the correlation between earning manipulation and financial distress, as calculated using the Beneish M-score and Altman Z-score, respectively, is positively correlated and statistically significant. As a result, businesses in financial distress have a propensity to manipulate earnings. Only EBITA negatively affects the M-score but the other three Z-score model components, except for RETA are significantly associated with the M-score. Multicollinearity was further analysed employing variance inflation factor (VIF) and tolerance value and there appeared to have no multicollinearity concern. Nevertheless, EBITA is highly correlated with NSTA. Then, the regression analysis was conducted by dropping one variable and the results remained the same.

Regression Analyses

Regression for Z-score

The multicollinearity test was performed to determine if the variables are suitable for predicting independent variables and verifying that the variables are unbiased. Regression is justified as being within acceptable bounds when the tolerance value exceeds 0.10 and the VIF is less than 10. Regression is justified as being within acceptable bounds when the tolerance value is more than 0.10 and the VIF is below 10. Table 7 shows that the tolerance and VIF values are within the acceptable range, permitting a regression analysis. Financial distress was used as the independent variable and the M-score was the dependent variable in the regression equation. Tables 7 and 8 present the regression analysis summary statistics and multicollinearity test for Z-score, respectively.

Table 7: Model summary for Z-score

Model Summary										
					Change Statistics					
Model	R	R-square	Adjusted R-square	Std. Error of the Estimate	R-square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	0.092	0.008	0.008	0.0109	0.008	27.548	1	3240	0	1.864

Predictors: (Constant), Z-score
Dependent variable: M-score

Table 8: Multiple regression and multicollinearity for Z-score

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.	95.0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	1.598	0.001		1644.03	0	1.596	1.6		
	Z-score	0.006	0.001	0.092	5.249	0	0.004	0.008	1	1

Dependent variable: M-score

Regarding the association between financial distress and earnings manipulation calculated using the Z-score and M-score, respectively, the regression equation is statistically significant at the 0.05 significance level (p = 0.05). The coefficient of financial distress and earnings manipulation is 0.092, suggesting that a small increase in financial distress is connected to a small increase in earnings manipulation.

Regression Z-score (Each Independent Variable)

Table 10 demonstrates that the tolerance and VIF values are within the acceptable range, permitting the regression analysis to be conducted. The regression equation for the Z-score was estimated with financial distress as the independent variable in the study and the M-score as the dependent variable. Tables 9 and 10 show the results of the multicollinearity test and regression analysis for the M-score.

Table 9: Model summary for M-score

Model Summary										
Model	R	R-square	Adjusted R-square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R-square Change	F Change	df1	df2	Sig. F Change	
1	0.195	0.038	0.036	0.011	0.038	25.475	5	3236	0	1.876

Predictors: (Constant), NSTA, WCTA, RETA, MVTL, EBITA
Dependent variable: M-score

Table 10: Multiple regression and multicollinearity for M-score

Model	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	95.0% Confidence Interval for B		Collinearity Statistics	
	B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
C	1.557	0.011		144.203	0	1.536	1.579		
WCTA	0.018	0.004	0.099	5.076	0	0.011	0.025	0.783	1.278
RETA	-0.026	0.008	-0.062	-3.197	0.001	-0.042	-0.01	0.803	1.246
EBITA	0.072	0.021	0.137	3.398	0.001	0.031	0.114	0.182	5.482
MVTL	0	0.001	-0.013	-0.647	0.518	-0.002	0.001	0.753	1.327
NSTA	0.173	0.025	0.288	6.868	0	0.124	0.223	0.169	5.927

Dependent variable: M-score

The relationship between financial distress (WCTA, RETA, EBITA, and NSTA) and earnings manipulation is statistically significant at the 0.05 significance level (p = 0.05). Observably, only the independent variable MVTL exhibited statistical insignificance with a p-value of 0.518.

Nonetheless, the R-square value indicated that the independent variables only accounted for 3.8% of the variation in the dependent variables. Meanwhile, the coefficient of financial distress represented by WCTA, EBITA, and NSTA towards earnings manipulation is 0.099, 0.137, and 0.288, respectively. Hence, a slight increase in financial distress can be linked with a slight increase in earnings manipulation, except for RETA, with a coefficient of -0.062. Table 11 shows the results of the hypotheses.

