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International Conference on Accounting Studies (ICAS) 2016
15-18 August 2016, Langkawi, Malaysia

Threat of Bankruptcy and the Integrity of Financial Statement

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Abstract

Financial statement fraud involves the manipulation of financial accounts by overstating assets, sales and profit, understating liabilities and expenses. One of the causes of financial statement fraud is due to threat of bankruptcy. This study explores the effectiveness of Altman Z-Score in predicting the occurrence of financial statement fraud. This study makes a comparison between non-fraudulent companies and fraudulent companies. The sample of non-fraudulent companies is selected from small market capitalization companies in Malaysia. Meanwhile, the sample for fraudulent companies is selected from companies which were charged by the Securities Commission for falsifying financial statements. The result shows that fraudulent companies display sign of bankruptcy before it is charged with falsification of financial statement fraud.

Keywords: Altman Z-Score, Small Market Capitalization Companies, Financial Statement Fraud

1. INTRODUCTION

The threat posed by financial statement fraud is significant up to this day as many organisations are still working to recover from past financial collapses caused by misconduct in financial markets. While important strides have been made in recent years, financial statement fraud continues to pose a threat to financial interests globally. The PWC (2014) in its survey report states that 45 percent of United States organisations suffered various effects from economic crime in the past two years. Fifty six percent of respondents who claimed that their organisations suffer from fraud reported an increase in the number of occurrences, representing a continuing upward trend in the occurrence of financial statement fraud. In Malaysia, a study by PWC Malaysia (2014) stated that the losses experienced by Malaysian companies through economic crimes is tremendous. Having said that, seven out of ten respondents say that their company had individually lost more than US$1 million since 2011. This indicates that financial statement fraud is still happening today and apparently no organisation is immune to this threat.

Financial fraud, unlike other hard crimes such as murder and rape is harder to be proven in the court of law. A study by Association of Certified Fraud Examiner in 2012(ACFE) concluded that financial fraud cases would normally take between three to six years to be detected. Usually, by the time financial frauds are detected, their related evidences would have either been removed or distorted. There is also no scientific tests such as DNA or finger print that could be conducted in this type of crime (ACFE, 2012).

There are three major classes of financial fraud; asset misappropriation, corruption and financial statement fraud. According to the study by ACFE (2014); PWC (2014); PWC Malaysia (2014), financial statement fraud accounts

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for lower number of incidents concerning financial fraud. Asset misappropriation and corruption tend to occur at a greater frequency, yet the financial impact of the latter crimes is less severe compared to the ones caused by financial statement fraud which had been accounted a median loss of $1 million (ACFE, 2014). Therefore, this study takes an initiative to cover only discussions pertaining to the financial statement fraud. The rationale behind this is that the fallout from the financial statement fraud can be significant to companies, where its effects include punitive damages, tainted corporate and brand image, lost revenue, dipping shareholder value, and inability to attract and retain human capital (KPMG Malaysia, 2014).

Although there are no evidence as to how many business failures were actually caused by financial fraud, lots of business undeniably succumb to bankruptcy each year due to fraud losses (Spathis, Doumpos, & Zopounidis, 2002). Spathis et al. (2002) states that Wells (1997) pointed out that financial fraud do not occur only in large companies, it can also occur in small companies. The impact of financial statement fraud was argued to be much worse in small companies as smaller companies, they have fewer resources to absorb losses. Thus, this study takes an initiative to use Altman Z-Score to detect possible bankruptcy identification on public listed companies charged by Securities Commission for submitting false information; and also on small market capitalization companies in Malaysia. As in fraud triangle theory, one of the factors is financial pressure where focuses on factors such as the threat of bankruptcy faced by those companies which may have motivated them to commit fraud.

Most of the previous studies had chosen large market capital companies as their main samples. For example, in studying audit committee effectiveness (Abbott and Parker (2000); Klein (2002); Lin and Hwang (2010); Lin, Li, and Yang (2006)) used large capital companies in their sample. However, lesser researches were conducted to study mid capital and small capital companies (Subramaniam, Carey, Sil Kang, Kilgore, & Wright, 2011). Besides that, regulators, analysts, investors and the public places more attention towards larger companies because of failure of larger companies would indirectly affect them (Arnott & Wu, 2012). This provides an opportunity to small capitalization companies to commit fraud.

