M-SCORE AND Z-SCORE FOR DETECTION OF ACCOUNTING FRAUD

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ABSTRACT

The purpose of this study is to compare two forensic accounting tools—the Beneish M-score and the Altman Z-score models—for the effective detection of fraud in corporate bodies. Using a data set from Toshiba's published corporate financial statements from 2008 to 2014, analyses is made with the primary intent of detecting malfeasance using the two models. The methodology used in this research is as suggested by Beneish Messod for M-score and Altman for Z-Score. The results show that whereas the Beneish model was not able to detect any fraud, the Altman Z-score provided some indication that the company's financial statements were flawed. Although the Beneish model is very popular for predicting fraudulent financial statements, the results of the present study do not indicate its efficacy. The study concludes that selecting the right forensic tool can influence the outcome of fraud detection. The outcome of the study provides useful direction to investors, financial auditors, and forensic auditors when making policy decisions. This paper provides some evidence on the effectiveness forensic tools in detection of financial statements fraud of corporate bodies. This is the first study to present the two popular tools on latest big corporate scandal - Toshiba, Japan.

Keywords: Fraudulent financial statements, Forensic tools, Fraudulent financial reporting, Fraud detection and examination, M-score, Z-score

INTRODUCTION

Accounting and fraudulent financial reporting (FFR) have increased in frequency in the last several years, attracting considerable attention from the public, investors, auditors, creditors, researchers, academia and other stakeholders. FFR usually occurs in the form of falsification of financial statements in order to obtain some form of benefit (Dalnial, Kamaluddin, Sanusi, & Khairuddin, 2014) and primarily consists of manipulating elements by overstating assets, sales and profit or by understating liabilities, expenses or losses (Charalambos, 2002).

Market participants such as investors and creditors experience significant financial losses when fraud occurs in publicly traded companies. For example, two well-known fraudulent exposures in Enron and WorldCom accounted for over $120 billion losses to investors (Sridharan, Caines, McMillan, & Summers, 2002). In addition, fraudulent financial reporting practices can potentially erode public confidence with regard to the reliability and accuracy of financial reporting in assessing a firm's future growth and decision making.

Some experts argue that the rate of fraudulent financial reporting will likely increase and further reiterate the importance of continuous research into ways to flush out frauds (Mintz, 2009). Fraud detection has therefore become one of the highest priorities for capital market participants and other stakeholders in the financial reporting process (Elliott, 2002; PCAOB, 2007).

The statement of auditing standards (SAS No. 82, 1991) places the responsibility for detecting accounting and financial statement frauds on audit firms by the corporations they are auditing. Auditors commonly use tools known as analytical procedures to assist them in detecting fraud (Albrecht, Albrecht, & Zimbelman, 2009).

Analytical procedures refer to the analysis of significant ratios and trends as well as the resulting investigation of fluctuations and relationships that are inconsistent with other relevant information or deviate from predicted values. As such, many researchers and fraud investigators recommend financial ratios as an effective tool to detect fraud (Subramanyam & Wild, 2009; Bai, Yen, & Yang, 2008; Spathis, 2002; Persons, 1995). Given the significant impact of these practices, it would be useful if organisations can identify at an early stage the possibility of tumbling into financial distress or detecting the possibility of fraudulent financial reporting by using some prediction tools such as the ratio analysis—the Beneish and Altman models (Barsky, Catanach, & Rhoades-Catanach, 2003; Ravisankar, Ravi, Rao, & Bose, 2011). Barsky et al. (2003) argued that if these models are applied individually, the resulting accounting statements possibly reveal some warning signs for the managers to take appropriate preventive or corrective actions at the initial stages. Other than the management of the organisations, investors, internal and external auditors and regulators can also take advantage of the application of these collective tools. Investors may adopt these tools to assess companies' financial soundness, before or after an investment, so that continuous decisions may be made in protecting their interests.

However, these tools are not the pinnacle or completely free from limitations. Each tool/model has its flaws and drawbacks in providing accurate results, and therein lies the confusion—which affects auditors and stakeholders—regarding the best model to use to detect various types of financial misstatements. Extant literature provides a plethora of statistical tools and techniques, and two statistical techniques (i.e., the Beneish M-score model and the Altman Z-score model) have been selected for this study because of their popularity, usage and applicability. The Z-score model is the most well-known model for predicting financial distress, but in this paper it has been used for a different purpose of detecting fraud.

