Detecting Fraudulent Financial Reporting through Financial Statement Analysis

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***Abstract*—Fraudulent financial reporting is a major concern for two primary regulators of Malaysia's capital market - the Securities Commission (SC) and Bursa Malaysia. Both authorities continue to refine the parameters that will ensure rigorous surveillance over public listed firms. The objective of current study is to examine the association between financial statement analysis and fraudulent financial reporting. Many researchers found indication of financial ratios to detect fraudulent financial reporting but others also have concluded otherwise. Most of these studies were conducted outside of Malaysia. The sample comprises of the Malaysian Public Listed firms and data used ranged between year 2000 to 2011. The result indicated that several financial ratios such as total debt to total asset, and receivables to revenue were found to be significant predictors to detect fraudulent financial reporting. This reflects that, financial ratios maybe helpful in the detection of fraudulent financial reporting. These findings add to the extant literature on the ability of financial ratios to detecting fraud.**

***Index Terms*—financial statement analysis, fraudulent financial reporting, public listed companies, Malaysia**

I. Introduction

Fraudulent Financial reporting (FFR) may occur anywhere and has become increasingly prominent in the eyes of the public and the world's regulators as it may be committed by individuals across all professions. Based on a recent survey on global economic crime 2005 [1] about forty five percent of companies worldwide have fallen victim to economic crime. While occurring less often than other types of fraud, FFR usually does the most harm to organizations.

Reports show some cases of FFR occurring on Malaysian firms such as cases of Megan Media and Transmile Bhd [2]. Transmile Bhd (an air cargo listed company in Bursa Malaysia) was reported to have accounting irregularities, overstating revenues in 2004, 2005 and 2006 by RM622 million. This case has led to several other listed companies in Malaysia being investigated such as Megan Media Holdings Bhd and Welli Multi Corp Bhd.

The increase in fraud indicates that there is a strong need for research that aims to identify effective methods for detecting potential fraud. McNeil [3] argues, in whatever nature and guise, it has to be detected first, as detection is an important prerequisite of rooting out any sort of fraud. This is simply because fraud by its nature does not present itself to being scientifically observed or measured in an accurate manner. One of the primary characteristics of fraud is that it is clandestine, or hidden; almost all fraud involves the attempted concealment of the crime [4].

Many fraud investigators recommend financial ratios as an effective tool to detect fraud [5]. Some include a list of common ratios [6], [7]. Yet, there seems to be a lack of empirical evidence on the financial ratios to detect fraud as researchers often obtain mixed results with these ratios. Persons [7] and Spathis [8] both agree that financial ratios are useful tools in detecting fraud. However, Kaminski *et al.* [9] concluded differently which denotes that financial ratios are not an effective means to detect the occurrence of fraud. The objective of this paper is to identify which financial ratios are significant to fraudulent reporting.

This paper is constructed as follow. The next section review the literature related to fraudulent financial reporting and theoretical development. This is followed by a discussion on the research method which includes sample and respondents questionnaires, response rate, and hypothesis development. Section four would highlight the data analyses and findings. Finally, the discussions on conclusion, implications, limitations as well as direction for future research are presented in section five.

II. Literature Review

A. Definition of Fraudulent Financial Reporting

FFR has received much attention from the public, the financial community and regulatory bodies. Among the earliest scholars to note was Eliott and Willingham [10], who defined FFR as a deliberate fraud committed by management that injures investors and creditors through misleading financial statements'' (page 4). In addition, FFR is described as a scheme designed to deceive, accomplished with fictitious documents and representations [11]. Following these definitions, we can conclude that such reports (financial statement reports prepared with the intention to deceive the users) are designed with the intention of fraud. Spathis [8] defines FFR as a financial statement that contains falsifications of figures which do not represent the true scenario. The

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Association of Certified Fraud Examiners (ACFE) [4] defines FFR as 'The intentional, deliberate, misstatement or omission of material facts, or accounting data to mislead and, when considered with all the information made available, would cause the reader to alter his or her judgment in making a decision, usually with regards to investments. This definition is important because ACFE emphasizes on the investors' decision making process which relies on the financial statements provided. In practice, financial fraud primarily consists of falsifying financial statements which include manipulating elements which is overstating assets, sales and profit, or understating liabilities, expenses, or losses. The current study defines fraud as firms that breach the offences of Bursa Malaysia which the offences include materially misstated information reported in the financial statement. In addition non fraud firms are firms matched with a corresponding fraud firm on the basis of industry, size and also time period. Firms in the same industry are subject to the similar business environment as well as similar accounting and reporting requirements [12].