The paper proceeds as follows: Section 2 reviews relevant prior research. Section 3 briefly introduces Altman Z-Score. Section 4 describes research method. Section 5 discusses on findings and discussion. Finally, Section 6 and 7 present concluding remarks, also future research and limitation respectively.

2. LITERATURE REVIEW

2.1 Threat of Bankruptcy and the Integrity of Financial Statement

A study by (Kinney and McDaniel (1989); Kreutzfeldt and Wallace (1986) suggested that the management of companies with weak financial condition are more likely to manipulate their financial statements as an attempt to disguise their actual condition. COSO (1999) reported that over half of the companies in their study had filed for bankruptcy upon the discovery of fraud. In a related study, Hasnan, Rahman, and Mahenthiran (2012) found that financial distress is related to occurrences of financial statement fraud. This is proven by real-life cases, such as Enron where upon discovery for financial statement fraud, the companies had to file for bankruptcy. Meanwhile, some of fraud companies in Malaysia are no longer operated upon discovery of manipulating financial statement (Omar, Said, & Johari, 2016).

The detection of financial statement fraud has recently been a major concern of researchers and the public alike, as an increment of fraudulent companies had been reported. Researchers have used various techniques and models to detect and predict financial statement fraud. Beneish (1999) created a model to detect manipulated financial reporting. His research was based on a research theory which hypothesized contract-based incentives for earnings management. This study adapted fraudulent companies whose data is publicly available as sample. This model was able to identify approximately half of the companies involved in earnings manipulation prior to public discovery. However, Beneish model is able to detect of aggressive earnings management but lack in bankruptcy. Besides that, it is crucial to look into threat of bankruptcy because it is major concern of each of companies which derived them manipulate their earnings.

Meanwhile, study by Kaminski, Sterling Wetzel, and Guan (2004) compared fraud versus non fraud firms for a two year period; the fraud year and the preceding year. This study performed univariate analysis on 21 financial ratios. The result showed that out of 21 ratios, 16 ratios were found to be significant. Three ratios were significant for three time periods and five were significant during the period before the fraud year occurred. Besides that, this result provided empirical evidence of the limited ability of financial ratios to detect or predict financial statement fraud. This is because only selected ratios can be used for a certain period. If they are used differently from what were suggested by previous studies; the result will not be reliable.

Moving from traditional method of using ratios analysis, study by Chen and Du (2009) applied Artificial Neural Network (ANN) and data mining techniques to construct a financial distress prediction model using 34 firms which are in financial distress, being matched with 34 non bankruptcy firms. Financial ratios pertaining to earnings ability, financial structure ability, management efficiency/ability, management performance, debt-repaying ability and non-financial factors were being used as input in ANN. These variables were selected based on the previous research. The result showed that ANN approach obtains better prediction accuracy than data mining clustering approach. However, this model is not applicable for fraud detection as it focuses on bankruptcy prediction.

Meanwhile, du Jardin (2008) applied 41 initial financial ratios which represent company's liquidity, solvency, financial structure, profitability, efficiency and turnover. The objective of the study was to examine the accuracy of bankruptcy prediction using ANN. The test samples consisted of 250 bankrupt and 250 non bankrupt retail firms which have assets were less than US$750,000. The validation set consisted of companies belonging to the same sector and same asset size category. The result showed that ANN provides higher accuracy of 94.03% as compared to logistic regression which accuracy is only at 90%. But the result is only limited to financially distressed companies and conversely, it is limited to predicting bankruptcy.

However, study by Persons (1995) used stepwise logistic model to predict financial statement fraud using a sample of 103 fraud firms for the fraud year and 100 firms for the preceding fraud year. Non-fraudulent firms were randomly drawn from COMPUSTAT firms of the same industry. The results found that financial leverage, capital turnover, asset composition and firm size are significant factors associated with financial statement fraud. He had also applied Altman Z-score ratios as the variables in his study. Findings from the study indicated that, Altman Z-Score is not only able to be used in predicting bankruptcy, but also fraud.

