Financial Information Fraudulence and Financial Distress: Evidence from Singapore

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Abstract: We investigate if Singapore listed companies engaged in financial information fraud during financial distressed after two years of US subprime mortgage crisis. We also investigate the impact of financial information fraudulence in bankruptcy prediction and misclassification errors. This study used consumer product companies listed on the main board and the timeframe is from 2011 till 2015. The Altman Z score indicates that 55 out of 110 companies are financially distressed. Meanwhile, the M score shows that 49 out of 351 observations are engaged in financial information fraudulence. However, these results are relatively low because the samples are taken from the main board and fraudulence in their financial statements might be done in lower magnitude in order to avoid sanctions by the Security Exchange Commission. Logistic regression was used to measure the predicting accuracy. The result of the overall accuracy percentage slightly improved by 2.4 after eliminating fraudulent companies. The confusion matrix result i.e. before and after the removal of financial information fraudulent companies, the misclassification errors for type one has improved by 1.7 percent and 3 percent for type two. This result met objective three, as the upward bias of financial information fraudulence is one of the explanations for the decline in financial distress prediction. This research will be beneficial to governments, monitoring agencies, and all involved in the insolvency process.
Keywords: Financial information fraudulence, financial distressed, Z score, M score, Misclassification errors, Singapore.

1. Introduction

Financial statement or financial report is a formal documentation record of a company's financial activities in a particular year (Supriyanto and Darmawan, 2018). It shows the financial, performance and liquidity strengths of the company. The objective of financial reporting is to provide a high quality report of companies' financial information which will allow users to make coherent decisions (Bushman and Smith, 2001). The international standard definition for accounting information quality is "the reliability and transparency of financial statement figures" (Minanoa and Campa, 2014). It is crucial for financial statements to represent the "true and fair view" of companies. Financial ratios extracted from financial statements have their own usability and provide various information but sometimes conflicting with each other (Supriyanto and Darmawan, 2018).

Hope, Thomas, and Kolk, (2011) found that credible financial information experience significant reductions in external financing constraint. It also reduces information asymmetry between the company and the external financial provider, alleviates information problems and makes managers more accountable for their job scope. Market price and security returns reflect the information embedded in the company's accounting reports (Beaver, Correia, and Mcnichols, 2012). This shows that the usefulness of the information contained in financial statements has not declined (Brown, Lo, and Lys, 1999) and instead has increased (Francis and Schipper, 1999).

The activities of financial information fraudulence have been showing an upward trend in the past decade. The activities consist of the fabrication of assets, income, liabilities and losses where they no longer represent the true picture of the company. There are several explanations as to why companies engage in financial information fraudulence including to raise capital through public offerings, to get tax exemptions, and to cover default payments and stock overvaluation (Lau and Ooi, 2016; C. Spathis, Doumpos and Zopounidis, 2002; Spathis, 2002). Misleading financial statements pose negative and significant consequences on the information user (Crawford and Weirich, 2011; Kirkos, Spathis, and Manolopoulos, 2007). Therefore, the GAAP that is used in preparing financial statement is violated (Feng and Li, 2012). Engaging in fraudulent financial information helps companies to increase their stock price (Rosner, 2003). Accounting fraud could entail fraudulent reporting and/or assets misappropriation (Kotsiantis *et al*., 2010; Song, Lee and Cho, 2013). However, companies with better quality information disclosure are less likely to engage in financial statements fraud. Impressive sales growth and high stock returns do not always indicate a good sign (Goel and Thakor, 2003). If the accrual is high, it could be due to financial information fraudulence since accrual is commonly used for this illegal activity (Trejo-Pech, Weldon, & Gunderson, 2016).

Prior research has shown that financial information fraud in distressed companies is still a concern, and that improvements have been made to hide it. Also companies with low levels of distress engage in financial information fraud for their own personal gain. This demonstrates how financial deception has progressed. Despite the fact that the topic has been debated for decades, there is no sign that it will be resolved anytime soon. The use of sophisticated accounting methods makes it much more difficult to spot. Since most early studies used distressed and fraudulent companies listed by the Securities Exchange Commission, it is important to detect fraudulent activities in the main market. Previous research has seldom emphasized the importance of financial information reliability in predicting bankruptcy. While distressed companies attempted financial information fraud, their poorer position is noticeable as compared to healthy companies. Perhaps more effectively than distressed companies, healthy companies mask their financial information fraudulence (Beaver, 1966)

In a matched sample of financially distressed and healthy companies listed on the Singapore Stock Exchange, this paper uses the Z score and the M score to identify financial information fraudulence among financial distressed companies. Second, to look into the effect of financial information fraudulence on bankruptcy prediction accuracy; and third, to provide empirical evidence that financial information fraudulence is a factor in misclassification errors.

This study adds to the existing body of information in many respects. First, it looks at financial information fraud among distressed companies that are still listed on the main board. Second, the study is limited to consumer goods companies only. It has been empirically shown that during financial crises, insolvency issues are more serious in these industries ((Hasan et al., 2017). Third, it emphasises the effect of financial data fraud on bankruptcy prediction accuracy as well as misclassification errors.

Our findings indicate that some distressed companies indulge in financial information fraudulence, and that the accuracy of bankruptcy prediction increased marginally after the fraudulence was eliminated. After removing financial information fraudulence companies from the study, the misclassification errors, has improved.

The following is how the paper is organised: Sections 2 and 3 address the methodology and calculation variables used in this paper; Sections 4 and 5 discuss and present the analytical results; and Section 5 summarises the findings and addresses their main consequences and limitations.

2. Literature Review and Hypotheses Development

2.1 Financial Information Fraudulence among Financial Distressed Companies.

During economic crises, companies have many incentives to minimize the negative effect of economic downturn in order to survive. Practically, earning management helps to clean the negative "signal" of financial distress (Jaggi and Lee, 2002; Sweeney, 1994) by sacrificing the integrity of financial reports (Kotsiantis, Kanellopoulos, and Tampakas, 2010; Minanoa and Campa, 2014). Fraudulence in financial information will hinder financial distress prediction performance. Manipulation activity is a deviation from normal operational practices, motivated by the top management's desire to mislead the information users into believing that certain financial objectives have been met in the operations normal course (Johnson, Fleischman, Valentine, and Walker, 2012)

Minanoa and Campa (2014) discovered that companies in financial distress are more likely to exploit their financial data. Fabrication of assets, profits, liabilities, and losses that no longer reflect the true reputation of the firm. Human beings, on the other hand, and errors are inextricably linked, whether deliberately or unintentionally. Spathis (2002) explained the distinction between errors and financial information fraudulence. Financial information fraud, he clarified, is a deliberate act, a scheme conceived by management to mislead stakeholders by creating fictitious documents to justify the activities. Mistakes, on the other hand, are unintended mistakes made during the financial reporting process, such as misstatements or disclosure omissions. Errors may often just be errors; however, a spike in errors will be suspicious and may be related to financial data fraud (Flanagan et al., 2008).Companies engage in financial information fraud for a number of purposes, including raising money through public offerings, gaining tax exemptions, and covering default payments and stock overvaluation (Lau and Ooi, 2016; C. Spathis, Doumpos and Zopounidis, 2002; Spathis, 2002).

Financial statements that are misleading have negative and important implications for the information consumer (Crawford and Weirich, 2011; Kirkos, Spathis, and Manolopoulos, 2007). Financial information fraud is characterised as the deliberate misrepresentation of a company's financial position by intentional misstatements, omissions, or disclosures in financial statements in order to mislead financial statement users. As a result, the GAAP used to prepare financial statements is breached (Feng and Li, 2012). Engaging in fraudulent financial information helps companies to increase their stock price (Rosner, 2003).

