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# Application of Beneish M-Score Model in Detecting Probable Earnings Manipulation in Malaysian Public Listed Companies

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## Abstract

*A tool to detect or predict earnings manipulation would be helpful to the stakeholders, practitioners, regulators, academicians, and professionals in the accounting field. Besides, an early detection tool is needed to alarm agencies and relevant parties to make further investigations or pursue legal actions. Therefore, the current study analysed the effectiveness of Beneish M-Score models and its eight accounting variables to detect the likelihood to engage in earnings manipulation in the case of Malaysian PLCs (Public Listed Companies). The financial data of 80 of PLCs from 2015 to 2017 were gathered. This study applied Beneish M-Score Model as a detection tool for earnings manipulation and anomalies of red flags and to classify the companies into two groups, which are manipulators and non-likely manipulators. The Independent T-tests were analysed to identify dominating ratios. The results of this study found that M-Score and its three indexes were significantly different for manipulators and non-likely manipulators, which are Sales Growth Index (SGI), Total Accruals to Total Assets (TATA) and Days' Sales Receivable index (DSRI). The percentage of manipulators had slightly decreased in 2016 and gradually increased in 2017. Hence, the inflation or overestimation of sales and revenues, as well as accruals, could signal earnings manipulation*

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## 1. Introduction

Malaysian Public Listed Companies or PLCs are those companies that were found to meet the listing requirements issued by Bursa Malaysia (Bursa Malaysia Securities Berhad, 2018). The first requirement is that for three to five years, the profit after tax (PAT) of PLCs does not continuously exceed RM20 million. Next, the PLCs should have the least of RM 6 million for its PAT in the most recent financial years (Bursa Malaysia Securities Berhad, 2018).In order to meet the requirement of profit of Bursa Malaysia, some listed firms in Malaysia do engage in earnings management activities.

Earnings manipulation occurs with the act of violating the accounting rules and principles (Paolone & Magazzino, 2014). The Malaysian PLCs are known to have engaged in earnings management especially when it comes to the accruals transactions to avoid being delisted from Bursa (Arshad, Mohamed Iqbal, & Omar, 2015; Boon, Tze, & Lau, 2017; Fawzi, Kamaluddin, & Sanusi, 2015; Kamal, Salleh, & Ahmad, 2016; PricewaterhouseCoopers, 2018). Earnings manipulation and earnings management are helpful in appropriately reflecting the companies' performance in terms of earnings. This is because the companies' performance could be viewed from different aspects by not just only looking at the presence of cash. However, some companies may take it to an extreme level where they manipulate their earnings aggressively that it would be regarded as financial fraud. This criminal or unethical conduct would jeopardize the performance of companies in the long run.

The extent of earnings manipulations in Malaysian PLCs had been worrisome that it would lead to fraudulent financial reporting (Arshad et al., 2015; Boon et al., 2017; Kamal et al., 2016; Mohamed Sadique, Roudaki, Clark, & Alias, 2010; PricewaterhouseCoopers, 2016). As the companies may feel threatened by the global economic issues, plus the current scandal faced by some of the leading companies might tarnish their reputation. Hence, they attempt to make their financial reports, especially their earnings, to look good in the eye of investors. The idea behind this is that by showing impressive and positive earnings with hopes that they could lure or influence the users in believing and having the idea that the companies are actually doing fine and performing well. However, the reality is that earnings manipulations and financial statement fraud are still happening among companies, of which it cost a huge deal that could jeopardize the company (Young & Peng, 2013).

Due to earnings manipulation activities, the investors are exposed to risk to invest in problematic companies. Hence, a tool is required to detect any probable earnings manipulations or red flags in a company which is convenient to use for investors, researchers, auditors, and enforcement agencies to take appropriate examination and execution for enforcement action. In this case, Beneish Model would be highly recommended (Kamal et al., 2016). The absence of professional guidance and a lack of experience with management fraud have led practitioners and researchers to develop models or decision aids for predicting management fraud (Hansen et al., 1996). Although there is greater attention had been paid in strengthening the enforcement and legislations, such Anti-Money Laundering and Anti-Terrorism Financing Act 2007 (AMLATFA) and Anti-Corruption Act 1997, it may just lead towards hazard than being helpful (PricewaterhouseCoopers, 2016). Hence, a model is needed to identify the tendency of a firm to engage in manipulations

Since there has been limited research on the degree of earnings manipulations practices in Malaysian context, as to what extent it becomes a trend that could lead to severe earnings manipulations and even worst to the probable of committing financial statement fraud. Therefore, this paper examines the Beneish M-score model and its eight accounting variables to identify the likelihood of Malaysian PLCs to engage in earnings manipulation. In the past, other studies have applied other forensic tools such as the Altman Z-Score, Benford's Law and financial statement analysis to detect earnings manipulations.