Table 11: Results of hypotheses

	Hypotheses	Result
H1	Z-score is significantly related to Beneish M-score	Accepted
H2a	Working capital to total assets (WCTA) is significantly related to Beneish M-score	Accepted
H2b	Retained earnings to total assets (RETA) is significantly related to Beneish M-score	Accepted (negative)
H2c	Earnings before interest and tax to total assets (EBITA) is significantly related to Beneish M-score	Accepted
H2d	Market value to total liabilities (MVTL) is significantly related to the Beneish M-score	Rejected
H2e	Sales to total assets (NSTA) are significantly related to Beneish M-score	Accepted

Discussions

According to the Beneish M-scores findings, which were based on annual calculations between 2014 and 2018, the average proportion of non-likely manipulator companies is higher (65%) than the average proportion of manipulator companies (35%). A range of 32% to 40% of yearly sampled companies are classified as earnings manipulators. Based on Z-score values, the bankrupt zone has the highest average percentage (54.5%) over the years, followed by the non-bankrupt zone (31%), and the lowest percentage is the grey zone (14.5%). Thus, many PLCs with a percentage between 51% and 59% in the yearly sampled companies have a high possibility of facing bankruptcy. Furthermore, the study discovered that 1,125 out of 3,242 observations are classified as manipulators and 32% are from the bankrupt zone. This finding is consistent with the explanation of the fraud triangle theory (Cressey, 1953), where financially distressed firms are pressured to manipulate earnings to impress investors. There is an opportunity when there is a lack of good governance, internal control, and lack of monitoring from stakeholders and regulators. Firms rationalise these actions by claiming them to enhance future performance as part of their strategies.

The regression analysis on the link between financial difficulty and earnings manipulation is statistically significant at the 0.05 level ($p = 0.05$). The coefficient of financial distress and earning manipulation is 0.092, which indicates that a slight increase in financial distress can be linked with a small increase in earnings manipulation. A separate analysis was conducted on each independent variable of the Z-score that represents financial distress towards earnings manipulation (M-score). The regression equation results are statistically significant in the association between financial distress variables (WCTA, RETA, EBITA, and NSTA) and earnings manipulation at the 0.05 significance level ($p = 0.05$).

Nevertheless, as an independent variable, only MVTL with a p-value of 0.518 is statistically insignificant. By contrast, the coefficient of financial distress represented by WCTA, EBITA, and NSTA towards the earnings manipulation is 0.099, 0.137, and 0.288, respectively. However, the independent variable, represented by RETA has a coefficient of -0.062. This result indicates that a small increase in financial distress may be associated with a small increase in earnings manipulation. Accounts of this kind are typically subject to the managers' judgement. A company's retained earnings do not adequately or accurately represent its total financial performance. However, a low RETA value may also indicate that a firm may be in a financial crisis or have trouble generating profits (Toly *et al*., 2020; Pratiwi *et al*., 2022). Hence, managers are compelled to manipulate earnings to maintain their relevance in the market, which parallels the connotation of the fraud triangle theory.

Conclusions

This study reveals that the Beneish M-score model determines the likelihood of earnings manipulation practices in Malaysian PLCs. The results showed that several PLCs had been involved in earnings manipulation yearly from 2014 to 2018 and for the entire period. On average, 35% of the PLCs have manipulated their earnings. Moreover, the variables in the Z-score and the financial distress variable are useful in determining the likelihood that PLCs are engaged in earnings manipulation practices. The results demonstrated that 32% of the manipulator companies come from the bankrupt zone.

The industry seeks to identify practical probable earnings manipulation-detection tools or red flags for fraud occurrence as it is critical in reducing and preventing the high costs of potential fraud losses (Dalnial *et al.*, 2014; Omar *et al.*, 2014). The tool aids in protecting users, investors, lenders, and the public from hazards or earnings manipulations and assists in forming wise economic decisions. The study outcomes are practically significant as these findings warn the users, directors, and shareholders about the likeliness of companies to practice earnings manipulation if they are financially distressed. The outcomes of this study contribute to the literature that employs the fraud triangle theory; from the perspective of a developing country that actively engages in many fraudulent activities as a result of pressure, there is an opportunity and enough justification for the activity to be conducted.

The earning manipulation activity may further negatively affect the company. Additionally, the research string adds knowledge to the fraudulent reporting literature by highlighting the relationship between the two ratios. Fraud triangle theory can be further explored in explaining various organisation behaviors that halt the future development of organisations. Future comparative studies between Malaysian PLCs and small and medium enterprises, including those within the industry by comparing the firms' present and historical performance with that of the rivals can apply the approaches. Future studies will be very beneficial to stakeholders such as lenders and investors, including professionals such as auditors, forensic accountants, analysts, and academics.

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Conflict of Interest Statement

The authors agree that this research was conducted in the absence of any self-benefits, commercial, or financial conflicts and declare the absence of conflicting interests with the funders.

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