Accounting fraud could entail fraudulent reporting and/or assets misappropriation (Kotsiantis et al., 2010; Song, Lee and Cho, 2013). High stock returns and impressive revenue growth aren't necessarily a positive sign (Goel and Thakor, 2003). Since accrual is widely used for this illegal activity, if the accrual is high, it may be attributable to financial information fraudulence (Trejo-Pech et al., 2016). Financial information fraudulent companies manipulate their production cost (real earnings) for two years before the fraud event and manipulate cash flow operations (accrual) prior to the fraud event (Md Nasir, Ali, Razzaque and Ahmed, 2018). Fraudsters prefer to manipulate earnings using accruals instead of real earnings due to the substitute nature of two forms of earnings management. The earnings quality for fraudulent companies is relatively low compared to the non-fraudulent companies

According to Minanoa and Campa (2014), firms that received "liquidation" decisions are more likely to be involved in upward earning management compared to firms that received "reorganise" decision and that this action leads to misclassification error. Moreover, companies that have weak economic and financial performance will use pervasive earning management techniques in an attempt to postpone their actual failure. Battiston et al. (2007) mentioned that the unexpected shock to revenue or cost that lowers down the company's average return is one example that triggers financial distress. When the company fails to fulfill the debt covenant, it may hamper supplier solvency and affect the upper level of its own supplier. It is like a domino effect where it will jeopardize the chain of the company where the repercussions are systematic.

Based on Beasley et al. (2010), financial information fraudulent companies experience abnormal stock price decline after the announcement. The tendency of these companies to face bankruptcy and delisting is much more higher compared to non-fraudulent companies. However, a company that receives the chance to restructure will take the opportunity to change its management, but additional tools is demanded to inspect the new management integrity. There is no certain size and industry for companies to commit fraud.

2.2 Hypothesis Development

Pressure received from the top management contributes to financial information fraudulence (Beasley et al., 2001). As much as 89 percent of financial information fraudulent cases involve Chief Executive Officers and Chief Finance Officers. The years of company fraudulence were significantly prolonged due to the years of experience of board of director in fraudulence detection arena (Beasley et al., 2010). Bad accounting practice has severe spillover effects on peers' investment with the element portrayed by the deceives agent (Beatty, Liao and Jiewei, 2013). The distortion signal of investment opportunity leads to the sum-optimal industry peer investment. Average loss made by the top management due to financial information fraudulence is USD 250 thousand (ACFE, 2020).

The idea that managers do not always serve shareholders very well creates an agency conflict that sometimes could cost the company. Agency cost happens when managers only consider doing things that would benefit themselves. Thus, corporate governance acts as a tool to discipline, scrutinize, and monitor management to ensure that they act in the shareholders' best interests (Holthausen, Larcker, and Sloan, 1995). Therefore, it helps to harmonize the action of the manager with the shareholder's objective and bring balance to the system. It has long been acknowledged that the manager's objective is to maximize shareholders wealth, but sometimes it diverges. Being unable to achieve the objectives leads to an agency conflict and sometimes triggers the manager's intention to commit fraud. This was proven by Hope et al., (2011) where the presence of a controlling shareholder and weak investors' protection rights reduce financial information credibility due to the extraction of private benefits.

Financial restatements give a bad image on manager integrity and reputation since the public expects the independence of management would associate negatively with this incident. To prevent this from happening, an evaluation of manager performance needs to be done. Abdullah et al., (2010) observed that the separation of jobs seems to be effective in ensuring that the manager continues to act in the best interest of the shareholders. The pattern of company ownership structure such as managerial ownership and large shareholder leads to agency cost and extends of management monitoring seems to be needed. They claim that outside blockholder could provide a monitoring mechanism for shareholders. Financial statements are a way to communicate manager performance to shareholders. Thus, it is vital to prepare it with a true and fair view, and free from errors and irregularities.

The agency theory exclusively focuses on the interconnection between the various motivations for engaging in financial information fraudulence during financial distress events. Manipulation of financial statements due to agency conflicts jeopardizes the financially distressed company's prediction accuracy as the financial statement is not reporting its true value. When this happens, the calculation of financial ratios will never be able to correctly classify the company and will end with misclassification errors. Therefore, this current study aims to extend the knowledge on how managers preserve the intention of maximizing shareholder wealth during financial distress events. Previous studies clearly stated that all financial information fraudulence cases occurred when the company is still listed on the main market, but none of the studies had used distressed companies listed on the main market to detect financial information fraudulence. Thus, the first research hypothesis is developed as follows:

Hypothesis 1: Companies that are facing financial distress practice fraudulence in their financial statements.

Earnings management and financial information fraudulence (fraud) are subsets of earning manipulation (Rosner, 2003). It is a technique employed by managers to achieve the desired levels of reported earnings. It is defined as a violation of the Generally Accepted Accounting Principles (GAAP) in order to beneficially represent the company's financial statement (Beneish, 1999; Goel and Thakor, 2003). It is an act of "a purposeful intervention in the external financing reporting process with the intent of obtaining some private gains" (Sharma, 2014; Trejo-Pech et al., 2016). The financial variable that is commonly used for financial information fraudulence is accrual (Trejo-Pech et al., 2016; Wells, 2002).

High magnitude financial information manipulation poses disastrous effects on the economy and significant financial losses to investors. Its misclassification as a healthy company is camouflaged by its "good" financial performance. Capital expenditure is significantly greater during financial information fraudulence period (Beatty et al., 2013). Beaver *et al*. (2012) state that the predictive power of financial distress diminishes with respect to both low and high discretionary accruals.

Accounting variables are widely used in prior studies to predict financial distress. Due to the dynamic nature of financial distress, researchers try to develop models that could detect financial distress. However, due to the popularity of the ratios, it is made as a target for the management to manipulate the accounting variables. This activity is known as window dressing and functions to destroy their utility (Beaver, 1966). Unreliability of financial information can erode public confidence as a means to assess future company prospects. Involvement in fraud will increase the likelihood of bankruptcy (Amershi and Feroz, 2000). Financially distressed managers intentionally misclassify core expenses as income decreasing special items in order to meet or beat earning benchmarks (Nagar and Sen, 2017). Special items such as loss on sales of assets, impairment of goodwill, settlement cost and restructuring cost will be re-added at the last stages of the financial reporting process. This income decreasing special items ultimately will inflate company income.

Normally, companies committing fraud were suffering net losses or close to breaking point prior to the fraud event. The pressure of financial distress provides the motivation for the management to commit financial fraudulent activities (Beasley et al., 2010; Spathis, 2002). Earlier research had examined managerial catalysts on both upward and downward earnings management. Debt convents requirement preservation is the main reason managers manage upwards earnings (Dichev and Skinner, 2002).

This study investigates the discrepancy in accuracy percentage by using financial information fraudulence (agency cost) as the moderating variable in predicting financial distress. Based on the effect of financial information distortion in hindering the prediction accuracy of financial distress as highlighted in prior studies, our second hypothesis for analysis is therefore developed as follows:

$H2$: Financial information fraudulence deteriorates bankruptcy prediction accuracy.

The misclassification error cost of financial information fraudulence is asymmetric as investor cost (losses) is considerably high when unintentionally investing in a fraudulent company than in a non-fraudulent company (Abbasi, Albrecht, Vance, & Hansen, 2012). Opportunity cost happens when the investor fails to invest in a legitimate company, and stock price of fraudulent company will decrease after being discovered. Financial information fraudulence is often linked with financial distress.