Tebogo (2011) took further initiative by investigating the Enron case. The data used in this study was based on 10K filings made by Enron Corporation from 1997 to 2001. Although Enron had deceived investors and regulators, its manipulation can be detected early if analysts had paid closer attention. This study adopted the Beneish Model, Pustylnick's Modified Altman Z-Score, Chanos Algorithm and Grove and Cook Ratios. The results showed that Enron case could have been detected earlier red flags where discovered when researcher enter financial data into the model. However, for other fraud companies, the result may not show preferable results as they did not have similar financial information due to differences in industry.

From previous studies, it can be concluded is that most studies used developed model based on ratios, where one of it serve as indicators for financial distress. This model was used to detect and predict fraud using sample from fraudulent and non-fraudulent companies. However, some of it used samples from bankrupt and non-bankrupt companies to predict financial distress. Less study was found to adapt Altman Z-Score as predictor of fraudulent financial statement using small cap companies from Malaysia as their sample to detect fraudulent financial statements. Thus, this study takes further steps in detecting and predicting financial statement fraud by using Altman Z-score in small market cap companies which are ranked by market capitalization as sample to examine the performance of these companies, whether they were implicated by financial statement fraud. This study also contributes to details of the literature on small cap companies.

2.2 Concept of Altman Z-Score

Altman (1968) modeled up to five financial ratios, including its weight are for each ratio. This model was based on standard categories of liquidity, profitability, leverage, solvency and activity ratio in order to predict bankruptcy in manufacturing companies. He used a statistical technique called multiple discriminant analysis (MDA) to compare non bankrupt companies with bankrupt companies. The result showed that MDA model proved to be accurate in predicting bankruptcy for up to two years prior to actual failure. The integration of these five variables in a single equation yielded the greatest success rate for predicting financial distress. The formula is as follows:

$$Z = 0.012X1 + 0.014X2 + 0.033X3 + 0.006X4 + 0.999X5$$

Where X1= Working Capital/ Total Asset
X2= Retained Earnings/ Total Asset
X3= Earnings before Interest and Taxes (EBIT)/ Total Asset
X4= Market Value of Equity/ Book Value of Total Liabilities
X5= Sales/ Total Asset
Z = Overall Index

Although Altman had originally developed the Z-Score based on small of manufacturing firms, other researches showed that it is also useful in other areas, such as healthcare, with some modifications mode to the model (Al-Sulaiti & Almwajeh, 2007). The study which used hospitals as samples revealed that both discriminant analysis and logistic regression models are able to predict service organizations' success or failure, with the latter being more predictive in a sample of 65 hospitals.

Besides that, Altman Z-Score had been used in retail firms to see the efficacy of the model in predicting financial distress. From the result, it was found that Z-Score accurately predicted bankruptcy filing at 94% at a time and accurately predicted financial distress over 90% of the time (Hayes, Hodge, & Hughes, 2010).

Meanwhile, a study by Ng, Mohammed, Ahmad, and Huam (2013) had applied Altman model in predicting financial distress of companies which are classified under PN17 in Bursa Malaysia. The analysis of this study was made on a sample of 52 companies, where their financial data were collected from records over the period from 2003 to 2010. This study found that not all of the PN17 companies were companies with financial failure. Thus, Altman Z-Score can also be used to detect financial distress of companies.

A study by Ijaz and Hunjra (2013) used Altman's Z-Score and current ratio to assess the financial status of sugar sector companies listed at Karachi Stock Exchange (KSE). Sugar sector is the second largest slice among all sectors listed at Karachi stock exchange. Total population sampling technique was used in this study and all 35 sugar sector listed companies at KSE were included in this study to get the deep insights of the issue. State bank's balance sheet analysis and companies' financial reports were used to compile the data for the years of 2009 and 2010. Results of the study showed that current ratio and Altman's Z-Score are reliable tools to assess financial health of sugar sector listed companies in Karachi stock exchange. This study further explored that there are financially distressed companies among sugar sector listed companies.