Effective as they may be, analytical tools have not been able to determine such fraudulent activities in total. Accordingly, financial and accounting fraud has appeared in the headlines of mainstream news worldwide. The problem therefore is, what are the most effective forensic accounting and financial detecting tools that will reveal malpractices in organisations? To address this problem and answer the pertinent question, first, we set out an objective to compare the effectiveness of the two popular forensic tools in detecting FFR using Toshiba Corporation as a case study. Next, we will determine the strengths and weaknesses of the tools through their thorough application to the real financial profile of Toshiba Corporation. Third is to assess the use of the tools independently by comparing the results and the discussion of the tools' relative effectiveness for direction to accounting and auditing practitioners on the selection of appropriate tool(s) in the detection of fraudulent cases during their auditing processes.

The rest of this paper is organised as follows: the next section presents a brief profile of the case company and some reported fraudulent activities uncovered recently. Next is a review of the selected forensic tools through extant literature and hypotheses development. The study then continues with a description of the methodology, analysis and results, followed by the discussions, and finally the conclusion and some recommendations.

Toshiba Corporation and the Accounting Fraud Detection from 2008 to 2014

Toshiba Group includes Toshiba Corporation, which has 598 combined auxiliaries, with main operations in energy and infrastructure, community solutions, health-care systems and services, electronic devices and components and lifestyle items and services. Toshiba Group's products are manufactured and sold worldwide. As of March 2015, the organisation's budget and stock information included a basic load of ¥439.901 million, and the quantity of shares issued was 4,237,600,000 (Toshiba Group Annual Report, 2014).

Toshiba Group is a widely admired Japanese-based company with ¥10.12 billion in business market capitalisation. This group, which has a 140-year history, had been undertaking an orderly 152-billion-yen (US$1.2 billion) expansion of benefits over the course of the 2008–2014 budgetary years. An accounting fraud surfaced after examinations prompted the renunciation of the organisation's main eight administrators, including the CEO, who assumed full responsibility for the misrepresentation (*The Economist*, 2015). An independent report on accounting irregularities at Toshiba found that the Japanese tech giant overstated its operating profit by a total of 151.8 billion yen ($1.22 billion or £783 million) over a 6-year period. This calls for an investigation to ascertain the overstatements and further explore with forensic tools and see if these tools could have detected the overstatement in a proactive manner.

LITERATURE REVIEW AND HYPOTHESES

With his seminal work on fraud, Cressey (1953) postulated the fraud triangle theory (FTT) and argued that three key elements of the occurrence or likelihood of fraud are pressure, opportunity and rationalisation (Skousen, Smith, & Wright, 2009). Pressure is an element that forces a person to commit a fraudulent act, opportunity arises when a person has the skill and ability to commit the fraud, and rationalisation means accepting this behaviour for various reasons. In this context, the PwC Global Economic Crime Survey (2009) found that '68% attributed greater risk of fraud to increased "incentives or pressures"; 18% to opportunities and 14% to rationalisation'.

Pursuant to the works of Cressey, the fraud diamond theory (FDT) was first presented by Wolfe and Hermanson in the *CPA Journal* in December 2004. It was viewed as an expanded version of the FTT. In the FDT, an element called capability was added to the three initial fraud components of the FTT. Wolfe and Hermanson (2004) claimed that although perceived pressure could coexist with an opportunity and a rationalisation, it is unlikely for fraud to take place unless the fourth element (i.e., capability) is also present. In other words, the potential perpetrator must have the skills and ability to commit fraud. Consequently, for any fraud to be detected, the instrument must have the utility to discover the remote cause of fraud concealment and the effective assessment of fraud risk using the classical fraud theory (Abdulahi & Mansor, 2015). The classical fraud theory is based on two major constructs: the analysis of significant ratios and trends and the resulting investigation of fluctuations and relationships consistent with other information on which financial reports deviate from predicted values. As such, many studies and fraud investigators recommend the classical fraud theory as an effective tool to detect fraud.

Beasley, Carcello and Hermanson (1999) argue that Fraudulent Financial Statements (FFR) frequently involves the overstatement of revenues and assets. As such, intentional misstatement in financial statements is noted much more frequently in revenues than misappropriation of assets. A report from the Central Audit Quality (2010) shows that if corporate executives exchange information, inconsistencies in financial reporting will be brought to the fore, and the opportunity to perpetrate FFR will be curbed. However, rapid asset growth, increased cash needs and external financing all increase the likelihood of fraud (Skousen, Smith, & Wright, 2008).