The restrictive assumptions in the traditional model are hard to apply in real data because financial data frequently violates the model's assumptions and this will lead to measurement errors (Shin and Lee, 2002). Traditional models such as the logistic regression, hazard model, and multivariate discriminate analysis allow users to determine which variables provide the best explanation for financial distress discrimination (Altman, Marco, and Varetto, 1994).

Owing to the fact, many researchers focused their effort in enhancing financial distress prediction so that beneficial decisions can be made for both parties. However, enhancements on financial distress prediction model do not always guarantee the reduction and elimination of misclassification errors (Tsai and Wu, 2008). Yet, it does improve prediction performance (Nanni and Lumini, 2009) if it is correctly applied and satisfies the assumption imposed by the model (Abellán and Mantas, 2014).

Theoretically, the ability to detect financial information fraudulence will improve financial distress prediction by making it a control variable. Thus, it helps to reduce or eliminate any irregularities in the prediction outcome that could lead to inconclusive decisions such as when the score falls under the "gray area"[1]. Cecchini et al. (2010) believe that there will be an evolvement in fraud concealment tactics in the future. Therefore, they suggest an inductive principle that anticipates this strategic behavior which might be useful in being a step ahead from the fraudster in detecting fraudulence.

Financial information fraudulence lowers the prediction model's power over time. However, market model prediction is not affected with the exclusion of restatement. Beaver et al. (2012) concluded that financial information fraudulence erodes the accounting model's predictability and cannot be offset by market-related variables. The authors found that there is a significant time trend in the frequency of restatements. The restatement variables significantly explained the differences in predictive ability over time. This error occurs when the model fails to correctly classify the company. Even if the market variables exhibit lower predictive power, there will be no declining time trend unlike that of the accounting variables. Therefore, due to the lack of debate in previous literatures on the factors of misclassification errors, this research aims to study the effect of fraudulence in financial information on misclassification errors. Our third hypothesis is hence developed as follows:

$H3$: Financial information fraudulence increases misclassification errors.

3. Methodology

3.1 Sample Selection The population of this study entailed the consumer products industry in Singapore The manufacturing sector had been widely used as the study sample in previous researches (Beaver, 1966; Chen, Zhang and Zhang, 2013; Foo, 2015; Kumar, 2012) due to the simplicity in ratios calculation, understandable accounting terms and finished products compared to other industries or sectors of which accounting terms are rather complex to understand. Focusing on a specific sector is essential for comparability (Andrés, Landajo, and Lorca, 2012). Comparing companies from different sectors would be problematic due to the different ratios distribution (Beaver, 1966). To make legit comparisons, the companies need to be in the same industry and of the same asset size (Thai, Goh, Teh, Wong, & Ong, 2014).

The collected data covered the period from 2011 to 2015. The time frame was selected to avoid the structural break due to the US sub-prime crisis that hit Malaysia in late 2007 until 2008 as Charalambakis (2015) claimed that financial crisis hinders the accuracy of financial distress prediction. This notion was also supported by Chiaramonte et al. (2015) who indicated weakened prediction accuracy during the 2007-2010 financial crisis compared to during when the economy was stable (2002 to 2006) i.e. 84.62 percent and 87.09 percent, respectively. The misclassification of type one error also increased during the financial crisis period i.e. to 15.38 percent from 12.91 percent during stable economy. Thus, this study had decided to collect data starting from 2011 so as to certify that Singapore is free from financial crisis and to circumvent the negative effect of systematic bias.

[1] Referring to the Z-score model by Altman (1968), if the company's Z-score falls below 1.81, it has the probability of going bankrupt or is currently facing financial distress. If the company's Z-score is above 2.99, it is a healthy company and free from financial distress. However, if the company's Z-score falls between 1.81 and 2.99, the result is inconclusive and a decision cannot be made. This area is known as the gray area.

There are significant number of consumer product companies fallen into the distressed status after the US sub-prime crisis (Kamaluddin, Ishak and Mohammed, 2019) and the share price of consumer product companies experienced continuous decline after the financial crisis (Pramudena, 2017). The prolonged share price decline indicates a disruption in the companies' financial performance which led to financial distress when no corrective actions were taken by the management. The aforementioned studies showed that consumer product companies in South East Asia are significantly affected by the financial crisis considering the decline in demand for non-essential goods.

This current study adopts the purposive sampling technique where samples are determined based on certain criteria (Supriyanto and Darmawan, 2018). The cross section model is employed whereby more than one variable is collected at the same time. This technique tends to highlight the sector used in this study within the total population of listed companies in both main markets. According to Sekaran and Bougie (2013), a total of 20 percent of the sample is considered sufficient for conducting the research. There are 110 listed consumer product companies and after calculating the Z-score (Equation 0-1), 55 companies are found distressed. Therefore, the 55 distressed companies are paired with the 51 healthy companies due to 4 companies Z score fall under gray area. The sample taken in this study is more than 20 percent as shown in Table 0-1.

Table 0-1: Calculation of proportionate purposive sampling

Countries	Number of companies	Proportionate sampling
Singapore	110	((55+51)/110) x 100% = 96%

3.2 Estimating of Financial Distressed

The Z-score model was introduced by Prof. Dr Edward I. Altman in 1968. It has been used widely to discriminate distressed companies with the healthy one. Therefore this study apply this model due to its ability to identify and utilize selected variables for discrimination purposes. Below is the linear combination of the Z-score model.

$$\text{(I)}Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.999X_5 \qquad \text{Equation 0-1}$$

Where X1 = Working capital/Total assets.
X2 = Retained Earnings/Total assets.
X3 = Earnings before interest and taxes/Total assets.
X4 = Market value equity/Book value of total debt.
X5 = Sales/Total assets.
Z = Overall Index.

A score lower than 1.81 indicates a financially distressed company and be denoted as 1. If a score higher than 2.99 indicates a healthy company and be denoted as 0. However, a score between 1.81 and 2.99 indicates that a conclusion cannot be drawn about whether the company is financially distressed or not. This area is called the gray area or the zone of ignorance. This step was repeated on all the companies for each year. If the company experienced distress for five years straight, the number of samples would be 5 because each distressed year was counted. Healthy and distressed companies are matched based on asset size and industry (Thai et al., 2014). A reasonable number of samples are needed to cut small sample bias. Apart from helping increase the number of samples, this method had been widely used by other researchers.

3.3 Estimating of Financial Information Fraudulence.

The Beneish model was coined by Professor Messod Daniel Beneish and was published in 1999 with the given title "The Detection of Earnings Manipulation". He combined several ratios into the model to identify the occurrences or tendency of financial information fraudulence. This model is also known as the M-score and acts as a barometer for the extent to which earnings have been manipulated. This model was formulated using the eight ratio variable analysis to identify financial fraud occurrence or tendency to engage in earnings manipulation (Beneish, 1999). This score will help detect companies that are involved in financial information fraudulence. Table 0-2 provides the eight ratio variables used in the Beneish model to detect earning manipulations. The eight ratio variables were then calculated using the formula below:

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 Equation 0-2

Table 0-2: Eight ratio variables of the Beniesh Model
(Source: Abdul Aris et al. (2013)))

Ratio	Formula
Sales Growth Index (SGI)	Sales t / Sales (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]
Assets Quality Index (AQI)	(Current assets + Property, plant and equipment) / total assets
Days' Sales in Receivable Index (DSRI)	(Receivable t / sales t) / (Receivable t-1 / sales 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)
Depreciation index (DEPI)	(Depreciation t / Depreciation t + PPE[2] t) / (Depreciation t-1 / Depreciation t-1 + PPE t-1)
Leverage Index (LVGI)	[(Long term debt t + Current Liabilities t) / Total Assets t] / [(Long term debt t-1 + Current Liabilities t-1) / Total Assets t-1]
Total Accrual To Total Assets (TATA)	(Δ Current assets - Δ Current liabilities - Δ short term debt - Depreciation and Amortisation – deferred tax of earning – Equity in Earning) / Total assets

An M-score result of less than -2.22 suggests that the company is not manipulating its earnings. However, an M-score of more than -2.22 signals that the company is likely engaged in earning manipulations. A comparison between the models developed by Benford, Law and Beneish in the study by Abdul Aris et al. (2013) showed that the variables incorporated in the Beneish model is considered related to fraud detection. Different aspects of a company's performance can be assessed simultaneously instead of in isolation. The model is presumed to be reasonable, accurate and up-to-date.