Though study by Smith, Ahmar Ahmad, and Shameer Mohamed (2004) proposed a model of PN4 classification among Malaysian listed companies, however, to some extend the model are limited in explaining the bankruptcy phenomenon. It solely based on the gearing ratios and focuses on specific three sectors such as construction, consumer and industrial product. Therefore, instead of using this model, this study applies Altman z-score since of its effectiveness.

Altman (1968) suggested that companies with a Z-Score less than 1.8 has the possibility to experience bankruptcy. Meanwhile, companies with a score of 1.8 to 2.99 were in grey zone in which financial distress may or not occur. Companies with a score that is more than 2.99 were likely to be financially sound. However, the score should not be interpreted independently. It should be interpreted together with the analysis of trend for each company. Table 1 presents the summary of Altman Z-Score benchmark.

Table 1 Summary of Altman Z-Score Benchmark

Indicators	**Z-Score**
Possible to bankrupt	<1.8
Grey zone	1.8-2.99
Financially sound	>2.99

3. RESEARCH METHODOLOGY

3.1 Sample Selection

This section is divided into two parts: the selection of non-financial statement fraud companies and the selection of financial statement fraud companies. The sample is selected based on previous studies relating to techniques in detecting financial statement fraud (Kaminski et al., 2004; Persons, 1995). The reason for adapting this type of sample is to compare fraudulent companies and non-fraudulent companies in order to predict whether small market capitalization companies have similar pattern as fraud companies charged by the Securities Commission.

3.1.1 Selection of Non-Fraudulent Companies
The selection of non-fraudulent companies is based on the ranking of market capitalization in Malaysia. The companies are selected between the rankings of 101 to 300. The reason for selecting these 200 companies is because they fall under the category of small market capitalization companies where their total market capitalization is between RM300 million to RM2 billion. Furthermore, companies that ranked as the top 100 market capitalizations already received much attention from the analysts, researchers, investors and the public. They are better known companies compared to companies that ranked below the top 100 notch.

3.1.2 Selection of Fraudulent Companies
The list of companies involved in financial statement fraud is obtained from press releases issued by the Securities Commission enforcement between the years from 1993 to 2013. This enforcement summarized criminal actions

taken against companies that failed to comply with rules and regulations set by the Securities Commission and Bursa Malaysia. For the purpose of this study, 30 fraudulent companies were selected based on the category of submission of falsified financial statements because this study focuses on financial statement fraud.

3.2 Data Collection

Data was collected for five financial years to develop a pattern for fraud companies and non-fraud companies. The reason for selecting five financial years' data is to develop a pattern between both types of companies in order to create a prediction model of financial statement fraud. The selection of five years financial data is supported by the study by (Tebogo, 2011) which also investigated the Enron case using five years of financial data. It was argued that by using five years of financial data, financial statement fraud can be detected earlier.

However, after data collection it was found that complete data were only available for 185 non-fraudulent companies. On the other hand, the complete data can only be gathered for fraudulent companies. This is due to unavailability of certain items such as sales, inventories and receivables variables in financial statement that is required to be obtained for computation of financial ratios. Table 2 shows the summary of data collection.

Table 2 Summary of Data Collection

Sample Selection	Data Collected	Data Available for Sample	Total Dataset Available for Sample
Non Fraud Companies	200	185	
Fraud Companies	30	29	214 x 5 = 1,070 firm's year
Total	230	214	

3.3 Variables for Estimating Models of Financial statement fraud

The Altman model was originally developed in 1968 for evaluating the bankruptcy risk of traditional public firms, such as manufacturing, energy, and retail. However it can also be applied to non-traditional and service public firms, such as software, consulting, and banking, as well as private firms (Grove & Basilico, 2011).

3.3.1 (Working Capital / Total Assets) x 1.2

This ratio is a measure of firm's working capital (or net liquid assets) relative to capitalization. A company with higher working capital will have more short term assets and able to meet its short term obligations more easily. This ratio is a strong indicator of a firm's ultimate discontinuance as low or negative working capital signifies that the firm may not be able to meet its short term capital requirements.