Cynthia H. (2005) expressed similar sentiments on preventing and detecting manipulated financial statements by noting that detecting FFR using normal audit procedures is extremely difficult, not only for auditors, but for all stakeholders.

Fanning and sCogger (1998) also stated that the difficulty of detecting frauds has three main reasons. First is the lack of knowledge concerning the characteristics of fraud management, second is auditors' lack of experience necessary to detect manipulated financial statements and third is the ability of managers to derive new techniques to mislead auditors and investors in their reports. Christopher et al. (2008) stated that fraud is very common currently and has various types, and financial fraud causes huge losses, not only to investors, but to the country's economy as a whole. Therefore, it is important to prevent and detect fraud before it causes the business to collapse, devastating investors and damaging the economy. Hence, knowledge and use of appropriate forensic tools, techniques and models are contingent to the detection of sophisticated frauds in organisations.

Based on the discussion above, there are two models for detecting FFR that resonate investigators and fraud detectors the most. The two models, the Atlman Z-score (bankruptcy prediction) and the Beneish M-score (earnings manipulation), are investment models that can be adopted in entity financial statement analysis by stakeholders. These models are considered on the premise that, when a firm is doing poorly, there is a greater motivation to engage in FFR. Hamer (1983), for example, suggested that most models predict bankruptcy with similar accuracy, which implies that poor financial conditions may motivate unethical insiders to improve the appearance of the firm's financial position or perhaps to reduce the threats of loss of clients or to garner as many resources as possible. Firms may therefore engage in overstating assets and revenue by recording revenue prematurely or by using fictitious records.

AN OVERVIEW OF THE BENEISH MODEL

The Beneish model was created by Professor Messod Daniel Beneish, who formulated several analytical ratios and variables to identify the occurrence of financial fraud or the tendency of a firm to engage in earnings manipulation. Data in the organisation's financial statements are fed into a model to create the M-score, which shows the degree to which earnings have been manipulated. Many researchers have applied the Beneish model to popular corporate scandals to identify financial statement manipulations. Joost Impink (2010) used the Beneish M-score in conjunction with the logit score models to examine the WorldCom scandal, and the outcomes demonstrated that the status of the organisation as an ongoing concern ought to have been changed to that of a perfect concern long before the fraudulent activities were uncovered. Impink (2010) revealed that WorldCom essentially depended on outside financing, inferring that this requirement for credit may have been the explanation behind the organisation's income controls. In other studies, Omar (2014) applied the Beneish model and Ratio Analysis to Megan Media Holdings Berhad (MMHB) and found the company to have manipulated its earnings to a large extent. In his conclusion, he indicated that the operating efficiency ratios, one of the key constructs in the Beneish model, showed that MMHB recorded fictitious revenue, proving that the Beneish model has the ability to reveal FFR. Muntari Mahama (2015) also noted that if the Beneish model had been applied to Enron Corporation, the scandal could have been discovered in a proactive manner as early as 1997, significantly before it petitioned for insolvency in 2001. In another investigation, Drabkova (2014), who tested five of the many statistical and mathematical models available for FFR detection (Beneish M-score model, total accruals to total assets [TATA] in the t-period, three Jones nondiscretionary accruals, and Altman Z-score model) found out that the Altman and Beneish models were much more responsive in identifying the financial health of an organisation.

Other studies, however, proved that the Beneish model is not an ultimate detector of fraud, and the ratios used in the model can only help flag the problematic areas for auditor review. In Cynthia's work (2005), it was proven that the Beneish model did not have the ability to consistently discover problems in FFR. Ugochukwu and Azubuike (2013) compared the effectiveness of the Beneish model on relevant items in the financial reports of 11 selected manufacturing companies in Nigeria for the period 2008–2013. The results showed that the five-variable version appeared to be more effective in predicting genuine existing risks of material misstatement. In another study conducted by Amoa (2014), who applied both the Altman and the Beneish model to FFR at Anglogoldashanti, it was found that the Altman model is more efficient in both predicting bankruptcy and detecting FFR than the Beneish model.