B. Detecting FFR

The American Institute of Certified Public Accountants (The Statement on Auditing Standard No. 82) defines two types of financial misstatement. The first type of misstatement arises from FFR, which refers to intentional misstatements or omissions of figures or disclosures in the financial statement with the intent to deceive the reader. The second type of misstatement arises from the misappropriation of assets known as employee fraud or defalcation.

In keeping with this definition, it is crucial to know whether the financial statement reviewed is in good order or contains materially misstated information. In addition, fraudulent financial reporting is in violation of accounting standards regarding the omission of existing figures or the inclusion of fictitious figures [13].

In order to assess the likelihood of fraud, various tools have been designed to help users analyze financial statements. One of the most common methods for financial analysis is by ratio analysis [6]. A large number of ratios have been proposed in literature such as Financial Leverage proxies by total debt and total equity ratios, Profitability proxies by net profit to revenue, Asset Composition represent by current asset to total asset, receivables to revenue, inventory to total asset and more. Persons [7] and Spathis [8] agree that items in current assets such as account receivables and inventories are more prone to manipulation. These items are considered as soft or liquid assets in the financial statement and are more easily manipulated compared to hard items such as sales and retained earnings [5]. As a result, fraudulent companies more often manipulate soft items than hard items, resulting in outliers being detected in the process of testing the variables [5].

Guan *et al.* [14] explored whether investors can successfully detect management fraud using a firm's financial statement. The study used sixty eight fraudulent companies derived from SEC's Accounting and Auditing Enforcement Releases (AAERs) in the period of 1982 to 1999. By having twenty one selected financial ratios obtained from the fraudulent firm's financial statement, they found that ratios analysis is grossly ineffective in detecting financial statement fraud. This study however, agrees that account receivables and inventory prove to be important variables. Account receivables permits subjective estimation which is more difficult to verify, thus enabling the figures to be easily falsified. Falsifying account receivables is done by recording sales before it is earned, which falsely implies a growth in sales [15].

Many researchers suggest that management may manipulate inventories. Persons [7] in his study to find the parsimonious models that identify factors associated with FFR indicate that inventories are found in relatively large amounts. In his study of 103 sample for fraud year and hundred samples from the preceding year sample of AAER for the period of 1982 and 1991, Persons [7] further elaborates that fraudulent firms tend to have high proportion of account receivables in current asset. Feroz *et al.* [16] find that an overstatement of inventory represents three-fourth of the United States Securities Exchange Commissions (SEC) enforcement cases. Some companies have been found reporting its inventory not at its actual value and recording obsolete inventory [17]. Moreover, due to the effect of inventory costs, the relationships between sales and the cost of goods sold become vulnerable to manipulation [18].

This figure is also estimated using subjective methods and using different accounting valuation often produces different values even within the same firms [19]. Loebbecke *et al.* [20] found that inventory and account receivables were involved in twelve and fourteen percent of FFR's respectively from their study.

Another item prone to manipulation is the gross margin. Firms may manipulate their sales by recording unearned sales in advance and do the same with corresponding costs of goods sold, which will increase the gross margin, net income and strengthen the balance sheet [15]. Spathis [8] found that fraudulent companies hold half of the gross margin compared to non-fraudulent firms. In addition to that, some fraudulent companies make it a practice to increase the amount of gross profit by recording less than actual values even when the amount of inventory in total assets is high.

Debt to total assets were found to be significant in assessing the likelihood of fraud. Dechow *et al.* [21] argue that demand from external financing depends not only on how much cash is generated from operations and investments but also on the funds readily available within firms. They suggest that the average capital expenditure during the three years prior to financial statement manipulation is the measure of the desired investment level during the period of financial reporting. Other researchers in support of the idea include Guan, *et al.* [22] who unanimously agree on its significance.

III. Methodology

A. Research Design

Sample selection: This study examined 130 samples consisting of 65 samples for fraudulent firms and 65 samples of non fraudulent firms from the Malaysian Public Listed Firms available between the years 2000 and 2011 with financial data collected from Datastream.

Selection of fraudulent financial reporting firms: Firms involving in fraudulent reporting are obtained from the Bursa Malaysia media centre. This list summarizes firms according to the offences made against the Listing Requirements of Bursa Malaysia Securities Berhad, most of which were reporting material misstatements in the financial reports. This assessment resulted in 91 preliminary sample firms.