3.3.2 (Retained Earnings / Total Assets) x 1.4

This ratio is a measure of firm's cumulative profits relative to its size. The age of the firm is implicitly considered due to the fact that relatively young firms have lower ratio and the incidence of business failures is much higher in a firm's early years.

3.3.3 (EBIT / Total Assets) x 3.3

A healthy company will be able to generate income using its assets on hand. If this ratio is low, it demonstrates that profitability is poor, and the company is in danger of bankruptcy because it is more vulnerable to market downswings, which affects earnings. This analysis is true for both manufacturing and service companies as this ratio is included not only in both versions of the bankruptcy model, but also in a private company model (Altman & Hotchkiss, 2010).

3.3.4 (Market Value of Equity / Book Value of Total Liabilities) x 0.6

This ratio adds a market emphasis to the bankruptcy model. It was theorized that firms with higher capitalizations would be less likely to go bankrupt because their equities have higher values. In addition, it will gauge the market expectations for the company which takes into account relevant future financial information. This market value of equity variable assumes that the efficient market hypothesis is applicable to the bankruptcy model.

3.3.5 (Sales / Total Assets) x 0.999

This ratio, also known as total asset turnover, demonstrates how effective the company is utilizing its assets to generate revenue. If this number is low, it indicates that the company is not being run efficiently, which creates a higher bankruptcy risk. Altman's service sector bankruptcy model dropped this variable to avoid bias (Altman & Hotchkiss, 2010). Table 3 presents the variables adopted from the study by Altman (1968) to calculate the financial statements data of fraud and non-fraud companies with small market capitalization

Table 3 List of Variables for Bankruptcy Detection

Variables	Notation	Description
X1	WC/TA	Working Capital/ total asset
X2	RE/TA	Retained earnings/ total asset
X3	EBIT/TA	Earnings before interest and taxes/ total asset
X4	MVE/TL	Market value of equity/ total liabilities
X5	SAL/TA	Sales/total asset
Z = 0.012X1 + 0.014X2 + 0.033X3 + 0.006X4 + 0.999X5		

The rationale for choosing these 5 ratios is because the variables are more likely to be manipulated by the fraudster. These variables include sales, accounts receivable and assets (Kranacher, Riley, & Wells, 2010; Schilit, 2010; Zimbelman, 2012). For instance, sales might include fictitious revenue where there is actually no such sale of goods or service taking place. This fictitious revenue eventually leads to fictitious accounts receivable.

On the other hand, the rationale of choosing total debt as an indicator is because higher debt may increase the likelihood of financial statement fraud. This is because management may manipulate financial statements in order to meet debt covenants. It was suggested that higher the level of debts may increase the likelihood of financial statement fraud (Beasley, Carcello, & Hermanson, 1999).

4. FINDINGS AND DISCUSSIONS

4.1 Descriptive Analysis of Non Fraud Companies

Based on the analysis, most of the companies that are ranked at the top 101 to 300 are from industrial product which consist of 46 companies, followed by 31 companies from both properties and trading/services industry, 20 companies from consumer products, 17 companies from plantation, 15 companies from finance, 10 companies from REITS, 7 companies from construction, 6 companies from technology and 2 companies from the hotel industry. Table 4 shows the number of companies selected by industry.

Table 4 List of Small Market Capitalization Companies According To Industry

Industry	Number of companies
Construction	7
Consumer Products	20
Finance	15
Hotels	2
Industrial Product	46
Plantation	17
Properties	31
REITS	10
Technology	6
Trading / Services	31
Total	185

The ranking is based on the total number of 185 companies selected as sample. From the table, companies from industrial products dominate each ranking, comprising of 13 companies from rank 101 to 150, 10 companies from rank 151 to 200 and 13 companies from rank 201 to 250. However, from rank 251 to 300, 13 companies were from the properties industry. Meanwhile, the lowest number of companies in rank 101 to 150 is from construction and hotel industry. Each industry is represented by 1 company. Only one company represents hotel industry under the ranking of 151 to 200. The rank 201 to 250 shows that there are no company representing the hotel industry and only one company came from the technology industry. The rank 251 to 300 shows zero number of companies from hotel and REITS industry and one company representing technology industry. Table 5 shows the number of companies by industry according to each rank of 50 intervals.

