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Detecting Financial Statement Frauds in Malaysia: Comparing the Abilities of Beneish and Dechow Models

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ABSTRACT

Financial statement frauds (FSF) are becoming rampant phenomena in current economic and financial landscapes. One of the ways to curb FSF is to detect them early so that preventive measures can be applied. This study aims to empirically investigate the abilities of two financial-based models namely the Beneish's M-score and Dechow's F-score, to detect and predict FSF for Malaysian companies. In addition, this study compares the accuracy including the error rates between the two models. Financial data of Malaysian listed companies from 2001 to 2014 are used using a matched pair in this study. The findings reveal that both Beneish and Dechow models are effective in predicting both the fraudulent and non-fraudulent companies with average accuracy at 73.17% and 76.22%, respectively. The results also indicate that Dechow F-score model outperforms the Beneish M-score model in the sensitivity of predicting fraud cases with 73.17% compared to 69.51%. On the efficiency aspect, the Dechow F Score model is found to have lower type II error (26.83%) than Beneish M Score model (30.49%). This finding suggests that Dechow F Score model is a better model that can be used by the regulators to detect FSF among companies in Malaysia.

Keywords: Beneish M-score; Dechow F-score; financial statement fraud; fraud detection; financial models

Introduction

Fraud is a significant threat to businesses worldwide. The reports by Association of Certified Fraud Examiners (ACFE) suggest that the occurrence of fraud has increased considerably over the recent years and is likely to continue to increase in the future (ACFE 2014, 2012, 2010). The reports and the reported cases of fraud involving Enron, Worldcom and Satyam resulted in losses estimated to be more than US$20 billion. According to ACFE, there are three types of fraud comprising financial reporting fraud, misappropriation of assets, and corruption. Amongst different types of fraud, it is reported that financial statement fraud contributes the highest loss compared to other reported corruption and asset misappropriation fraud cases (ACFE 2014). Malaysia is not spared as cases involving Megan Media, Transmile Berhad, United U-Li and Repco Holdings Bhd proved that fraud is prevalent here too. Organizations are reported to lose an estimated average of 6 percent of their annual revenues due to fraud. Due to increasing the number of fraud cases and its detrimental negative impacts, it is vital to spend a significant amount of time to find an effective model to detect fraud.

Several researchers suggest that financial ratios are effective in fraud detection (Bai et al. 2008; Subramanyam & Wild 2009; Dalnial et al. 2014). In contrast, Kaminski et al. (2004) concluded differently in which they argued on the limitations of financial ratios. The results on effectiveness of financial ratios on fraud detection are mixed.

Several models such as Beneish and Dechow F-score, use different financial ratios for fraud detection. The application of these models are mostly in detecting earning manipulation but their abilities in financial statement fraud detection are also confirmed by prior studies. The objective of this paper is to compare the detection power between Beneish model and Dechow F-score model for financial statement fraud in Malaysia. These models were originally developed using United States (US) data and different financial ratios. Although the usefulness of these models in detecting financial statement fraud have been ascertained separately in prior studies, the models' abilities are yet to be compared in determining which model provides better results (Nwoye et al. 2013; Omar et al. 2014). In addition, as both the Baneish and Dechow models were recently developed, there is still limited evidence that can affirm the models' abilities to detect fraud incidences in a developing country like Malaysia. There are many reasons why Malaysian data on fraud are considered unique. Firstly, the regulatory regime in Malaysia is considered lax (Aluko & Bagheri 2012). This is compared to its counterpart the US, where the models were first developed. A lax regulatory regime may create an environment whereby the occurrences of financial statements fraud may be more rampant in the US. Secondly, Malaysia and US apply different financial reporting standards, and therefore there will be differences in arriving at the financial data reported in the financial statements. These differences may affect each model's ability to predict fraud, hence this study is warranted.

This paper is constructed as follows: the next section reviews the literature of fraud. This is followed by explanation on the mechanics of Beneish and Dechow

F-score models. Comparison between these models is discussed in the subsequent section. The last section presents the conclusion.

Fraud Literature

This section presents fraud literature, its evolution and current statistics of fraud.