## 2. Literature Review

**Earnings Manipulation and Earnings Management**

The meanings of earnings management and earnings manipulation had been distinguished in terms of its practicality and technicality by previous researchers despite both concept are highly correlated (Bisogno & De Luca, 2015). Previously, the concept of earnings management (EM) is based on the Generally Accepted Accounting Principles (GAAP). It is stated that the essential part of engaging EM is to make earnings to be disclosed in the report is almost at a desired level of earnings in the eye of the users like the investors and public stakeholders (Bartov, 1993; Roy, & Debnath, 2015; Tibbs, 2003). Meanwhile, earnings manipulation is out of the league GAAP. However, the clear distinction could be perceived in terms of the magnitude of the misstatement or the intention of deceiving to exploit figures and numbers of the financial statements to delude through material modifications, which is more prominence or highlighted in earnings manipulation than in earnings management (Rezaee, 2005; Bisogno & Deluca 2015).

Earnings manipulation can be detected through examining the financial statements (Dalnial, Kamaluddin, Sanusi, & Khairuddin, 2014). The examinations in financial statements are necessary to evaluate a company's performance, financial health, and management control as it contains useful financial information for users to make economic decision as well to manage their resources (Lau & Ooi, 2016). Therefore, earnings manipulation should be curbed by way of having an effective tool to detect earnings manipulation or red flags for fraud.

Earnings manipulation is committed by the management to deceive the external users into believing that the company has always been performed well and has a good reputation in the industry. For instance, they may slightly loosen up the credit terms to accelerate the revenues or intentionally to report lower cost of goods sold. It can be done through the high amount of closing inventories resulting from overproduction, and also, the managers may purposely overlooked the Research and Development (R&D) projects (Roychowdhury, 2006; Chariri & Basundra, 2018; Dimitrijevic, 2015). Prior studies showed that earnings manipulation primarily done through the recognition and the process forecasting the companies' discretionary accruals of which in a way becomes the notable tunnel or tools to detect earnings manipulations (Dechow, Sloan, Sweeney, Sloan, & Sweeney, 1996; Healy, 1985; Jones, 1991). Generally, most often, manipulations can be in terms of depleting or not disclosing liabilities, accelerating the stock's value, simulating the cash inflow and outflow transactions inflating revenue, deflating expenses, and exploiting of receivables particularly in the timing of debt collection (Dimitrijevic, 2015).

Every organization especially the one whom listed in the stock exchange has the pressures to perform particular performances or events like to beat or meet the analysts' targets; to comply and maintain the debt covenants or lending agreements; and to achieve an acceptable standard of growth which in the context of having an upwards slope of earnings (Arshad et al., 2015; Healy, 1985; Paolone & Magazzino, 2014; PricewaterhouseCoopers, 2016). Managers used EM technique to manipulate their earnings due to the compliance of debt covenants or to maintain the lending agreements that at certain extend lead them to commit fraud when started to recognize the fictitious sales and other unethical conducts.

Based on the prior studies, Beneish M-Score model are widely used as a tool to detect earnings manipulation and financial fraud (Aghghaleh, Mohamed, & Rahmat, 2016; Aris et al., 2013; Arshad et al., 2015; Dimitrijevic, Obradović, & Milutinović, 2018; Kamal et al., 2016; Mahama, 2015; Omar, Koya, Sanusi, & Shafie, 2014; Repousis, 2016). This is due to its comprehensive measurement that comprises of eight indexes or accounting variables that cover both accruals and cash flow perspectives.