Table 5 Number of Companies by Industry According to Each 50 Rank Interval

Industry	101-150	151-200	201-250	251-300
Construction	1	2	2	2
Consumer Products	8	2	5	5
Finance	3	6	2	4
Hotels	1	1	0	0
Industrial Product	13	10	13	10
Plantation	7	5	2	3
Properties	3	9	6	13
REITS	3	4	3	0
Technology	2	2	1	1
Trading / Services	5	6	12	8
Total	**46**	**47**	**46**	**46**

4.2 Descriptive Analysis of Fraud Companies

From the analysis, nine fraud companies are from industrial product, six are from trading or services, five companies from properties, three companies from construction, two companies from finance and technology respectively and one company from both consumer products and plantation industry. It can be concluded that most of the fraud companies that commit falsified financial statements are from the industrial product industry as shown in table 6 which presents the number of fraud companies by industry and the number of company selected for sample.

Table 6 List of Fraud Companies According To Industry

Industry	Number of companies
Construction	3
Consumer Products	1
Finance	2
Industrial Product	9
Plantation	1
Properties	5
Technology	2
Trading / Services	6
Total	**29**

4.3 Results of Small Market Capitalization Data using Altman Z-Score

This analysis uses benchmark score from Altman Z-Score to compare data from small market cap companies in Malaysia. The total of firm's year that is used the analysis is 925. The result shows that 30 firm's year have the possibility to experience bankruptcy in the first rank. Meanwhile 67 of firm's year are in grey zone where they may or may not experience financial distress and 133 of firm's year are financially sound which indicates that their finance is stable.

Under second ranking, 74 firm's year have the possibility to experience bankruptcy while 69 firm's year are in the grey zone and 92 firm's year are financially sound. Third ranking shows that only 49 firm's year have the possibility to experience bankruptcy while the other 72 and 109 firm's year are categorized under grey zone and respectively, financially sound respect. The final rank shows that 65 of firm's year have the possibility to experience bankruptcy while 64 and 101 firms year are classified under grey zone and financially sound correspondingly. Table 7 presents the summary of benchmarking of small market cap companies data to the Altman Z-Score.

Table 7 Benchmarking of Small Market Cap Companies Data to the Altman Z-Score

Ranking	Possibility experience bankruptcy	Grey Zone	Financially sound	Total firm's year
	<1.8	**1.8-2.99**	**>2.99**	
101-150	30	67	133	230
151-200	74	69	92	235
201-250	49	72	109	230
251-300	65	64	101	230
Total	218	272	435	925

4.4 Results of Fraud Companies' Data using Altman Z-Score

This analysis uses benchmark score from Altman Z-Score to compare with data from fraud companies in Malaysia. The total of firm's year which is used for the analysis is 145. From the result, it shows that 113 fraud companies' firm's year experience bankruptcy. Meanwhile, only 18 firm's year are in grey zone area where financial distress may or may not happening and 14 firm's year are financially sound.

This result indicates that most fraudulent companies in Malaysia had experienced bankruptcy. Thus, it could strengthen the prior studies with further arguments that financial distress among companies could be an indicator if the companies committing fraud. Table 8 presents the summary of benchmarking of fraud companies data to the Altman Z-Score.

Table 8 Benchmarking of Fraud Companies Data to the Altman Z-Score

Benchmark	Score	Total firm's year
Possibility experience bankruptcy	<1.8	113
Grey Zone (financial distress may or may not happening)	1.8-2.99	18
Financially sound	>2.99	14
Total		**145**

4.5 Discussions

Based on the results, small market companies could experience a possibility of bankruptcy based on the firm's year. Out of 925 firm's year, 218 firm's year shows that the companies have the possibility of experiencing bankruptcy and 272 are in grey zone. It shows that more than 50 percent of the companies' financial are not financially sound enough. On the other hand, 113 of the total 145 (77%) firm's year shows that fraud companies shows sign of bankruptcy. It indicates that the companies could have faced financial instability before being charged by Securities Commission.