FRAUD DEFINITION AND CLASSIFICATIONS

Fraud is defined as a deliberate performance by individuals, which results in misrepresentation of financial statement (KPMG 2005; ACFE 2008). The American Institute of Certified Public Accountants, Association of Certified Fraud Examiners (2008), The Institute of Internal Auditors, and Malaysian Approved Standards on Auditing (ISA 240) defined fraud similarly as a deliberate performance by individuals, which results in misrepresentation of financial statement. Asare (2006) explained that although fraud does not have exact legal meaning, it can be defined as "a situation where a person appropriates by deception a property belonging to another with the intention of permanently depriving the other of it". The term fraud has been described by researchers in different forms, but generally it is believed that fraud can be defined ultimately as "the intentional act of misleading or committing harm to others with the aim of securing an unfair or unlawful advantage".

Prior studies had identified different types of fraud from various perspectives. For instance, fraud can be external which is committed by a client or other third parties or internal, which is committed by employees or managers. The Malaysian Approved Standards on Auditing, AI 700 outlines two forms of fraud including fraudulent financial reporting and misappropriation of assets (Jaffar et al. 2008). Fraud can also be classified based on its nature. A joint-report by The Institute of Internal Auditors, American Institute of Certified Public Accountants and ACFE (2008) categorized fraud into financial reporting fraud, misappropriation of assets, and corruption.

Financial reporting fraud, one major type of fraud, involves intentional misstatement or omission of material information from the organisation's financial report. In accordance with ACFE (2014), only 9% of fraud cases involved financial statement fraud; but those cases caused the greatest financial impact, with a median loss of US$1 million. Therefore, finding ways to detect financial statement fraud early to prevent further damage to the organization is crucial.

FRAUD STATISTICS

The stability of a business can be in danger as the result of significant financial losses due to fraud. It is reported that organizations lose 6% of their revenues because of fraud yearly (ACFE 2014). The statistics below indicate the frequency and losses from three types of fraud determined by ACFE from 2010 to 2014. This evidence reveals that the frequency of asset misappropriation or employee fraud has decreased in recent years. In contrast, both corruption and financial statement fraud have increased considerably and they are likely to continue unless a drastic measure can be found to curb them.

Similar to other countries, Malaysia is not exempted from fraud occurrence. The number of fraud cases reported had increased during the time. Statistics reported by Securities Commision (SC), Malaysia for the year 2006 and 2007 showed that there were 10 and fourteen 14 enforcement actions respectively. The reports for years 2009 and 2010 by this commission indicated an increase in fraud cases at 18 and 26 cases, respectively (Hasnan et al. 2012). Reports such as Pricewaterhorse Coopers (PwC) (2009, 2011) revealed a considerable decrease in financial performance among Malaysian companies of more than 60 percent (66%) due to fraud. KPMG (2013) reported that 89% of the respondents believed that fraud cases have been increasing over the past three years. It is also indicated that 42% of the reported fraud incidents were within the range of RM10,001 to RM100,000. The reviewed evidences show that fraud remains a problematic issue in Malaysia. Therefore, a useful and appropriate tool is needed to solve this problem.

FRAUD DETECTION

Despite the reports of the ACFE, most frauds are not detected in time because they are normally hidden from the eyes of the public or even the auditors. The high losses due to fraud reported by different organizations also confirmed failure in detection. Therefore, an effective tool is required to identify the signals of fraud. There are a number of tools developed to assist regulators as well as auditors in analyzing financial statements and assessing

TABLE 1. Frequency and median loss of different types of fraud

Types	Asset misappropriation		Corruption		Fraudulent Financial Reporting	
Year	Frequency (Percent)	Median loss (USD 'M)	Frequency (Percent)	Median loss (USD 'M)	Frequency (Percent)	Median loss (USD 'M)
2010	86.3	0.135	32.8	0.25	4.8	4.1
2012	86.7	0.12	33.4	0.25	7.6	1.0
2014	85.4	0.13	36.8	0.20	9.0	1.0