**Beneish M-Score Model as a Tool to Detect Earnings Manipulation and Financial Fraud**

Messod Daniel Beneish developed Beneish M-Score model in 1999. This model is a mathematical or statistical equation that has eight accounting variables that were developed to detect earnings manipulations, and it is also helpful for professional investors to use it as a screening device (Beneish, 1999; Aris et al., 2013). The eight accounting variables or financial ratios and indexes suggested by Beneish (1999) were adopted and combined to create an M-Score. This model can be applied in firms with the condition that two years financial data are available to calculate the ratios in measuring the tendency of a firm to engage in earnings manipulations (Beneish, 1999; Aris et al., 2013; Shanmugam, Nair, & Suganthi, 2010**;** Kara, Uğurlu, & Körpi, 2015)**.**

Beneish (1999) found that the probit-model developed could identify 76% manipulators based on the financial data gathered from 74 firms within 1982 to1992. This model is widely used due to its cost-effective, which it only requires at least two years of accounting data which can be easily gathered from financial statements (Beneish, 1999; Aris et al. 2013).

**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**

**Table 1. The Formula of Eight Indexes or Accounting Variables of Beneish M-Score Model (1999).**

| Ratios | Formula |
|---|---|
| Days' sales in receivable index (DSRI) | (Receivables t / Sales current year t ) / (Receivables t-1 / Sales prior t-1) |
| Gross margin index (GMI) | [(Sales t-1 / Cost of goods sold t-1) / Sales t-1] / [(Sales t / Cost of goods sold t) / Sales t] |
| Asset quality index (AQI) | [1-(Current assets t + PPE t / Total assets t)] / [1-(Current assets t-1 + PPE t-1 / Total assets t-1)] |
| Sales growth index (SGI) | Sales t / sales t-1 |
| Depreciation index (DEPI) | [Depreciation t / (Depreciation t + PPE t)] / [Depreciation t-1 / (Depreciation t-1 + PPE t-1)] |
| Sales, general, and administrative expenses index (SGAI) | (Sales, general and administrative expenses t / Sales t) / (Sales, general and administrative expenses t-1 / Sales t-1) |
| Total accruals to total assets (TATA) | (Total current assets t - Total cash - Total current liabilities t - Total long term debts t - Income Tax payable t - Depreciation and amortization t ) / Total assets t |
| LVGI (Leverage Index) | [(Total long term debt t + current liabilities t) / Total assets t] / [( Total long term debt t-1 + current liabilities t-1) / Total assets t-1] |

Notes: t = Current year; t-1 = Prior year; PPE = Property, plant and equipment.

The eight variables would not only be used to detect earnings manipulation but also incentives for possible or likelihood of fraud which allow users and forensic accountants to indirectly assess companies' performance in different angles as this model is primarily used and acceptable in not only corporate, institutional but also in educational purposes (Kumar et al., 2018; Petrík, 2016; Omar, Koya, Sanusi, & Shafie, 2014, Özcan, 2018; Repousis, 2016; Tarjo & Herawati, 2015; Dimitrijevic, Obradović, & Milutinović, 2016; Kamal, Salleh, & Ahmad, 2016; Aghghaleh, Mohamed, & Rahmat, 2016; Ahmed & Naima, 2016)..

An M-Score with more than -2.22 proposed that the company is likely to be a manipulator and if smaller than -2.22, then it signals that the company is a non-manipulator company (Beneish, 1999; Kumar et al., 2018; Petrík, 2016; Omar et al., 2014, Özcan, 2018; Repousis, 2016; Tarjo & Herawati, 2015; Dimitrijevic et al., 2016; Kamal et al., 2016; Aghghaleh et al., 2016; Ahmed & Naima, 2016). Each of the M-Score's variables could be distinguished or assessed independently to assist in investigating which part in the financial statement is affected or manipulated the most. In order to complement this, based on the mean score calculated, Beneish (1999) proposed a defined threshold for each of the eight accounting variables to assist in scrutinizing the likely manipulators and non-likely manipulators which are the followings:

**Table 2. The Threshold for Eight Accounting Variables of Beneish M-Score based on Beneish (1999).**

| Index Type | Manipulators | Non-Manipulators |
|---|---|---|
| DSRI | 1.465 | 1.031 |
| GMI | 1.193 | 1.014 |
| AQI | 1.254 | 1.039 |
| AGI | 1.607 | 1.134 |
| DEPI | 1.077 | 1.001 |
| SGAI | 1.041 | 1.054 |
| LVGI | 1.111 | 1.037 |
| TATA | 0.031 | 0.018 |