5. CONCLUSION

The number of financial statement fraud is continuously increasing. Thus, the auditing practices nowadays have no choice but to cope with such increment. Many techniques have been implemented not only to detect but also to predict financial statement fraud. Each of the techniques mentioned in previous studies claim that they have advanced classification and prediction capabilities which would help the auditors to combat financial statement fraud. The aim of this study is to identify whether threat of bankruptcy appear in fraudulent companies before being charged and also to apply Altman Z-Score model in detecting financial statement fraud among small cap companies. Based on the result, prior to being charged, fraudulent companies' shows sign of bankruptcy which could have been a motivation for the companies to be involved in manipulating their financial reporting. It indicates that, threat of bankruptcy is one of the important factors in studying financial statement fraud. Meanwhile, based on the prediction result, it can be concluded that small market companies had shown signs of bankruptcy where 218 of the firm's year have possibly experienced bankruptcy. However, it was suggested by Altman (1968) to look into business trend over time in order to better interpret the score, rather than just looking at the score itself.

6. FUTURE RESEARCH AND LIMITATION

Future research could use this prediction model and compare it with other techniques. While this study has significant results by using Altman Z-Score, there is still a need to justify the result by observing the business trend.

ACKNOWLEDGEMENT

The research was supported by the ARI HICOE research grant, Fundamental Research Grant Scheme (FRGS) of the Ministry of Higher Education Malaysia and Universiti Teknologi MARA (UiTM).

REFERENCES

Abbott, L. J., & Parker, S. (2000). Auditor selection and audit committee characteristics. *Auditing: A journal of practice & theory, 19*(2), 47-66.

ACFE. (2012). Report to the Nations on Occupational Fraud and Abuse 2012 Global Study: ACFE Austin.

ACFE, A. o. C. F. E. (2014). Report to the Nations on Occupational Fraud and Abuse: 2014 Global Fraud Study: Association of Certified Fraud Examiners.

Al-Sulaiti, K., & Almwajeh, O. (2007). Applying Altman Z-score model of bankruptcy on service organizations and its implications on marketing concepts and strategies. *Journal of International Marketing and Marketing Research, 32*(2), 59.

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The journal of finance, 23*(4), 589-609.

Altman, E. I., & Hotchkiss, E. (2010). *Corporate financial distress and bankruptcy: Predict and avoid bankruptcy, analyze and invest in distressed debt* (Vol. 289): John Wiley & Sons.

Arnott, R. D., & Wu, L. J. (2012). The Winners Curse: Too Big to Succeed? *Available at SSRN 2088515*.

Beasley, M. S., Carcello, J. V., & Hermanson, D. R. (1999). *Fraudulent Financial Reporting: 1987-1997: An Analysis of US Public Companies: Research Report*: AICPA.

Beneish, M. D. (1999). The detection of earnings manipulation. *Financial Analysts Journal, 55*(5), 24-36.

Chen, W.-S., & Du, Y.-K. (2009). Using neural networks and data mining techniques for the financial distress prediction model. *Expert systems with applications, 36*(2), 4075-4086.

COSO, C. o. S. O. o. T. T. C. (1999). Fraudulent Financial Reporting: 1987-1997-Analysis of US Public Companies. *New York: American Institute of Certified Public Accountants*.

du Jardin, P. (2008). Bankruptcy prediction and neural networks: the contribution of variable selection methods. *Proceedings of ESTSP*, 271-284.

Grove, H., & Basilico, E. (2011). Major Financial Reporting Frauds of the 21st Century: Corporate Governance and Risk Lessons Learned. *Journal of Forensic and Investigative Accounting, 3*(2).