Similarly, a recent study conducted by Ofori (2016) noted that both the Beneish M-score and the Altman Z-score detected FFR in Enron Corporation in 1998, 2000 and 2001. Both models were used to analyse data retrieved from Enron Corporation's annual reports, and each report displayed flaws. Both models suffered from the effects of defining the metrics used to perform the financial analysis. Hence, each model produced different values for some of the metrics used to calculate the ratios. As a result, the models could result in differing predictions of a company's default risk and earning manipulations if not applied appropriately.

There are similarities between the Beneish M-score and the Altman Z-score except that the M-score emphasises on assessing the degree of profit control as opposed to deciding when an organisation may reach bankruptcy. Few studies have tried to apply two modals, most have used the Beneish model as one of the two models used. Nooraslinda Abdul Aris, Rohana Othman, Siti Maznah Mohd Arif, Mohamad Affendi, Abdul Malek and Normah Omar (2013) compared the use, process and application of Benford's law and the Beneish model in detecting accounting fraud and concluded that both techniques appear to have benefits in detecting and preventing fraud. From the discussion above, we propose the first null hypothesis as follows:

H0 (1) = The Beneish eight-factored and five-factored variables cannot effectively detect frauds in an organisation's FFR.

AN OVERVIEW OF THE ALTMAN Z-SCORE MODEL

Altman's model has been used in various sectors to predict bankruptcy in addition to its use in detecting FFR. The model, according to its originator, Altman (1968), can correctly predict financial failure in 95% of firms 1 year prior to their demise. Altman (1968) postulates that 2 years prior to insolvency, accuracy decreases to 72%, and 3 years out, to 52%. A study by Hawariah et al. (2014) found that Z-scores, which measure the probability of bankruptcy, are sufficient to detect FFR. They compared Z-scores with other individual variables that were expected to return negative figures, as firms with poorer financial conditions (and, therefore, smaller Z-scores) are more likely to engage in fraudulent financial reporting. Mehta et al. (2012) found that the Z-scores model has a high likelihood of distinguishing FFR in a specimen organisation. The Altman Z-score model incorporates the accompanying variables: (1) the proportion of inventory to sales, (2) the proportion of total debt to total assets, (3) the proportion of net profit to total assets and (4) money related pain (the Z-score). The analysts found that the model effectively anticipated variables, with a general precision of 81.28%. All in all, the pointers entered in the model were connected with the company's FFR. Per the outcomes, organisations with high inventories as for sales, high debt regarding total assets, low net profit as for total assets and low Z-scores will probably distort their monetary articulations. Charalambos (2013) reinforced this assertion when he used Z-scores and other techniques on published data from 76 firms, finding that Z-scores can detect FFR. Charalambos found that Z-scores classified the entire sample with accuracy rates of more than 84%, and their general indicators were associated with FFR in the selected firms. This led us to propose the second null hypothesis as follows:

H0 $_{(2)}$ = The Altman Z-score cannot be used effectively in the detection of fraud in the financial statements of organisations.

In addition to the second and third hypotheses, there is a need to assess the efficiency of ratios under the two models in the detection of FFR; hence, we proposed a third null hypothesis as follows:

H0 (3) = The ratios used in the Beneish (M-score) model and the Altman (Z-score) model are not efficient in the detection of FFR.

METHODOLOGY

In order to achieve the objectives of the study, both the Beneish and the Altman model were used to examine Toshiba's financial statement. The statement was obtained from Toshiba's corporate website as the organisation is a listed reputable company. The data sample utilised for the study was retrieved from 2008–2014 financial statements obtained from the entity's website.

A summary of the Altman's Z-score and the Beneish M-Score models are stated below:

Altman Z-score

$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5$

where:

Z = Overall index

X_1 = Working Capital / Total Assets. [An entity's net liquid assets are compared to total capitalization. Entities incurring persistent losses have lessening current assets relative to total assets (Altman, 1968).]

X_2 = Retained Earnings / Total Assets. [This measures the earnings capacity of entity]

X_3 = Earnings before Interest and Tax / Total Assets. [An entity's worth is derived from its earnings prowess of assets thus leading to bankruptcy in the event liabilities are greater than assets (Altman, 1968)]

X_4 = Market Value of Equity / Book Value of Total Liabilities. [The ratio reveals degree To which entity assets can weaken in value before liabilities exceed assets (Altman, 1968)]

X_5 = Sales/ Total Assets. [This measures the entity's ability to generate sales utilizing its assets. (Altman, 1968].