Source: ACFE (2014)

likelihood of fraud occurrences. Models consisting financial ratios are found to be the most common models developed for fraud detection. According to prior studies, these ratios are widely used and suggested to be a useful tool in business failure forecast, fraud detection and performance evaluation (Green & Calderon 1995; Green & Choi 1997; Guan et al. 2008; Persons 2011; Dani et al. 2013; Omoye & Eragbhe 2014; Dalnial et al. 2014; Kanapickienė & Grundienė 2015). The literature suggests a variety of ratios including financial leverage, profitability, asset composition and liquidity. Recent studies such as Omar et al. (2014), Omoye and Eragbhe (2014) and Nia (2015) had expanded on the types of financial used in the models and confirmed the ability of these financial ratios to detect fraud. Kotsiantis et al. 2006 used profitability, leverage, liquidity, efficiency and cash flow to predict financial statement frauds; while Dechow et al. (2011), and Kaminski et al. (2004) applied other financial ratios in their respective models to predict fraud.

Various models using financial ratios have been developed by accounting research to predict different events including fraud, earning manipulation, earning management and bankruptcy. These models include Beneish, Jones model, Altman Z-Score and Dechow F-score (Jansen et al. 2012). This paper aims to compare the ability of two of these models, namely Beneish and Dechow F-score models in detecting fraud using Malaysian data.

RESEARCH METHOD

This study examines 164 samples consisting of 82 fraudulent and 82 non-fraudulent companies from the Malaysian Public Listed companies available between the years 2000 and 2014 with financial data collected from Osiris and annual reports. Samples classified as fraudulent companies are companies that have been reported to have fraud in the enforcement releases obtained from SC. A matched pair samples is used; whereby each fraudulent company is matched with a corresponding non fraudulent firm on the basis of industry obtained from the SIC code and financial year. Financial statement variables of non-fraudulent companies are obtained from the same year as the fraudulent companies in order to control for general macroeconomics conditions. This one-for-one matching process is used in an effort to enhance the discriminatory power of the models.

The following section evaluates the ability of Beneish and Dechow F-score models in detecting fraud using collected data.

BENEISH MODEL

Beneish Model or Beneish M-score is the manipulation score created by Beneish (1997, 1999). It is a mathematical model that uses eight financial ratios to identify manipulated earnings and to detect financial statement fraud (Jansen et al. 2012). The variables are constructed from the company's financial statements and a score is derived from the model to describe the degree to which the earnings have been manipulated (Nwoye et al. 2013). Beneish (1999) profiled firms that are likely to manipulate earnings (firms either charged with manipulation by the SEC, or admitted to manipulation in the public press) and developed a statistical model to discriminate manipulators from non-manipulators. Therefore, this model helps to uncover companies that are likely to manipulate their reported earnings. Furthermore, Beneish and Nichols (2009) refined this model with five and eight variables for detecting financial statement fraud. Eight variables of Beneish model are explained in Table 2 and calculated using following formula:

$$M = -4.84 + 0.92*\mathrm{DSRI} + 0.528*\mathrm{GMI} + 0.404*\mathrm{AQI} + 0.892*\mathrm{SGI} + 0.115*\mathrm{DEPI} - 0.172*\mathrm{SGAI} + 4.679*\mathrm{TATA} - 0.327*\mathrm{LVGI}$$

The M score is the derived figure from the model. M-score of less than -2.22 indicates that a company does not manipulate the financial statements in the accounting period. M-score greater than -2.22 signals that the company will likely be a manipulator.

These parameters are calculated from data in company financial reports issued in two consecutive years. Hence, the following data are needed: Sales, Cost of Goods, Net Receivables, Current Assets, Property, Plant and Equipment, Depreciation, Total Assets, Selling, General and Administrative Expenses, Net Income, Cash Flow from Operations, Current Liabilities and Long-Term Debt.