Hasnan, S., Rahman, R. A., & Mahenthiran, S. (2012). Management motive, weak governance, earnings management, and fraudulent financial reporting: Malaysian evidence. *Journal of International Accounting Research, 12*(1), 1-27.

Hayes, S. K., Hodge, K. A., & Hughes, L. W. (2010). A Study of the Efficacy of Altmans Z To Predict Bankruptcy of Specialty Retail Firms Doing Business in Contemporary Times. *Economics & Business Journal: Inquiries & Perspectives, 3*(1), 130-134.

Ijaz, M. S., & Hunjra, A. I. (2013). Assessing the Financial Failure Using Z-Score and Current Ratio: A Case of Sugar Sector Listed Companies of KSE. *World Applied Sciences Journal, 23*(6), 863-870.

Kaminski, K. A., Sterling Wetzel, T., & Guan, L. (2004). Can financial ratios detect fraudulent financial reporting? *Managerial Auditing Journal, 19*(1), 15-28.

Kinney, W. R., & McDaniel, L. S. (1989). Characteristics of firms correcting previously reported quarterly earnings. *Journal of accounting and economics, 11*(1), 71-93.

Klein, A. (2002). Audit committee, board of director characteristics, and earnings management. *Journal of accounting and economics, 33*(3), 375-400.

KPMG Malaysia. (2014). Fraud, Bribery and Corruption Survey 2013: KPMG: Forensic.

Kranacher, M.-J., Riley, R., & Wells, J. T. (2010). *Forensic accounting and fraud examination*: John Wiley & Sons.

Kreutzfeldt, R. W., & Wallace, W. A. (1986). Error Characteristics in Audit Populations-Their Profile and Relationship to Environmental-Factors. *AUDITING-A JOURNAL OF PRACTICE & THEORY, 6*(1), 20-43.

Lin, J. W., & Hwang, M. I. (2010). Audit quality, corporate governance, and earnings management: A meta‐analysis. *International Journal of Auditing, 14*(1), 57-77.

Lin, J. W., Li, J. F., & Yang, J. S. (2006). The effect of audit committee performance on earnings quality. *Managerial Auditing Journal, 21*(9), 921-933.

Ng, K. S., Mohammed, A. A. E., Ahmad, A., & Huam, H. T. (2013). Applicability of Altman's revised model in predicting financial distress: a case of PN17 companies quoted in Malaysian Stock Exchange.

Omar, N., Said, R., & Johari, Z. A. (2016). Corporate crimes in Malaysia: a profile analysis. *Journal of Financial Crime, 23*(2).

Persons, O. S. (1995). Using financial statement data to identify factors associated with fraudulent financial reporting. *Journal of Applied Business Research, 11*(3), 38.

PWC. (2014). Global Economic Crime Survey—US Supplement: Economic Crime: A Threat to Business Processes: PWC.

PWC Malaysia. (2014). PwC's 2014 Global Economic Crime Survey—What You Don't Know Can Hurt You: Economic Crime— A Threat to Malaysian Business: PWC Malaysia.

Schilit, H. (2010). *Financial shenanigans*: Tata McGraw-Hill Education.

Smith, M., Ahmar Ahmad, S., & Shameer Mohamed, A. (2004). Modelling PN4 classification among Malaysian listed companies. *Asian Review of Accounting, 12*(2), 57-73.

Spathis, C., Doumpos, M., & Zopounidis, C. (2002). Detecting falsified financial statements: a comparative study using multicriteria analysis and multivariate statistical techniques. *European Accounting Review, 11*(3), 509-535.

Subramaniam, N., Carey, P., Sil Kang, W., Kilgore, A., & Wright, S. (2011). The effectiveness of audit committees for low-and mid-cap firms. *Managerial Auditing Journal, 26*(7), 623-650.

Tebogo, B. (2011). Does the Enron Case Study Provide Valuable Lessons in the Early Detection of Corporate Fraud & Failure? *Available at SSRN 1906045*.

Wells, J. T. (1997). *Occupational fraud and abuse*: Obsidian Publishing Company.

Zimbelman, M. F. (2012). *Forensic accounting*: South-Western Cengage Learning.