3.4 Estimating of Bankruptcy Prediction

Logistic regression is used for examining prediction accuracy and misclassification errors for objectives 2 and 3 respectively. It is run twice to attain improvement in prediction accuracy and misclassification errors. For the first run, the model is as follows:

$$L_i = \ln\left(\frac{P_{i+fraud}}{1-P_{i+fraud}}\right) = \beta_1 + \beta_2 leverage\ ratios + \beta_3 profitability\ ratios$$
$$+\beta_4 Liquidity\ ratios + u_i \qquad \text{Equation 0-3}$$

In which, the financial information fraudulent companies are included in financial distressed prediction in $P_{i+fraud}$. As for the second run, the financial information fraudulent companies are excluded from the financial distressed prediction. The model is as follows:

$$L_i = \ln\left(\frac{P_{i-fraud}}{1-P_{i-fraud}}\right) = \beta_1 + \beta_2 leverage\ ratios + \beta_3 profitability\ ratios$$

$$+\beta_4 Liquidity\ ratios + u_i \qquad \text{Equation 0-4}$$

This study used 17 financial ratios at the preliminary stage. Previous researchers had used these variables and found them to be useful in providing statistical evidence of distress. The stepwise method is used in the process of reducing the variables set to an acceptable number in determining the 'best' variables within the given variables set (Bae, 2012).

Table 0-3 lists the explanatory variables employed in this current study of which selection is based on their significant predictive ability as suggested in previous studies.

Table 0-3: Table of Explanatory Variables

	Variable name	Variable definition
Profitability	S/TC	Sales/Total Capital
	S/TD	Sales/Total Debt

[2] Property, plant and equipment.

	Return on total assets	Earnings Before Interest And Tax/Total Assets
	Δ in sales	Change in Sales
	ROA	Profit/ Total Assets
	ROE	Profit/ Total Equity
	P/S	Profit/Sales
	P/TC	Profit/Total Capital
	Δ in profit	Change in Profit
Liquidity	WC/LTD	Working Capital/Long Term Debt
	C/CL	Cash/Current Liabilities
	Current ratio	Current Assets/Current Liabilities
	C/TA	Cash/Total Assets
Leverage	Debt ratio	Total Debt/Total Assets
	TD/TE	Total Debt/Total Equity
	Interest coverage	Earnings Before Interest and Tax/Finance Cost
	MKTCAP/TD	Market Capital/Total Debt

A suitable or best set of independent variables might give a better degree of discriminative power between the two groups of companies. The process in finding the acceptable number of variables that are closely related to the financial distress determinants is important. Further variable selection techniques were supplied for the model development process. The pair stepwise method was adopted to determine the final set of variables to be included in the discrimination model. The method starts with the step-by-step forward selection where the procedure begins with no variables in the model. Each variable's weight was evaluated at each step to determine which variable contributes most to the model's discriminative power. Variables that failed to meet the criterion (measured by Wilks' l statistics) were removed. This study chose the 0.80 tolerance level to stop the stepwise selection process. This is to help in choosing high-quality results with a low percentage of predictor errors, where the predictor's capability decreases as the time horizon increases.

The final profile of the variables was selected based on the following procedure: 1) observing the statistical significance of each independent variable to find the contribution; 2) checking the interrelation among the independent variables; 3) observing the variables' predictive accuracy, and 4) discussing the results.

3.5 Misclassification errors.

Misclassification happens when a company is wrongly assigned. In objective three, type one and type two errors were calculated to observe the differences with and without the use of fraudulent companies as a control variable in predicting financial distress. Objective three applied the same variables and method as in objective two, but was split into two groups which original sample was maintained in this first round and another samples was without financial information fraudulent companies. Then, objective three produced 2 results for the misclassification errors. Below is the summarization for objective three.

Table 0-4: Classification accuracy table (Source: Altman, 1968)

	True healthy	True financially distress
Prediction of healthy companies	P_{11}	$1 - P_{11}$ (Type I error)
Prediction of financially distressed companies	$1 - P_{22}$ (Type II error)	P_{22}

Based on the table above, P_{11} and P_{22} represent the correct classifications (hits) for healthy and financially distressed companies, respectively. Type 1 denotes misclassified financially distressed companies as healthy companies and type 2 denotes misclassified healthy companies as financially distressed companies. The results of these two misclassification errors were compared with before and after the removal of financial information fraudulent companies. This is to assess any significant differences in the misclassification results with and without financial information fraudulent companies. This study projected a differentiation in the misclassification result by taking financial information fraudulence into consideration. The expectation is that, by taking financial information into consideration, the misclassification errors could be reduced especially for type 1 error since the negative impact is more severe compared to the type 2 error.

4. Discussion and Result

4.1 Financial Information Fraudulence Practice among Distressed companies.

As presented in table 4-1 the Z- score ratios were calculated for each company and it was found that there were 55 financially distressed companies. This indicates that companies listed on the main board are not always healthy. However, the companies will remain on the main board as long as they fulfill the minimum listing requirements. Financially distressed companies require some time to recover and become healthy again. The financial distress condition might be mild and the companies may still be able to meet their debt obligations.

Table 4-1: Financial Condition Analysis

Country	Distress	Healthy	Total
Singapore	55 companies (184 observations)	51 companies (167 observations)	106 companies (351 observations)

As depict in table 4-2, results from the Beneish model (M score) indicated that 28 (49 observations) out of 55 (184 observations) distressed companies in the sample i.e. 51 percent had been involved in financial information fraudulence at least one. This proves that half of financially distressed companies engage in financial information fraudulence to improve their financial performance and to achieve other benefits (Spathis, 2002). This also proves that main market companies (distressed companies) also engage in financial information fraudulence as supported by Agrawal and Chatterjee (2015). As this study used main board public listed companies, the financially distressed companies are generally healthy according to the security exchange; they were identified as financially distressed due to the Z-score.

The time frame of the study played a significant role in highlighting the consequences of economic growth relating to financial information fraudulence. After a certain economic crisis, some companies became unsustainable thus prompting their managers to embark on financial information fraudulence (Lau and Ooi, 2016). Prolonged growths have rendered corporate monitors such as regulators and auditors to believe in the companies' high performance instead of the risk indicators. Thus, this result prove that some distressed companies did practice financial information fraudulence in order to stay in the main market. Therefore, the null hypothesis is rejected and the result confirm that distressed companies practice financial information fraudulence .

Table 4-2: Financial information Fraudulence Analysis.