The calculations of eight ratios are given in the following table:

TABLE 2. Ratio analyses used as Beneish M-score

Ratio	Formula
DSRI	$(Net\ Receivables_t / Sales_t) / (Net\ Receivables_{t-1} / Sales_{t-1})$
GMI	$[(Sales_{t-1} - Cost\ of\ Goods\ Sold_{t-1}) / Sales_{t-1}] / [(Sales_t - Cost\ of\ Goods\ Sold_t) / Sales_t]$
AQI	$[1 - (Current\ Assets_t + PPE_t / Total\ Asset_t)] / [1 - (Current\ Assets_{t-1} + PPE_{t-1} / Total\ Asset_{t-1})]$
SGI	$Sales_t / Sales_{t-1}$
DEPI	$[Depreciation_{t-1} / Depreciation_{t-1} + PPE_{t-1}] / [Depreciation_t / Depreciationt + PPE_t]$
SGAI	$[sales, general\ and\ administrative\ expenses_t / Sales_t] / [sales, general\ and\ administrative\ expenses_{t-1} / Sales_{t-1}]$
TATA	$Total\ Accruals_t / Total\ Assets_t$
LEVI	$[LTD_t + Current\ Liabilities_t / Total\ Assets_t] / [LTD_{t-1} + Current\ Liabilities_{t-1} / Total\ Assets_{t-1}]$

Source: Beneish (1999)

The explanation of each ratio used in the model is explained below:

1. Days Sales in Receivables Index (DSRI)
   Measured as the change in receivables in the first year that the manipulation is discovered (year t) by comparing them with the same measure in year t-1 according to sales. It measures whether the receivables and revenues are in balance in two successive years. As long as there is no extreme change in the policy of credit sales of the company, this index is expected to have a linear structure. An important increase in this index is based not only on the accountancy of consignment sales recorded as trade receivables and sales toward the increase in income as well as profit of the company, but also on the creation of trade receivables from current accounts of group companies. These two applications are considered as the indicators of the manipulation of financial information. According to Beneish (1997) a large increase in days' sales in receivables could be the result of a change in credit policy to spur sales in the face of increased competition, but disproportionate increases in receivables relative to sales could also suggest revenue inflation. As a consequence, it is expected that a large increase in receivables increases the likelihood of earnings manipulation.

2. Gross Margin Index (GMI)
   Measured as a ratio of total sales revenue minus the cost of goods sold divided by sales in year t-1 to the corresponding measurement in year t. A GMI above 1 indicates a decline in gross margins, which in turns is related to poorer business prospects and a higher probability of manipulation. Dikmen and Küçükkocaoğlu (2010) suggested that GMI and the probability of earnings manipulation are positively correlated.

3. Asset Quality Index (AQI)
   This measure is the percentage of total assets that are intangible assets this year divided by the same percentage calculation for last year. An increase in this index may represent additional expenses that are being capitalized to preserve profitability. An increase in this measure is predicted to increase the probability of manipulation. An AQI greater than 1.0 indicates that the company has potentially increased its cost deferral or increased its intangible assets, and committed earnings manipulation (Warshavsky 2012). Asset quality index and financial information manipulation are suggested to be positively correlated.

4. Sales Growth Index (SGI)
   The index is a measure of growth in revenue in one year over revenue of a prior year. An index greater than 1.0 represents a positive growth while less than 1.0 represents a negative growth in the year under review. Though other factors may be responsible, growth in sales does not necessarily prove the manipulation of financial information. According to prior studies such as Dikmen & Küçükkocaoğlub (2010), companies that take sales growth into account are more likely to have earning manipulation compared to other companies. This happens due to the structure of debt or equity and the needs of resources which resulted in pressure on managers to have high rate of sales in their companies. This pressure will increase if the prices of stock decrease, and in turn manipulation of financial statements increases.

5. Depreciation Index (DEPI)
   This variable is computed as the rate of depreciation in year t-1 divided by the depreciation rate in year t, with the rationale that lower depreciation expenses results in more discretion over income; and thus a higher probability of manipulation. If this proportion is greater than 1, it is suggested that the company reduces its depreciation expenses to have high profit by considering that the expected useful life of plant, property and equipment will be lengthened or depreciation method will be changed in order to reduce expenses.

6. Sales, General and Administration Index (SGAI)
   Since the relationship between SG&A and sales is known to be quite static, it is alarming when SG&A expenses increase without a simultaneous increase in sales. Calculated as a ratio of SG&A to sales in year 1 relative to the corresponding measure in year t-1, it is expected that a higher SGAI increases the likelihood of manipulation.