DSRI, AQI, DEPI, and TATA are used to detect misrepresentation or falsification of financial statements due to earnings manipulation. Meanwhile, the other four variables, which are SGI, SGAI, GMI, and LVGI, are used to identify the signs of the tendency to engage in earnings manipulations (Repousis, 2016). Generally, all the combination of eight ratios or indexes of the M-score model showed that the revenue increases and cost postponement or decrease, is impossible to occur without manipulating assets or liabilities. This further deduced that this model could be helpful to stakeholders like managers, regulators, auditors, bankers, enforcement agencies, and forensic accountants in deterring fraud and identifying red flag. Hence, corresponding to the prior studies mentioned above, the main hypothesis is drawn as follows:

**H1:** There are significant differences in the eight accounting variables of Beneish M-Score Model from manipulator companies and non-manipulator companies.

Additionally, in order to support the main hypothesis, the sub-hypotheses **H1a, H1b, H1c, H1d, H1e, H1f, H1g,** and **H1h** are developed.

**H1a:** There is a significant mean difference between manipulator companies and non-manipulator companies for DSRI.
**H1b:** There is a significant mean difference between manipulator companies and non-manipulator companies for GMI.
**H1c:** There is a significant mean difference between manipulator companies and non-manipulator companies for AQI.
**H1d:** There is a significant mean difference between manipulator companies and non-manipulator companies for SGI.
**H1e:** There is a significant mean difference between manipulator companies and non-likely manipulator companies for DEPI.
**H1f:** There is a significant mean difference between manipulator companies and non-likely manipulator companies for SGAI.
**H1g:** There is a significant mean difference between manipulator companies and non-manipulator companies for TATA.
**H1h:** There is a significant mean difference between manipulator companies and non-manipulator companies for LVGI.

## 3. Research Methods

This study examines 80 non-financial public listed companies in Malaysia for three consecutive years from 2015 to 2017, where the data is extracted from the Thomson Reuters Eikon database with the final samples are 140 samples. There are two (2) groups of variables (manipulator companies and non-likely manipulator companies) offered in this current study, which are calculated by using the Beneish M-score Model. Messod Daniel Beneish designed the Beneish M-Score model in 1999, whereby this mathematical or statistical equation has eight accounting variables or ratios. The ratios developed to detect earnings manipulations which are helpful for professional investors to apply these eight accounting variables as the screening devices (Beneish, 1999; Aris et al., 2013). The eight indexes or ratios are Days' Sales Receivable Index (DSRI), Gross Margin Index (GMI), Asset Quality Index (AQI), Depreciation Index (DEPI), Sales Growth Index (SGI), Sales, General and Administrative Index (SGAI), Total Accruals to Total Assets (TATA) and Leverage Index (LVGI).

## 4. Results

Table 3 showed the proportions of manipulators and non-likely manipulators in the selected sample of PLCs for 2015, 2016, and 2017 respectively. This helps to discover whether there is any pattern or trend in the overall plot of earnings manipulation from 2015 to 2017. For overall companies, there are 32 manipulators, which are less than 30% have been detected by using M-Score and a total of 108 of non-likely manipulators, which was greater than the total of manipulators. From the table, it is shown that the number of manipulators had decreased by 6.5%, which is two companies (N=7) in 2016 and surprisingly had increased by 20.8%, which is nine companies (N=16) in 2017. The increased numbers of manipulators indicated a bad sign that more companies were engaged in earnings manipulations in 2017. One of the control mechanisms taken prior to the increased of the manipulators, a new revised Malaysian Code on Corporate Governance 2017 ("MCCG 2017") had been introduced in April 2017 by the Securities Commission Malaysia because to control any possible problematic events in relation to companies management which would affect the occurrence of earnings manipulation which in a way would decrease the possible threat, hazard or fraud risks (Boon et al., 2017). Hence, the manipulators increased in 2017 could notably be due to the inefficacy of the regulations or legislation enforcement in regards with the newly MCCG of 2017 had not yet taking into fully effect towards the first preceding year as it was only released on April 2017 (Boon et al., 2017; PricewaterhouseCoopers, 2018).