Data are obtained for a look back period of five years. First, a fraudulent year is identified. A fraudulent year is the year in which fraud is detected. Next, the data of four preceding years were obtained. For example, if the fraudulent year falls in 2011, then data for that particular firm is obtained for four earlier years which is 2010, 2009, 2008 and 2007. This resulted in selecting a total of 5 years worth of data. Financial statement data for the fraudulent year is the original data before any correction was made. Fraudulent reporting firms from the financial and insurance sectors are excluded from the sample data as the former does not deal with account receivables and inventory whilst the latter had insufficient data for empirical testing. The final sample consists of 65 samples for fraudulent firms and 65 samples for non-fraudulent firms. Most of these firms are in the industrial products sector.

Selection of non fraudulent financial reporting firms: Each fraudulent firm is matched with a corresponding non fraudulent firm on the basis of industry, size and also time period. Firms in the same industry are subject to the similar business environment as well as similar accounting and reporting requirements [12]. Financial statement variables of non fraudulent firms are obtained from the same time period as the fraudulent firms in order to control for general macroeconomics and the probability of a company involving in fraud. This one-for-one matching process is used in an effort to enhance the discriminatory power of the models. Non fraudulent firms are also required to have sufficient financial data during the matching period. This selection process resulted in 65 non fraudulent firms. Below is a detailed explanation about the matching process for fraudulent firms and non fraudulent firms. Both categories are matched with regards to: (i) time period, (ii) firm size, and (iii) industry.

B. Data Collection Method

This study utilizes the secondary data obtained from published audited financial statements as the main source of information from the corporate annual reports of the public listed firms in Malaysia and also from Data Stream for a retrospective period of 5 years since all information can be extracted from Data Stream such as Retained Earnings. Annual reports are regarded as the main form of communication with shareholders as well as the public [23] and they are widely distributed and are the most commonly produced documents [24].

C. Independent Variables, Dependant Variables and Control Variable

Independent variables and control variable: For the purpose of this study, five aspects of firm's financial ratios were identified. These variables are presented in Table I.

The dependant variable is as follows:

1) Fraudulent firms: This research is an attempt to investigate the significant differences between the mean of financial ratios among fraud and non fraud Malaysian Public Listed firms. In addition, the current research further investigates the significant predictor among financial ratio which is relevant to fraudulent financial reporting. Fraud firms are identified through offences made against the listings requirement of Bursa Malaysia.

TABLE I. Measurement of Independent Variable and Control Variable

	Formula	Acronyms	Reference
Independent Variable			
Financial Leverage	Total Debt/Total Equity Total Debt/Total Asset	TD/TE TD/TA	[15]
Profitability	Net Profit/Revenue	NP/REV	[8], [26]
Asset Composition	Current Assets/ Total Assets Receivables/Revenue Inventory / Total Assets	CA/TA REC/REV INV/TA	[12], [16], [20], [27], [28], [29]
Liquidity	Working Capital to Total Assets	WC/TA	[8], [26]
Capital Turnover	Revenue to Total Assets	REV/TA	
Control Variable			
Size	Natural Logarithm of book value of total assets at the end of the fiscal year	SIZE	[16]

Following the Listing Requirements in the Bursa Malaysia handbook, a listed firm must ensure that any statement, information or document presented, submitted or disclosed pursuant to these Requirements: (i) is clear, unambiguous and accurate; (ii) does not contain any material omission; and (iii) is not false or misleading.

In line with this study's definition of fraud, firms selected satisfy these criteria and were obtained from the Bursa Malaysia Public Enforcement or Company Advisor website, following scrutiny by the regulatory body. Fraudulent firms in this study have therefore breached the Main Market Listing Requirement and disciplinary action has been taken on these companies.

2) Non fraudulent firms: Non fraudulent firms are defined as not included in the Public Enforcement or

Company Advisor List and were controlled by time period, size of the total assets and the firms are within the same industry as fraudulent firms.