Country	Healthy	Distress		Total
		Fraud	Non-fraud	
Singapore	167 observations	49 observations	135 observations	351 observations

4.2 The effect of financial information fraudulence on bankruptcy prediction accuracy.

4.2.1 Regression Analysis before Financial Information Fraudulence Removal

The variables selected were based on the stepwise discriminate analysis. Based on the stepwise debt ratio, return on total assets and cash over total assets were found to be statistically significant at a 1 percent level whilst interest coverage and current ratio were significant at a 5 percent level. Only five variables were selected in this study as an effort to maintain the accuracy of financial distressed prediction. Fallahpour, Lakvan and Zadeh (2017) investigated the number of features that should be included in the prediction model to achieve the highest accuracy. They tested 5, 10, 15 and 20 features and found that 5 features lead to the highest accuracy. This finding was in line with that of Gogas, Papadimitriou and Agrapetidou (2018) who found that cutting the set size leads to maximum improvement over the replaced based variables. The authors indicated 6 variables for financial distress prediction.

Table 4-3: Descriptive Analysis for Singapore before removing Fraud companies.

	Healthy		**Financially distress**	
	Mean	**Sta. Deviation**	**Mean**	**Sta. Deviation**
Debt ratio	0.3126	0.1899	0.6119	0.3421
Interest coverage	1.4401	1.1673	0.6276	0.5747

Return on total assets	0.0761	0.2119	-0.1744	0.6694
Current ratio	4.4332	6.5786	1.4179	1.1980
Cash/TA	0.2339	0.3459	0.1213	0.1357

Table 4-3 exhibits the mean and standard deviation for all the variables of the healthy and financially distressed companies. All the variables selected were extracted from the stepwise method where the significant level for each variable is at a 1 percent level of significance. The mean for the healthy companies is greater than that of the financially distressed companies except for debt ratio. The gearing ratio for the healthy companies is twice lower than their counterpart as they can be used for internal financing such as retained earnings to finance the companies. Interest coverage for the healthy companies is more than twice greater than that of the financially distressed companies. In conclusion, the financial performance of healthy companies is distinct from that of their counterpart.

Table 4-4: correlation matrix for Singapore before removing Fraud companies.

	Debt ratio	**Interest coverage**	**Return on total assets**	**Current ratio**	**Cash/TA**
Debt ratio	1				
Interest coverage	0.003	1			
Return on total assets	-0.225***	0.010	1		
Current ratio	-0.370***	0.167***	-0.108**	1	
Cash/TA	-0.097	0.222***	-0.036	-0.163***	1

*** Significant at a 1% level
** Significant at a 5% level
* Significant at a 10% level

All the variables were not correlated with each other as all the correlations were not more than 0.6 and not less than -0.6. As portrayed in table 4-4, the Pearson correlation coefficient was used to ensure that the pairwise correlations among the variables were uniformly low. Only debt ratio and interest coverage, debt ratio and cash over total assets interest coverage and return on total assets and return on total assets and cash over total assets had satisfied the requirement. The rest were statistically significant at one and five percent. Debt ratio has low correlations with return on total assets and current ratio even when they are statistically significant at one percent. Similarly, although interest coverage is statistically significant at a 0.01 level with current ratio and cash over total assets, the correlation is low. Return on total assets and current ratio is statistically significant at five percent, but the correlation between them is low. Current ratio and cash over total assets is significant at five percent and has low correlation. Overall, Singapore companies are clean from multicollinearity issue.

Table 4-5: Logistic result for Singapore before removing Fraud companies.

	Coefficient	**Standard Error**
Debt ratio	-9.144***	1.905
Interest coverage	3.793***	0.553
Return on total assets	15.584***	2.733
Current ratio	0.865***	0.234
Cash/TA	-0.789	1.700
constant	-1.655	1.054

*** Significant at a 1% level
** Significant at a 5% level
* Significant at a 10% level

Debt ratio, interest coverage, return on total assets, current ratio and cash over total assets are used as the determinants of financial distress for the Singapore companies by using the stepwise logistic regression. According to table 4-5, all the variables are found to be statistically significant at one percent except for cash over total assets. All the variables contradicted the expected findings. Theoretically, an increase in debt ratio will pose certain degrees of financial difficulties where a lack of management discipline in generating profit to service debt will make the company vulnerable to financial distress. However, this is not true in the Singapore companies' case whereby a lack of debt posed some difficulties for them to operate. This could probably be due to the manipulation of certain items in debt such as accrual and total assets like inventory and account receivable. This result has been empirically proven by Perols and Lougee (2011) who found a positive interaction between discretionary accruals and earnings management. The authors explained further that fraudsters try to control their debt in order to preserve the debt covenant. Moreover, loan is among the top 4 fraud cases and account misstatements. Apart from that, receivables and inventory are also among the most frequently manipulated (Beasley et al., 2010; Rosner, 2003). Perhaps this could explain why companies that have lower debt ratios are susceptible to financial distress due to the concealment they made in order to meet and beat analysis forecast.

The bigger the amount of earnings before interest and tax to cover every single penny of interest is good as it shows the extra money that the company has to service the interest. Apart from that, it is a sign of strong financial performance and good financial management. However, interest coverage has a positive association with financial distress. This is in line with the debt ratio coefficient stated earlier where the companies need capital in order to survive; thus, low interest coverage is due to high interest that the companies have to pay to ensure sustainability. However, fraudulent companies purposely inflate their revenue in order to maintain positive or increasing earnings. This is supported by Perols and Lougee (2011) who found evidence that earnings management in prior years is also associated with a greater likelihood that the company with inflated revenue is committing fraud. This could justify the positive association between low interest coverage and distressed prediction where fraudsters inflate their revenue to increase the interest coverage ratio.

Return on total assets has a positive relationship with financial distress which is different from the expected projection. Initially, underutilized assets would affect company revenue if the cost cannot be covered and hence put the company into financial distress prompting it to borrow just enough to cover the cost. Healthy companies will produce at economic order quantity which is the oldest method in the production scheduling model on inventory management. As part of asset management, economic order quantity is a tool for monitoring the quantity that needs to be produced in order to cover the total cost borne by the company. However, return and total assets items are commonly used in earning management. Fraudsters tend to inflate these two financial items (Perols and Lougee, 2011; Rosner, 2003). Therefore, there is a possibility for return on total assets to be incorporated in financial information fraudulent activity.

The coefficient of the current ratio for Singapore is contradicts with the expected finding whereby an increase in current ratio will lower the capability of the company to serve its short term debts and increase its tendency of falling into financial distress. Perhaps, Singapore face the same situation where there is a tendency for current assets items to be manipulated. Rosner (2003) found that account receivable, inventory and account payable are often used by the manipulator for earning management; hence, the financial items contained in current assets may have been manipulated. This result is in line with that of Beasley et al. (2010) which indicated that the first and second highest cases of fraud and assets accounts misstatements are inventory and account receivable. Although it is not important, this could explain the positive coefficient for current assets.

Last but not least, although cash/TA is not statistically significant, it exhibits a negative relationship with financially distressed companies and thus confirms the expected finding. It shows that cash generated by financially distressed companies is low compared to that of healthy companies when it comes to assets utilization. As expected, assets management is vital in ensuring the sustainability of a company. High returns will generate more cash to meet short term obligations or can even be used during emergencies.

In conclusion, the result shows that all the independent variables failed to follow the expected signs except for cash/TA. The possible justification for this is that 28 companies are found to be engaged in financial information fraudulence once making it 49 observations out of 184 observations. This is supported by Liou and Yang (2008) who stated that financial information fraudulence render distressed prediction less effective.