**Table 3. Classification of Manipulators and Non-likely Manipulators Companies**

| | 2015 | 2016 | 2017 | Total |
|---|---|---|---|---|
| Manipulators (M-Score>-2.22) | 9 | 7 | 16 | 32 |
| | 20.50% | 14.00% | 34.80% | 22.90% |
| Non-likely Manipulators (M-Score<-2.22) | 35 | 43 | 30 | 108 |
| | 79.50% | 86.00% | 65.20% | 77.10% |
| Total | 44 | 50 | 46 | 140 |
| | 100.00% | 100.00% | 100.00% | 100.00% |

Table 4 shows the summary of overall descriptive results together with the value of threshold limit for each index, which was set by Beneish in 1999. If a company was to have indexes' value above the threshold limit, it deems that the company deemed to manipulate the respective input variables for that particular index. The highest mean among the eight accounting variables of Beneish Model for all companies are Days' Sales Receivable Index (DSRI) of 1.114 with the minimum value of 0.298 and the highest value of 2.492 and the lowest mean among the eight accounting variables is TATA which is -0.033 (Min= -0.288, Max=0.201). The highest variable mean, which is DSRI, indicates that there is a probability of companies to change their credit policy to boost up sales due to the competitive environment. However, abnormal increases in receivables to sales could also signal revenue inflation (Beneish, 1997, 1999). A significant inflation in this index may due the consignment sales recorded as trade receivables, the short credit terms imposed to debtors to earn immediate income, profit or earnings of the company and might as well due to the presence of trade receivables from current accounts of group companies (Aghghaleh et al., 2016; Dikmen & Güray, 2010; Warshavsky, 2012).

**Table 4. Descriptive Statistics of All Companies *(N=140)***

| | DSRI | GMI | AQI | SGI | DEPI | SGAI | TATA | LVGI |
|---|---|---|---|---|---|---|---|---|
| Minimum | 0.298 | -0.559 | 0 | 0.598 | 0.703 | 0.582 | -0.288 | 0.419 |
| Maximum | 2.492 | 2.115 | 2.001 | 1.942 | 1.233 | 2.002 | 0.201 | 1.547 |
| Mean | 1.114 | 0.994 | 0.926 | 1.027 | 0.977 | 1.065 | -0.033 | 1.003 |
| Std. Deviation | 0.344 | 0.269 | 0.394 | 0.185 | 0.109 | 0.239 | 0.083 | 0.186 |
| Index Threshold Limit | 1.465 | 1.193 | 1.254 | 1.607 | 1.077 | 1.041 | 1.111 | 0.031 |
| Companies above threshold limit | 16 | 16 | 11 | 2 | 26 | 70 | 0 | 140 |
| Companies above threshold limit (%) | 11% | 11% | 8% | 1% | 19% | 50% | 0% | 100% |

Based on table 5, DSRI has the highest mean for manipulators with 1.372 (maximum=2.49, minimum=0.79, and standard deviation=0.457), and the lowest mean is M-Score of -1.759 (maximum=-0.52, minimum=-2.22 and standard deviation=-0.405). Similarly, table 6 show that DSRI has the highest mean primarily in 2017 of 1.151 (maximum=2.49, minimum=0.56, and standard deviation=0.443). The result of the highest mean for manipulator companies is consistent with the prior study by Repousis (2016). Repousis (2016) found that for manipulators, results using F-distribution reflected that days sales in receivable index (DSRI), asset quality index (AQI), depreciation index, selling, general and administrative expenses index (SGAI), total accruals to total assets index and leverage index (LVGI) are significant at 99 per cent confidence level in its effect on Beneish M-score.

### Table 5. Descriptive Statistics of Manipulators *(N=32)* and Non-likely Manipulators *(N=108)*.

| | Mean | | Std. Deviation | | Minimum | | Maximum | |
|---|---|---|---|---|---|---|---|---|
| | Manipulators | Non-likely Manipulators | Manipulators | Non-likely Manipulators | Manipulators | Non-likely Manipulators | Manipulators | Non-likely Manipulators |
| DSRI | 1.37205 | 1.03725 | 0.457227 | 0.259099 | 0.795 | 0.298 | 2.492 | 1.955 |
| GMI | 1.05775 | 0.97472 | 0.251366 | 0.2722 | 0.558 | -0.559 | 1.852 | 2.115 |
| AQI | 0.99042 | 0.90684 | 0.360417 | 0.403169 | 0 | 0 | 1.757 | 2.001 |
| SGI | 1.15664 | 0.98854 | 0.238107 | 0.146205 | 0.766 | 0.598 | 1.942 | 1.511 |
| DEPI | 0.98151 | 0.97525 | 0.105892 | 0.110853 | 0.777 | 0.703 | 1.182 | 1.233 |
| SGAI | 1.00837 | 1.08144 | 0.235288 | 0.238733 | 0.604 | 0.582 | 1.757 | 2.002 |
| TATA | 0.0452 | -0.05668 | 0.065986 | 0.072921 | -0.035 | -0.288 | 0.201 | 0.146 |
| LVGI | 0.9869 | 1.00716 | 0.223636 | 0.174199 | 0.419 | 0.461 | 1.443 | 1.547 |