7. Total Accruals to Total Assets Index (TATA)
   This index is used to measure the extent to which sales are made on cash basis. It is an indication of the quality of cash flows of the company. The total accruals metric is computed as change in working capital (except cash) less depreciation for the year under review adjusted for changes in income tax payable and current portion of long term debt. An increasing degree of accruals as part of total assets would indicate a higher chance of manipulation (Prevoo 2007). The reason behind this variable being included into this model, is to determine any manipulation of financial information applications based on increase in revenue or decrease in expense or vice versa within the framework of accrual basis. In this context, if this variable, in other words, non-cash working capital increases or decreases dramatically, it is assumed that manipulation of financial information takes place.

8. Leverage Index (LEVI)
   Leverage describes a company's financial structure and measures the long-term risks of a company

(Abdullah & Ismail, 2008). The leverage index measures the ratio of total debt to total assets. An index of greater than 1.0 is interpreted as an increase in the gearing of the company and for that matter, exposed to manipulation (Mahama 2015). When an entity reaches M-score higher than -2.22, calculated from the above eight variables, the model assumes that it is probable that the entity has manipulated accounting data for the accounting period or is strongly motivated to manipulate accounting data (Beneish 2001; Drábková 2014).

This model considers variables related to both the likelihood and incentives for fraud, and it allows the user to assess the different aspects of a firm's performance simultaneously instead of reviewing them in isolation. It should be noted that this is a probabilistic model, so it will not detect manipulators with 100% accuracy. Using all the companies in the Compustat database between the years 1982-1992, Beneish found that the model correctly identifies 76% manipulators, whilst only incorrectly identifies 17.5% of non-manipulator. Over the past decades, a number of studies confirmed the ability of this model in detecting financial statement fraud. For instance, ACFE (2004), Küçükkocaoğlu et al. (2005), Cynthia (2005) and Schuetze (2007) suggested that this model can be used for identifying falsified financial statements and classifying indicators on the manipulation of financial information. It is also found that the model helps external auditors, forensic accountants/experts and certified fraud examiners to flag possible problem areas in the financial statement, considering its ability to distinguish and discriminate between manipulators and non-manipulators, especially as it has been successfully deployed by many researchers in assessing the financial statements of companies such as Enron, Worldcom, ZZZZ Best and other cases (Prevoo 2007). Recent studies such as Nwoye et al. (2013) and Omar et al. (2014) suggested that Beneish model effectively improves auditors' chances of detecting fraud in the financial statements. As its acceptance has grown over the last years, the Beneish model is now being taught at universities globally and has become an accepted tool in detecting fraud in organizations. The findings report that this model correctly identifies 57 fraud cases out of 82 fraudulent firms determined by SC Malaysia (Table 4).

DECHOW F-SCORE

The F-model is developed by Dechow et al. (2011). It is a general fraud risk assessment tool that generates an output (F-score), an indication of the probability of fraudulent financial reporting. Dechow et al. (2011) followed a methodology similar to Beneish (1997, 1999) in developing a score to predict which companies have material accounting misstatements. The F-score model is claimed to be more comprehensive since it is based on an examination of all Accounting and Auditing Enforcement Releases (AAERs) issued by the SEC between 1982 and 2005. while the Beneish study is based only on AAERs issued between 1982 and 1992.

In total, 28 variables clustered around 5 information types are tested on their capabilities of discriminating between the fraudulent firms and the non-fraudulent firms. The variables included are accrual quality, performance, non-financial measures, off-balance sheet activities and market-based measures. Consequently, 3 logistic regression models are estimated, resulting in models that retain respectively 7, 9 and 11 variables that have the most discriminatory power. Model 1 contains variables from the primary financial statements, Model 2 adds off-balance sheet and non-financial measures, and Model 3 adds market-related variables. Dechow et al. (2011) found that their first model offers the "bulk of the power" in predicting material accounting misstatements. This study uses model 1 of Dechow et al. (2011) because it only takes into consideration the financial ratios, and therefore consistent with the objective of this study.