According to Hosmer and Lemeshow, a chi-square of 488.567 is not statistically significant. This means that the regression model for predicting financially distressed companies in the context of Singapore is fitting. The R square for this model is between 73 percent and 97 percent to describe the variance in the dependent variable which is quite high and good for the distress prediction.

Table 4-6: Confusion Matrix

	True healthy	**True distressed**	**Class Precision**
Prediction healthy	157	10 (Type 1)	94.6%
Prediction distress	10 (Type 2)	174	94.00
Overall percentage			94.3%

The original samples entailed 55 financially distressed companies and 49 healthy companies. Total number of observations was 353, but 2 observations were dropped due to missing values; thus, there were 351 number of observations. The total number of observations for healthy and financially distressed companies is 167 and 184, respectively. The system dropped the 2 observations to reduce the outlier and maintain the robustness of the result. Based on table 4-6 above, 157 observations were correctly classified as healthy companies and only 10 were misclassified as distressed companies. Type two error was only 6 percent meaning that the missed chance for investors to invest in healthy companies in Singapore is relatively low. The logistic regression was able to correctly classify 174 financially distressed companies and only 10 observations were misclassified. The misclassification type two error was only 5 percent which is very low. The overall performance of the logistic model prediction was 94.3 percent which is splendid.

4.2.3 Regression Analysis after Financial Information Fraudulence Removal

Table 4-7: Correlation matrix for Singapore after Fraud.

	Debt ratio	Interest coverage	Return on total assets	Current ratio	Cash/TA
Debt ratio	1				
Interest coverage	0.072	1			
Return on total assets	-0.281***	-0.018	1		
Current ratio	-0.398***	0.162***	-0.108	1	
Cash/TA	-0.098	0.223***	-0.028	-0.161***	1

*** Significant at a 1% level
** Significant at a 5% level
* Significant at a 10% level

Table 4-7 above shows the correlation matrix for Singapore after removing financial information fraudulent companies. It can be observed that the significant level between the variables are the same as the previous results except for return on total assets and current ratios which became insignificant after such action was taken. Multicollinearity does not exist even though after removing the financial information fraudulent companies. Thus, it can be concluded that the variables are stable and reliable to be used as financial distress prediction for Singapore.

Table 4-8: Logistic model for Singapore after Fraud.

	Coefficient after fraud	Coefficient before fraud
Debt ratio	-12.513***	-9.144***
Interest coverage	5.354***	3.793***
Return on total assets	25.396***	15.584***
Current ratio	1.138***	0.865***
Cash/TA	1.528	-0.789
Constant	-2.146	-1.655

To check the validity of the improvement of accuracy in financial distress prediction, the same sample and variables are adopted. In analyzing the result, all the variables play a significant role in explaining financial distress in Singapore after financial information fraudulent companies are eliminated except for cash over total assets. It is found to be statistically significant at a one percent significant level and has the same signs as the previous logistic regression. All the variables demonstrate a positive relationship with financial distress except for debt ratio. The result concludes that removing financial information fraudulent companies pose significant changes to the financial distress prediction. The effect of high return on total assets (25.396) renders the companies to be approximately 5 times more vulnerable to financial distress as compared to high interest coverage (5.345) and not much different from the previous effect between these variable coefficients. The effect of high interest coverage (5.345) is slightly three times higher compared to the effect of cash/TA (1.528).

This implies that the fraudulence of financial data distorts the predictive power of the independent variables as stated by previous researchers (Beasley et al., 2010; Perols and Lougee, 2011; Rosner, 2003) who indicated that certain items such as sales, expense, accruals and cash flow have been manipulated to generate decent profit. On top of that, Franceschetti and Koschtial (2013) reported that financial information fraudulence is associated with stable businesses leaning towards insolvency. Rosner (2003) also supports the claim that healthy businesses generate more red flags than distressed businesses. Perhaps, healthy companies also engage in financial information fraudulence which is why the coefficient signs did not change and explain the opposite.

After removing financial information fraudulent companies from the analysis, the R square for this model is between 68 percent and 92 percent to describe the variance in the dependent variable which is quite high and good for the distress prediction. The distress prediction however deteriorates after the removal of the financial information fraudulent companies from the analysis. One explanation is that perhaps since the study did not cover the fraudulent activities carried out by the healthy companies, there is hence a possibility that the healthy companies might also engage in financial information fraudulence but in different magnitudes (mild or low).

Table 4-9: Confusion Matrix for Singapore after Fraud.

	True healthy	True distress	Class Precision
Prediction healthy	162	5 (Type 1)	96.3%
Prediction distress	5 (Type 2)	130	97%
Overall percentage			96.7%

Table 4-9 above shows the confusion matrix of Singapore after removing financial information fraudulent companies. From the Beneish M-score model, we detected that 28 financially distressed companies had engaged in financial information fraudulence at least once within 5 years i.e. between 2011 and 2015. Thus, the number of observations engaged in financial information fraudulence is 49. Total observations after removing financial information fraudulence is 304 with 2 missing cases making the total observations for this round as 302. Hence, there were a total of 135 and 167 financially distressed and healthy observations made, respectively.

As portrayed in the table 4-9 above, 162 observations were correctly classified as healthy and 5 misclassified as financially distressed. A majority of the financially distressed companies were correctly classified and only 5 out of 135 were misclassified as healthy. Thus, the type one and two errors are 4 and 3 percent, respectively. When compared to the previous confusion matrix (table 4-6), type one and two errors are 6 percent each but the accuracy was improved by 2 and 3 percent for the respective errors. Overall accuracy prediction for the regression model is 96.7 percent. Thus, it can be concluded that after removing financial information fraudulent companies, the prediction accuracy has improved from the previous result.

4.3 The determinants for Misclassification Errors

This sub-topic aims to confirm whether the misclassification error is caused by financial information fraudulence especially on the main board market. Table 4-10 show that the misclassification error for types one and two declined by 1.7 and 3 percent respectively from 5.4 and 6 percent before removing the financial information fraudulent companies. The overall misclassification error also shrinking by 2.4 from 5.7 to 3.3 percent.

Table 4-10: Misclassification Errors for Singapore.

Country	Type 1		Type 2		Total	
	before	**after**	**before**	**after**	**before**	**after**
Singapore	5.4%	3.7%	6%	3%	5.7%	3.3

The predictive ability had improved overtime after treating the sample. This proves that misclassification errors do happen on the main board. The result indicates that accuracy prediction becomes more robust when financial information fraudulent companies are removed. This is in line with the findings by Liou and Yang (2008) which suggest that removing financial information fraudulent companies in advance from the financial distressed prediction can effectively enhance prediction accuracy. In their study, the prediction accuracy increased by 3 percent i.e. from 88 percent to 91 percent after removing financial information fraudulent companies. Thus, it can be concluded that financial information fraudulence is one of the determinants in misclassification error especially for type one.

5. Conclusion

Pertaining to the first objective, the study is motivated by the lack of literatures that highlight the existence of established models that can be directly utilized in the main market instead of waiting for authoritative bodies to come out with investigation reports or rumors on company financial information fraudulence activities. The result revealed that some companies still have financially distressed symptoms according to the Z-score value even after three years of the economic crisis. The result shows that developing countries take a long time to recover after the crisis. The Beneish M-score result unfolded that there were initiatives taken by the top management to conceal the companies' poor financial performance.

Comparative action has been taken to investigate the progress after fraud companies have been removed in evaluating the effect of financial information fraudulence on bankruptcy accuracy results. After financial information fraudulence was excluded from the study, the logistic result indicated that bankruptcy prediction accuracy improved. If we compare the type one, type two and overall percentage of misclassification errors with before and after financial information fraudulence, it has been shrinking from 5.7 to 3.3 percent. Therefore, we concluded that financial information fraudulence is one of the determinants of misclassification errors.