### Table 6. Descriptive Statistics of 2015 *(N=44)*, 2016 *(N= 50)* and 2017 *(N=47)*.

| | Mean | | | Std. Deviation | | | Minimum | | | Maximum | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 2015 | 2016 | 2017 | 2015 | 2016 | 2017 | 2015 | 2016 | 2017 | 2015 | 2016 | 2017 |
| DSRI | 1.11776 | 1.0764 | 1.15058 | 0.273182 | 0.294446 | 0.443243 | 0.606 | 0.298 | 0.566 | 2.012 | 1.955 | 2.492 |
| GMI | 0.98214 | 0.95816 | 1.04338 | 0.193038 | 0.335377 | 0.24768 | 0.224 | -0.559 | 0.564 | 1.328 | 2.115 | 1.852 |
| AQI | 0.96381 | 0.91461 | 0.90206 | 0.353271 | 0.412456 | 0.416163 | 0 | 0 | 0 | 1.65 | 2.001 | 1.896 |
| SGI | 1.01975 | 1.00997 | 1.05235 | 0.157513 | 0.169375 | 0.222278 | 0.778 | 0.655 | 0.598 | 1.615 | 1.519 | 1.942 |
| DEPI | 0.97399 | 0.99506 | 0.95927 | 0.107983 | 0.103089 | 0.116441 | 0.723 | 0.776 | 0.703 | 1.233 | 1.205 | 1.214 |
| SGAI | 1.08114 | 1.11396 | 0.99555 | 0.242768 | 0.250898 | 0.209458 | 0.614 | 0.582 | 0.604 | 1.757 | 2.002 | 1.711 |
| TATA | -0.03762 | -0.04246 | -0.01949 | 0.075672 | 0.087569 | 0.084904 | -0.234 | -0.288 | -0.236 | 0.201 | 0.168 | 0.162 |
| LVGI | 1.01144 | 0.98738 | 1.01048 | 0.168154 | 0.209664 | 0.177622 | 0.686 | 0.419 | 0.649 | 1.547 | 1.512 | 1.384 |

**Table 7. Independent Samples Test for the year 2015, 2016, and 2017**

| | | 2015 | | 2016 | | 2017 | |
|---|---|---|---|---|---|---|---|
| | | Sig. (2-tailed) | Mean Difference | Sig. (2-tailed) | Mean Difference | Sig. (2-tailed) | Mean Difference |
| DSRI | Equal variances assumed | 0.001 | 0.329599 | 0.134 | 0.180669 | 0.001 | 0.426881 |
| | Equal variances not assumed | 0.032 | 0.329599 | 0.131 | 0.180669 | 0.010 | 0.426881 |
| GMI | Equal variances assumed | 0.023 | 0.161789 | 0.935 | -0.01127 | 0.524 | 0.049553 |
| | Equal variances not assumed | 0.042 | 0.161789 | 0.913 | -0.01127 | 0.556 | 0.049553 |
| AQI | Equal variances assumed | 0.187 | 0.175523 | 0.490 | -0.11761 | 0.228 | 0.156744 |
| | Equal variances not assumed | 0.094 | 0.175523 | 0.539 | -0.11761 | 0.205 | 0.156744 |
| SGI | Equal variances assumed | 0.045 | 0.117096 | 0.000 | 0.270427 | 0.040 | 0.140024 |
| | Equal variances not assumed | 0.171 | 0.117096 | 0.010 | 0.270427 | 0.071 | 0.140024 |
| DEPI | Equal variances assumed | 0.789 | -0.01097 | 0.207 | 0.053429 | 0.823 | 0.008204 |
| | Equal variances not assumed | 0.752 | -0.01097 | 0.283 | 0.053429 | 0.817 | 0.008204 |
| SGAI | Equal variances assumed | 0.481 | 0.064836 | 0.190 | -0.13484 | 0.217 | -0.08063 |
| | Equal variances not assumed | 0.564 | 0.064836 | 0.116 | -0.13484 | 0.206 | -0.08063 |
| TATA | Equal variances assumed | 0.000 | 0.107125 | 0.000 | 0.120885 | 0.001 | 0.086184 |
| | Equal variances not assumed | 0.003 | 0.107125 | 0.003 | 0.120885 | 0.000 | 0.086184 |
| LVGI | Equal variances assumed | 0.248 | 0.073299 | 0.206 | -0.10886 | 0.418 | -0.04514 |
| | Equal variances not assumed | 0.348 | 0.073299 | 0.325 | -0.10886 | 0.461 | -0.04514 |
| M-Score | Equal variances assumed | 0.000 | 1.02819 | 0.000 | 0.98453 | 0.000 | 1.03994 |
| | Equal variances not assumed | 0.000 | 1.02819 | 0.000 | 0.98453 | 0.000 | 1.03994 |