Following Dechow et al. (2011), F-score is computed as follows:

$$\text{Value} = -7.893 + 0.790^{*}\text{RSST} + 2.518^{*}\Delta\text{REC} + 1.191^{*}\Delta\text{INV} + 1.979^{*}\text{SOFTASSETS} + 0.171^{*}\Delta\text{CASHSALES} - 0.932^{*}\Delta\text{ROA} + 1.029^{*}\text{ISSUE}$$

The value is converted to a probability as follows: (VALUE)/ (1+ VALUE). The resulting probability is then divided by the unconditional probability of misstatement (=0.0037)[1] to obtain the F-score. An F-Score of 1.00 indicates that the firm has the same probability of misstatement as the unconditional expectation (the probability of misstatement when randomly selecting a firm from the population). F-Scores greater than one indicate higher probabilities of misstatement than the unconditional expectation.

The detail explanation of each variable is discussed below:

9. RSST Accruals
   This variable measures changes in current assets (excluding cash), less changes in current liabilities (excluding short-term debt) and depreciation. Also factored into it are changes in long term operating assets and long-term operating liabilities.

10. Change in Receivables
    The change in receivables from last year to this year is scaled by average total assets. It is indicated that large changes in accounts receivables show revenue and earnings manipulation. The manipulation can occur through the fraudulent recognition of revenue and large changes in accounts receivable falsified cash flows from operating activities.

11. Change in Inventory
The change in inventories from last year to this year is scaled by average total assets. Large changes in inventory may indicate inventory surpluses, shortages, obsolescence, or liquidation. For example, if the company uses the last-in first-out (LIFO) method of accounting for inventory in a period of rising prices, selling older inventory will result in lower cost of goods sold, i.e., LIFO liquidation of inventory units or layers. This practice leads to inflated earnings.

12. Soft Assets
This measure is defined as total assets less the sum of PP&E and cash and cash equivalents (scaled by total assets). It is suggested that when soft asset is high in the balance sheet, managers have more abilities to change and adjust assumptions to influence short-term earnings.

13. Change in Cash Sales
This measure is the percentage change in cash sales from last year to this year. For a firm not engaged in earnings manipulation, the growth rate in cash sales could be compared to the growth rate in revenues but these researchers did not include such an analysis. They argued and modelled that just the change in cash sales is a key metric to monitor when evaluating the potential for earning manipulation.

14. Change in ROA
This measure is a percentage calculated as earnings divided by total assets this year less the same measure last year. Volatile earnings may be indicator of earnings manipulation. According to Dechow, Ge, Larson, and Sloan (2007), a consistent theme among manipulating firms is that they have shown strong performance prior to manipulation. The cause for such manipulation may be a current decline in performance, which the management team attempts to cover up by manipulating financial reporting.

15. Actual Issuance of Stock
This measure is a dummy variable that is 1 if additional securities are issued during the manipulation year and is 0 if no such securities are issued. Such issuances may indicate operating cash flow problems that need to be offset by additional financing. In addition, issuance of stock may indicate management is exercising

TABLE 3. Item analyses used as the F-score variables

Items	Formulas
RSST	*(ΔWC + ΔNCO + ΔFIN) / Average Total Assets* *WC = [Current Assets – Cash and Short-term Investments] – [Current Liabilities – Debt in Current Liabilities];* *NCO = [Total Assets – Current Assets – Investments and Advances – [Total Liabilities – Current Liabilities – Long-term Debt];* *Fin = [Short-term Investments +Long-term Investments] – [Long-term Debt + Debt in Current Liabilities + Preferred Stock]*
ΔREC	*Δ Accounts Receivables / Average Total Assets*
ΔINV	*Δ Inventory / Average Total Assets*
SOFTASSETS	*[Total assets – PPE – Cash and cash equivalents] / Total Assets*
ΔCASHSALES	*Percentage change in cash sales [Sales – Δ Accounts Receivables]*
ΔROA	[Earnings $_t$ / Average total assets $_t$] – [Earnings $_{t-1}$ / Average total assets $_{t-1}$]
ISSUE	*An indicator variable coded 1 if the firm issued securities during year t*

TABLE 4. Comparison between Beneish and Dechow models

	Beneish M-score		Dechow F-score	
	Predicted		Predicted	
Observed	Non-Fraudulent	Fraudulent	Non-Fraudulent	Fraudulent
Non-Fraudulent	63 (76.83%)	19 (23.17%)	65 (79.26%)	17 (23.74%)
Fraudulent	25 (30.49%)	57 (69.51%)	22 (26.83%)	60 (73.17%)

stock options. The exercise of stock options may signify that managers are attempting to sell at the top because they foresee future underperformance of the company. Such insider sales resulted in the criminal conviction of Qwest's Chief Executive Officer and has been a significant non-financial red flag in many fraud cases, like Enron, Global Crossing, and WorldCom. For example, Qwest and Enron insiders made $2.1 billion and $1.1 billion, respectively, by exercising and selling their stock options before their firms' financial reporting problems became public.