This study is important for creating awareness among investors that financial information fraudulence is happening in the capital market because the management needs to meet or beat the analysis forecast (Perols and Lougee, 2011). This unlawful activity will persist as long as it is not detected by the Security Exchange Commission (Lau and Ooi, 2016). Creditors and financial institutions may utilize the findings of this study to measure the financial status of companies before granting loans and credit facilities. This is to avoid giving credit facilities to distressed companies that are suspected to be engaged in financial information fraudulence. The findings of this study are also beneficial for auditors in evaluating the going concern status of current and future companies that they would like to investigate. This study also highlights the importance of setting a standard in selecting auditors and clearing benchmarks for nominating an audit committee. Therefore, the audit work can be done in a diligent and transparent manner. This explains the government's initiative in having companies to rotate their auditor every five years (Anastasopoulos and Anastasopoulos, 2012).

Several areas had been identified for exploration in future research. Firstly, there is room to explore in other sectors in Malaysia or even other countries. Findings on other sectors and countries will contribute to the existing knowledge on financial information fraudulence and financial distress. Therefore, in-depth investigations can be conducted by result comparison. Secondly, this research had only focused on main market and public listed companies. Thus, future studies can focus on other markets such as the secondary market, the ACE market or private companies. These markets are rarely explored due to issues regarding data availability; however, explorations on these markets will give a variation to the intended discipline. Thirdly, future researchers can use other methods than the Altman Z-score and the Beneish M-Score to identify financial distress and financial information fraudulence such as the Jones model and Modified Jones model. The main reason for using the Altman Z-score and Beneish M-Score is their simplicity. Perhaps, using sophisticated discriminate models could produce more reliable and robust results.

Reference

1. Abbasi, A., Albrecht, C., Vance, A., & Hansen, J. (2012). Meta Fraud: A Meta-Learning framework for detecting financial fraud. *MIS Quarterly*, *36*(4), 1293–1327.
2. Abdul Aris, N., Othman, R., Mohd Arif, S. M., Abdul Malek, M. A., & Omar, N. (2013). Fraud Detection : Benford ' s Law vs Beneish Model. In *IEEE Symposium in Humanities, Science and Engineering Research (SHUSER)* 726–731.
3. Abdullah, S. N., Yusof, N. Z. M., & Nor, M. N. M. (2010). Financial restatements and corporate governance among Malaysian listed companies. *Managerial Auditing Journal*, *25*(6), 526–552.
4. Abellán, J., & Mantas, C. J. (2014). Improving experimental studies about ensembles of classifiers for bankruptcy prediction and credit scoring. *Expert Systems with Applications*, *41*(8), 3825–3830.
5. ACFE. (2020). Report to the Nations on Occupational Fraud and Abuse
6. Agrawal, K., & Chatterjee, C. (2015). Earnings Management and Financial Distress : Evidence from India. *Global Business Review*, *16*(5), 140–154.
7. Ak, B. K., Dechow, P. M., Sun, Y., & Wang, a. Y. (2013). The use of financial ratio models to help investors predict and interpret significant corporate events. *Australian Journal of Management*, *38*(3), 553–598.
8. Altman, E. I., Marco, G., & Varetto, F. (1994). Corporate distress diagnosis: Comparisons using linear discriminant analysis and neural networks (the Italian experience). *Journal of Banking & Finance*, *18*(3), 505–529.
9. Amershi, A. H., & Feroz, E. H. (2000). The occurrence of Finobacci numbers in time series of financial accounting ratios: Anomalies or indicators of firm survival, bankruptcy and fraud? An exploratory study. *Managerial Finance*, *26*(11), 5–20.
10. Anastasopoulos, N. P., & Anastasopoulos, M. P. (2012). The Evolutionary Dynamics of Audit. *European Journal of Operational Research*, *216*(2), 469–476.
11. Andrés, J. De, Landajo, M., & Lorca, P. (2012). Bankruptcy prediction models based on multinorm analysis: An alternative to accounting ratios. *Knowledge-Based Systems*, *30*, 67–77.
12. Ardekani, A. M., Younesi, N., & Hashemijoo, M. (2012). Acquisition, Earnings Management and Firm's Performance: Evidence from Malaysia. *Journal of Business Studies Quarterly*, *4*(1), 91–110.
13. Bae, J. K. (2012). Predicting financial distress of the South Korean manufacturing industries. *Expert Systems with Applications*, *39*(10), 9159–9165.
14. Battiston, S., Delli Gatti, D., Gallegati, M., Greenwald, B., & Stiglitz, J. E. (2007). Credit chains and bankruptcy propagation in production networks. *Journal of Economic Dynamics and Control*, *31*(6), 2061–2084.
15. Beasley, M. S., Carcello, J. V, and Hermanson, D. R. (2001). Financial Reporting Fraud: Could It Happen to You? *The Journal of Corporate Accounting and Finance*, 12(4), 3–9.
16. Beasley, M. S., J. V. Carcello, D. R. Hermanson, and T. L. Neal. (2010), Fraudulent Financial Reporting: 1998–2007. An Analysis of US Public Companies (Committee of Sponsoring Organizations of the Treadway Commission, Durham, North Carolina), [Internet document] (Committee of Sponsoring

Organizations of the Treadway Commission) [created May 2010], available from: http://www.coso.org/.