D. Regression Model

The following logic model was estimated using the financial ratios from the firms to determine which of the ratios were related to FFR. By including the data set of fraudulent and non fraudulent firms, we may discover what factors significantly influence them:

$$FFR = b_o + b_1(SIZE) + b_2(TD/TE) + b_3(TD/TA) + b_4(NP/REV) + b_5(CA/TA) + b_6(REC/REV) + b_7(INV/TA) + b_8(WC/TA) + b_9(REV/TA) + e \quad (1)$$

where:
SIZE = Size
TD/TE = Total debt/Total equity
TD/TA = Total debt/Total Asset
NP/REV = Net Profit/Revenue
CA/TA = Current Assets/Total Asset
REC/REV = Receivable/Revenue
INV/TA = Inventories/Total Assets
WC/TA = Working Capital/Total Assets
REV/TA = Revenue/Total Assets

IV. Findings and Discussion

A. Sample of Fraudulent Firms and Non Fraudulent Firms

The sample was drawn from various selected sectors, and can be described according to the type of industries as presented in Table II.

Table II indicates that industrial product category tops the list of sample fraudulent firms with 40%. This was followed by construction (17.7%), and consumer and trading services (both tied at 15.4%). The lowest percentage was found in the technology category with only 3.1%.

TABLE II. The Type of Industry

Type Industry	Frequency	Percentage (%)
Technology	4	3.1
Trading services	20	15.4
Consumer	20	15.4
Industrial product	52	40.0
Construction	23	17.7
Properties	11	8.5

B. Test of Normality

Table III presents normality of data using Kolmogorov-Sminorv and skewness. In the present study, skewness and kurtosis were used as main indicators to determine the normality of data. Seven of the ratios, which were, LgSIZE, LgNP/REV, LgCA/TA, LgREC/REV, LgINV/TA, LgWC/TA, LgREV/TA, were expressed as log transformation. The ratio being TD/TA was used in its original form as the normality of the ratios did not improve after transformation while one ratio being TD/TE was expressed in Square log transformations. This is to mitigate the effect of normality and ensure the sample sizes were not affected [30]. However, based on the central limit theorem, bigger sample distribution (more than 30) tend to be normal regardless of the population distribution, and it is more evident as the sample count increases [31]. Thus, the TD/TA is retained for further analysis.

TABLE III. Normality of Data

Variables	Kolmogorov-Smirnov	Skewness (p-value)	Kurtosis
Lg SIZE	0.0001	0.141	-0.465
Square/Log TD/TE	0.0001	-0.396	1.066
TD/TA	0.0001	7.93	87.03
LgNP/REV	0.0001	0.736	8.181
LgCA/TA	0.0001	0.300	14.21
LgREC/REV	0.0001	1.354	9.157
LgINV/TA	0.0001	-1.740	4.192
LgWC/TA	0.0001	0.687	20.99
LgREV/TA	0.0001	0.238	13.33

LgSIZE: Size, Square/LogTD/TE: Total Debt/Total Equity, TD/TA: Total Debt/Total Asset, LgNP/REV: Net Profit/Revenue, LgCA/TA: Current Assets/Total Asset, LgREC/REV: Receivable/Revenue, LgINV/TA: Inventories/Total Assets, LgWC/TA:Working Capital/Total Assets, LgREV/TA: Revenue/Total Assets

C. Pearson's Correlation

Pearsons's Correlation Product Moment was used to determine the direction and strength of the association between two variables. Based on Guilford's Rule of thumb the strength of relationship can be associated as negligible (<0.2), low (0.2 - 0.4), moderate (0.4 - 0.7), high (0.7 - 0.9) and very high (>0.9). Table IV presents the Persons's Correlation analysis between the ratios.

From the results, it is indicated that all of the variables have an association with each other and the strongest relationship is shown between LgWC/TA and LgCA/TA with 0.574 units. This can be further expand that, an increase in 0.574 units of working capital to the total assets ratio will increase the same amount of unit in current assets and total assets.

TABLE IV. Pearson's Correlation

	Variables	1	2	3	4	5	6	7	8	9	10
1	Square/Log TD/TE	1									
2	TD/TA	.369**	1								
3	LgNP/REV	-.155**	-.187**	1							
4	LgCA/TA	-.150**	044	-.083	1						
5	LgREC/REV	.085*	.067	.241**	.033	1					
6	LgINV/TA	-.059	-.057	-.162**	.199**	-.187**	1				
7	LgWC/TA	-.275**	-.029	.037	.574**	-.018	.191**	1			
8	LgREV/TA	.001	179**	-.487**	.241**	-.540**	. 150**	.077	1		
9	Lg Asset	.111**	-.126**	.124**	-.289**	.044	.211**	-.321**	-.195**	1	
10	Non-Fraudulent / Fraudulent	-.000	-.044	-.007	.045	.106**	-.003	0.27	-.013	.003	1