Notes: DSRI = Days' Sales Receivable Index; GMI = Gross Margin Index; AQI =Asset Quality Index; SGI = Sales Growth Index; DEPI= Depreciation Index; SGAI = Sales, General and Administrative Index; TATA =Total Accruals to Total Assets; LVGI = Leverage Index.

According to table 7, from the year 2015 to 2017, it was found that only SGI, TATA, and M-score are statistically significant in the differences of mean based on manipulators and non-likely manipulators for over three years and two years for DSRI which are 2015 and 2017 respectively. Although GMI found to have a significant difference between manipulators and non-likely manipulators in the year 2015, this index then cease to have significant differences in 2016 and onwards. The rest indexes or ratios did not have any significant differences in its mean for two types of companies over the year 2015, 2016, and 2017. Therefore, the two hypotheses of SGI (H1d) and TATA (H1g) are supported and accepted as both ratios have significant differences throughout the three years. Meanwhile, DSRI (H1a) in this study is partly supported as it had a significant difference in 2015 and 2017 but not in 2015, which made it less potent as compared to the other two significant and dominating ratios of SGI and TATA. The findings are consistent with Ahmed & Naima (2016) which found DSRI and TATA, played important roles in distinguishing the likely manipulator firms from the non-likely manipulator firms, SGAI and AQI were also shown in Ahmed and Naima (2016) as reflective of how the firms under study might be manipulating earnings. However, in the current study, SGAI and AQI were found as non-significant to detect manipulation.

The main hypothesis (H1) is partially supported or accepted as only three ratios are found to be significantly different including M-Score in the three consecutive years for manipulators and non-likely manipulators which indicates that M-Score's predictability and reliability in detecting the likelihood of earnings manipulation was proved (Ahmed & Naima, 2016).

## 5. Conclusion and Suggestion

Based on this study, there are three significant dominating ratio which are SGI, TATA and DSRI by which suggested that the inflation or overestimation of sales and revenues, as well as accruals, could signal an early indication to earnings manipulation in Malaysian PLCs. These main drivers of the three indexes involve managers' discretionary and decision in the firm's earnings or financial reporting.

This study improvised the scope for stakeholders such as users, investors, lenders, analysts, auditors, forensic accounting and other financial experts to use M-Score model and allows the non-financial experts (public users) to determine earnings manipulations through this presumably convenient and friendly statistical equations in aiding them in making economic and investment decisions. This study also helps regulators and other practitioners to detect manipulations and to add value for auditing, accounting, and financial professions, especially in terms of using or focusing on the dominating ratios suggested in this study. This study is not without limitation where the sample could not solely represent the whole situation or current state of the economic performance of PLCs in Malaysia.

In relation with the limitations of this study, it is necessary to use the M-score model with a bigger sample that would secure or give better protection for investor and the same time add-in Malaysian's literature contribution in this scope of study (Ahmed & Naima, 2016; Özcan, 2018; Kamal et al., 2016). A future research on comparative study among Malaysian PLCs and SMEs (small and medium enterprises), including within the industry by way of analysing its future and past performances with the competitors, can also be conducted by using these methods. This type of future research would be very helpful for professionals like auditors, forensic accountants, analysts, academicians and stakeholders, including lenders and investors.

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