17. Beatty, A., Liao, S., & Jiewei, J. (2013). The spillover effect of fraudulent financial reporting on peer. *Journal of Accounting and Economics*, *55*(2–3), 183–205.
18. Beaver, W. H. (1966). Financial Ratios as Predictors. *Journal of Accounting Research*, *4*, 71–111.
19. Beaver, W. H., Correia, M., & Mcnichols, M. F. (2012). Do differences in financial reporting attributes impair the predictive ability of financial ratios for bankruptcy ? *Review of Accounting Studies*, *17*(4), 969–1010.
20. Beneish, M. D. (1999). The Detection of Earnings Manipulation. *Financial Analysts Journal*, *55*(5), 24–36.
21. Brown, S., Lo, K., & Lys, T. (1999). Use of R2 in accounting research: measuring changes in value relevance over the last four decades. *Journal of Accounting and Economics*, *28*(2), 83–115.
22. Bushman, R. M., & Smith, A. J. (2001). Financial accounting information and corporate governance. *Journal of Accounting and Economics*, *32*(1–3), 237–333.
23. Cecchini, M., Aytug, H., Koehler, G. J., & Pathak, P. (2010). Detecting Management Fraud in Public Companies. *Management Science*, *56*(7), 1146–1160.
24. Charalambakis, E. C. (2015). On the prediction of corporate financial distress in the light of the financial crisis: Empirical evidence from Greek listed firms. *International Journal of the Economics of Business*, 22(3), 407-428.
25. Chen, Y., Zhang, L., & Zhang, L. (2013). Financial Distress Prediction for Chinese Listed Manufacturing Companies. *Procedia Computer Science*, *17*, 678–686.
26. Chiaramonte, L., Croci, E., & Poli, F. (2015). Should we trust the Z-score? Evidence from the European Banking Industry. *Global Finance Journal*, *28*, 111–131.
27. Crawford, R. L., & Weirich, T. R. (2011). Fraud guidance for corporate counsel reviewing financial statements and reports. *Journal of Financial Crime*, *18*(4), 347–360.
28. Dichev, I. D., & Skinner, D. J. (2002). Large-sample evidence on the debt covenant hypothesis. *Journal of Accounting Research*, *40*(4), 1091–1123.
29. Fallahpour, S., Lakvan, E. N., & Zadeh, M. H. (2017). Using an ensemble classifier based on sequential floating forward selection for financial distress prediction problem. *Journal of Retailing and Consumer Services*, *34*, 159–167.
30. Feng, M., and Li, C. (2012*).* How do earnings manipulators guide investors? *Working paper, University of Pittsburgh and University of Washington*
31. Flanagan, D. J., Muse, L. A., & O'Shaughnessy, K. C. (2008). An overview of accounting restatement activity in the United States. *International Journal of Commerce and Management*, *18*(4), 363–381.
32. Foo, S. L. (2015). Financial Health & Corporate Performance of Listed Manufacturing Companies in Hong Kong & Singapore : A Comparative Study of the Two Asian Tigers, *03*(2), 148–154.
33. Franceschetti, B. M., & Koschtial, C. (2013). Do bankrupt companies manipulate earnings more than the non- bankrupt ones ? *Journal of Finance and Accountancy*, *12*, 1–22.
34. Francis, J., & Schipper, K. (1999). Have financial statements lost their relevance? *Journal of Accounting Research*, *37*(2), 319–352.
35. Goel, A. M., & Thakor, A. V. (2003). Why do firms smooth earnings?. The Journal of Business, 76(1), 151-192.
36. Gogas, P., Papadimitriou, T., & Agrapetidou, A. (2018). Forecasting bank failures and stress testing: A machine learning approach. *International Journal of Forecasting*, *34*(3), 440–455.
37. Hasan, M. S., Omar, N., Barnes, P., & Handley Schachler, M. (2017). A cross-country study on manipulations in financial statements of listed companies Evidence from Asia. *Journal of Financial Crime*, *24*(4), 656–677.
38. Holthausen, R. W., Larcker, D. F., and Sloan, R. G. (1995). *Annual bonus schemes and the manipulation of earnings*. *Journal of Accounting and Economics* 19(1), 29-74.
39. Hope, O.-K., Thomas, W., & Kolk, A. (2011). Financial credibility, ownership, and financing constraints in private firms. *Journal of International Business Studies*, *42*(7), 935–957.
40. Jaggi, B., & Lee, P. (2002). Earnings Management Response to Debt Covenant Violations and Debt Restructuring. *Journal of Accounting, Auditing & Finance*, *17*(4), 295–324.
41. Johnson, E. N., Fleischman, G. M., Valentine, S., & Walker, K. B. (2012). Managers ' ethical evaluations of earnings management and its consequences *. *Contemporary Accounting Research*, *29*(3), 910–927.
42. Kamaluddin, A., Ishak, N., & Mohammed, N. F. (2019). Financial Distress Prediction Through Cash Flow Ratios Analysis. *Internatinal Journal of Finance Research*, *10*(3), 63–76.
43. Kim, S. Y., & Upneja, A. (2014). Predicting restaurant financial distress using decision tree and AdaBoosted decision tree models. *Economic Modelling*, *36*, 354–362.
44. Kirkos, E., Spathis, C., & Manolopoulos, Y. (2007). Data Mining techniques for the detection of fraudulent financial statements, *32(4)*, 995–1003.
45. Kotsiantis, S., Kanellopoulos, D., & Tampakas, V. (2010). Financial application of Multi-Instance Learning: Two Greek case studies. *Journal of Convergence Information Technology*, *5*(8), 42–53.
46. Kumar, K. (2012). A comparison of bankruptcy models. *International Journal of Marketing, Financial Service and Management Research*, *1*(4), 76–86.
47. Lau, C. K., & Ooi, K. W. (2016a). A case study on fraudulent financial reporting: Evidence from Malaysia.

Accounting Research Journal, *29*(1), 4–19.
48. Lau, C. K., & Ooi, K. W. (2016b). A case study on fraudulent financial reporting: evidence from Malaysia Chee. *Accounting Research Journal*, *29*(1), 4–19.
49. Liou, F., & Yang, C. (2008). Predicting business failure under the existence of fraudulent financial reporting. *International Journal of Accounting & Information Management*, *16*(1), 74–86.
50. Md Nasir, N. A. binti, Ali, M. J., Razzaque, R. M. R., & Ahmed, K. (2018). Real earnings management and financial statement fraud: evidence from Malaysia. *International Journal of Accounting and Information Management*, *26*(4), 508–526.
51. Minanoa, M. del- M. C., & Campa, D. (2014). Integrity of financial information as a determinant of the outcome of a bankruptcy procedure. *International Review of Law and Economics*, *37*, 76–85.
52. Nagar, N., & Sen, K. (2017). Do financially distressed firms misclassify core expenses? *Accounting Research Journal*, *30*(2), 205–223.
53. Nanni, L., & Lumini, A. (2009). An experimental comparison of ensemble of classifiers for bankruptcy prediction and credit scoring. *Expert Systems with Applications*, *36*(2), 3028–3033.
54. Perols, J. L., & Lougee, B. A. (2011). The relation between earnings management and financial statement fraud. *International Journal of Cardiology*, *27*(1), 39–53.
55. Pramudena, S. M. (2017). The Impact of Good Corporate Governance on Financial Distress in the Consumer Goods Sector. *Journal of Finance and Banking Review*, *2*(4), 46–55.
56. Rosner, R. L. (2003). Earnings manipulation in failing firms. *Contemporary Accounting Research*, *20*(2), 361–408.
57. Sekaran, U., & Bougie, R. (2013). Research Methods for Business: A Skill-Building Approach (6th ed.). In *Jhon Wiley and Sons.* (pp. 240–252).
58. Sharma, K. (2014). Detecting Earnings Management in India : A sector-wise study. *European Journal of Business and Management*, *6*(11), 11–18.
59. Shin, K. S., & Lee, Y. J. (2002). A genetic algorithm application in bankruptcy prediction modeling. *Expert Systems with Applications*, *23*(3), 321–328.
60. Song, D. B., Lee, H. Y., & Cho, E. J. (2013). The association between earnings management and asset misappropriation. *Managerial Auditing Journal*, *28*(6), 542–567.
61. 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.
62. Spathis, C. T. (2002). Detecting false financial statements using published data: some evidence from Greece. *Managerial Auditing Journal*, *17*(4), 179–191.
63. Supriyanto, J., & Darmawan, A. (2018). the Effect of Financial Ratio on Financial Distress in Predicting Bankruptcy. *Journal of Applied Managerial Accounting*, *2*(1), 110–120.
64. Sweeney, A. P. (1994). Debt-covenant violations and managers' accounting responses. *Journal of Accounting and Economics*, *17*(3), 281–308.
65. Thai, S. B., Goh, H. H., Teh, B. H., Wong, J. C., & Ong, T. S. (2014). A Revisited of Altman Z- Score Model for Companies Listed in Bursa Malaysia. *International Journal of Business and Social Science*, *5*(12), 197–207.
66. Trejo-Pech, C. J. O., Weldon, R. N., & Gunderson, M. A. (2016). Earnings Management through Specific Accruals and Discretionary Expenses: Evidence from U.S. Agribusiness Firms. *Canadian Journal of Agricultural Economics*, *64*(1), 89–118.
67. Tsai, C., & Wu, J. (2008). Using neural network ensembles for bankruptcy prediction and credit scoring. *Expert Systems with Applications*, *34*(4), 2639–2649.
68. Wells, P. (2002). Earnings management surrounding CEO changes. *Accounting and Finance*, *42*(2), 169–193.