* Significant at $p < 0.05$, ** Significant at $p < 0.001$

D. Multiple Linear Regressions

Stepwise multiple linear regressions were used to determine the association between all independent variables. Before conducting regression analysis, all variables were checked for normality, multicolinearity and outliers. Normality assumption was met based on the skewness and kurtosis after transformation (Table III). Multicolinearity assumes that one independent variable is redundant with the other. In such case of multicolinearity, independent variables do not add any predictive value over other independent variables. Values of 0.7 and above showed that independent variables are highly correlated with each other. Following Table IV Pearson Correlation, there was no multicolinearity between independent variables**.** Table V depicts the stepwise logistic regression with univariate.

TABLE V. STEPWISE MULTIPLE LINEAR REGRESSION

Independent Variable	Unstandardised Coefficient	S.E.	Sig.
Model 1			
Square/Log TD/TE	0.945	0.143	0.001
Lg REC/REV	2.049	0.608	0.001
Lg INV/TA	-0.565	0.261	0.030
LgREV/TA	1.181	0.503	0.019
Constant	1.008	0.469	0.032
X2 (Chi Square)	10.197		0.251
R^2_L	0.305		
N	130		
Correctly predicted:			
Non-Fraud	85.71%		
Fraud	55.1%		
Overall	74.7%		

According to the result, the overall percentage of correct classification, by means of the proposed model, was 74.7%. This implies that 56 (85.71 %) out of the 65 non fraudulent firms and 36 (55.1 %) out of the 65 fraudulent firms were classified correctly.

The results also indicate that only four ratios are significant enough to predict misleading financial statement. The ratios are, Square/Lg TD/TE, Lg Lg REC/REV, Lg INV/TA and LgREV/TA. All of this ratios are significant at p = 0.05. The ratio Square/Lg TD/TE showed a significant positive effect with β = 0.945. It means that firms with increase Square/Lg TD/TE ratio increase probability of being classified as fraudulent firms. The same goes to Lg Rec/Rev where it coefficients is at β = 2.049. Lg INV/TA has a significant negative effect at β = -0.565. Hence the company with decrease value of Lg INV/TA has increase probability to be classified as non fraudulent firms. The ratio of LgREV/TA showed a significant positive effect with β = 1.181. Hence, the firms with increase value of LgREV/TA have increase probability to be classified as non fraudulent firms.

As stated in the model, there are four variables regarded as significant predictor to detect the likelihood of fraud. Thus, the linear regression model's equation is:

$$FFR = 1.008 + 0.945(Square/Log\ TD/TE) + 2.049(Lg\ Rec/Rev) - 0.565(Lg\ INV/TA) + 1.181(LgREV/TA) + e \quad (2)$$

V. CONCLUSION

The results show that Leverage proxies by total debt to total equity is a significant result as indicator for fraud analysis, This ratio is consistent with that Spathis [8] while Fanning and Cogger [15] suggest that firms with higher debt to equity ratios would be a good indicator for fraudulent firms. Furthermore, it means that firms with a high total debt to total equity value have an increased probability to be classified as fraudulent firms. Capital Turnover proxies by receivables to revenue also have significant results. High ratios of account receivables to sales are consistent with research suggesting that accounts receivables is an asset with a higher incidence of manipulation. The variables may show fraudulent firms manipulating the underlying variables. Asset Composition proxies by inventory to total asset also show significant results. It can be concluded that, Leverage, Capital Turnover, and Asset Composition were significant predictors for fraud detection. This is supported by the result of the study with the rate of correct classification exceeding 74.7%. This result is consistent with Skousen *et al.* [32] who report the correct classification of about 73% predicting sample for fraudulent and non-fraudulent firms. However, the percentage is inconsistent with that of Spathis [8] which reported a higher percentage of 78.95% for fraudulent firms and 86.84% for non-fraudulent firms.

The limitation of this study is the sample size was reduced since some of the information from Datastream was not available. Hence the findings may not truly portray the sample for fraudulent firms since the percentage of correct classification is only 55.1%. In addition, this study had only used financial data obtained from Datastream and this limits other sources of information that might be useful in detecting FFR. Additionally, this study examined a sample of companies for which fraud was discovered and reported by Bursa Malaysia by acquiring the listing issued by them. Hence, the other undiscovered types of fraud and those that may be discovered during the audit were not included.

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