The value of the study by Dechow et al. (2011) is also supported by the relatively high number citations it has received compared to other studies in this field. Several researchers had recently tested some variables of Dechow model and found empirical support for them (Cecchini et al. 2010; Lennox & Pittman 2010; Price III et al. 2010). It is also suggested that the ability of F-model in detecting companies subject to SEC AAER's is better compared to the Beneish model (Price III et al. 2010).

COMPARISON BETWEEN MODELS

Clearly, both techniques can be used to detect fraud in financial data as the predictive ability of both models is higher than 70%. Table 4 compares the statistics between the two models. The findings suggest that Dechow F-score provides higher accuracy in detecting fraud compared to the Beneish model.

Furthermore, as suggested by Cleary and Thibodeau (2005), the error rates of the fraud detection models should be examined by considering Type I and Type II errors. A Type I error occurs when the model wrongly classifies a fraudulent company as a non-fraudulent company. A Type II error occurs when the model wrongly classifies a non-fraudulent company as a fraudulent company. The cost of these two types of errors is different for each type of users. From auditors' point of view, Type II error is more costly than Type I. When a fraud case is not detected on time and is revealed later, the auditor is going to be sued by investors or sanctioned by the regulators. On the other hand, Type I error is related to efficiency and may result in auditor losing client or decreasing their margin of profit in an engagement. Since Type II error which is related to audit effectiveness is more costly to the auditors, a model that makes lower Type II error would be preferable to the auditors.

As indicated in Table 5, the Type I error rate of Beneish model is 30.49%. This result for Dechow model is found to be 26.83%. The Type II error for Beneish and Dechow models are 23.17% % and 20.73% respectively. The results confirmed the efficiency of F-score in detecting fraud cases (73.17%) compared to Beneish model (69.51%). In conclusion, the performance of Dechow F-score model with lower Type II error (20.73%) and correct classification (76.21%) is found to outperform the Beneish model in detecting fraud cases.

TABLE 5. Examination of error rates

	Beneish	Dechow
Type I error	30.49% (1)	26.83%
Type II error	23.17% (2)	20.73%

Notes:
Type I error is calculated as (19/82)
Type II error is calculated as (25/82)

CONCLUSION

Fraud is a serious problem that has plagued the business community. The concerns of preventing fraud are mounting as the occurrences and negative impact of fraud have escalated over the years. Financial statement fraud is found to be the most worrying as it involves management of the company and causes the highest loss to investors. Several mathematical models have been developed to help regulators and auditors to detect fraud early.

This study responds to the concerns of the public and the policy makers by identifying an appropriate model associated with financial statement fraud. This study examines whether the Beneish M-score and Dechow F-score (2011) fit and have the association with financial statements fraud in relation to Malaysian fraud cases. These models use financial ratios which are readily and publicly available from companies' annual reports. The results indicate that the ability of Dechow F-score in detecting fraud is higher than Beneish model; whereby it predicts 73.17% of fraud cases correctly compared to 69.51%. The Type II error also is reported to be lower in Dechow model compared to Beneish model. Therefore, it can be concluded that Dechow F-score fits more to Malaysian financial statement fraud cases from the year 2000 until 2014. The limitation of this study is the utilisation of fraud models which are limited to financial data; hence, non-financial data which play important role in detecting fraud are ignored. The future studies are suggested to compare these financial models with other fraud models comprising financial and non-financial variables such as fraud triangle model or fraud diamond model. In addition, future studies can examine the performance of these models amongst ASEAN countries.

NOTE

1. Unconditional probability of misstatement is equal to the number of misstatement firms divided by the total number of firms in Dechow et al.'s (2011) sample.

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