The interpretation of the Z-score provided below:

$Z > 2.67$ "safe" zone

$1.81 < Z < 2.67$ "grey" zone

$Z < 1.81$ "distress" zone

Beniesh M-score

Whilst the Z score focuses on bankruptcy prediction, the M-Score seeks to uncover manipulation of earnings. Warshavsky (2012) postulates the adoption of the Beneish model as a tool in the evaluation of prospects of manipulating earnings. The model has two versions that are as stated below:

Eight variable model:

M=-4.84 + 0.92* DRSI + 0.528*GMI + 0.404*AQI + 0.892*SGI + 0.115*DEPI – 0.172*SGAI+4.679*TATA – 0.327*LVGI

where:

DRSI = Days' sale in receivables index. [The day sales in receivable of the current and prior year are compared with the objective of revealing inflated revenue (Beneish, 1999)]

GMI = Gross margin index. [The ratio measures the gross margin or current and compares with prior year. An entity with poor growth prospect is more likely to manipulate (Beneish, 1999)]

AGI = Asset quality index. [Non-current assets excluding property plant and equipment are compared with total assets with an AQI greater than 1 revealing the entity has either increased its intangibles or cost deferral hence creating earnings manipulation (Beneish, 1999)]

SGI = Sales growth index. [The ratio measures current sales versus prior year (Beneish, 1999)]

DEPI=Depreciation index. [The ratio measures the depreciation rate of the current compared to prior year. Slower rates of depreciation may indicate an entity is revising useful life upwards or is adopting an income friendly method of depreciation (Beneish, 1999)].

SGAI = Sales, General and Administrative Expenses Index. [The ratio compares current sales, general and administrative expenses with that of prior year (Beneish, 1999)]

LVGI = Leverage Index. [Total debt is compared with total assets of current to prior year (Beneish, 1999)].

TATA=Total Accruals to Total Assets. [The ratio measures the extent to management undertake discretionary accounting policies that translate into altering of earnings (Beneish, 1999).

The Beneish five-variable model, truncated version, is as follows:

$$M = -6.065 + 0.823*DRSI + 0.906*GMI + 0.593*AQI + 0.717*SGI + 0.107*DEPI$$

Results and Analysis of the Empirical Application of the Beneish Model to Toshiba Corporation

The results of the application of the Beneish model is set out in Table 1 with data spanning from 2008 to 2014 from Toshiba's financial statement.

Table 1 Beneish M Score of Toshiba for the years 2008 to 2014

Variables	2014	2013	2012	2011	2010	2009	2008
Day's Sales Receivable Index	0.964	1.105	1.227	0.922	1.160	0.939	0.896
Gross Margin Index	0.973	0.984	0.978	0.975	0.856	1.288	1.015
Asset Quality Index	0.973	1.017	1.085	1.027	1.004	1.089	0.895
Sales Growth Index	1.135	0.955	0.956	1.023	0.963	0.883	1.079
Depreciation Index	1.326	1.344	0.995	1.082	1.119	0.903	0.769
Sales, General and Administrative Expenses Index	0.984	1.015	1.049	0.939	0.905	1.057	1.000
Leverage Index	0.978	0.995	1.024	0.960	0.898	1.123	0.989
Total Accruals to Total Assets	-0.046	-0.022	-0.058	-0.070	-0.083	0.003	-0.042
Beneish M Score , 8 Variable Version	**-2.58**	**-2.49**	**-2.58**	**-2.83**	**-2.76**	**-2.50**	**-2.75**
Beneish 5 Variable Version	**-2.87**	**-2.83**	**-2.73**	**-2.96**	**-2.93**	**-2.75**	**-3.02**

Toshiba's general M-score results for 2008–2014 are not exactly the benchmark of –2.22, meaning that, by and large, Toshiba was not controlling its income in the years under survey. Despite the fact that Toshiba's FFR for 2008–2014 has been demonstrated by the Japanese government and different powers with access to the confirmation, the Beneish model did not recognise this extortion. Based on these results, the present study's H0 (1) is accepted, which means that *the Beneish eight-factored and five-factored variables cannot effectively detect frauds in the organisation's FFR.*

Compared with the eight-variable adaptation of the model, whose results were similarly weighed against that of the five-variable version, the present study did not identify a possible danger of material misstatements in Toshiba's distributed figures/monetary information for the years analysed.

The M-score pointers for 2008–2014 (–2.75, –2.50, –2.76, –2.83, –2.58, –2.49 and –2.58, per the eight-variable model, and –3.02, –2.75, –2.93, –2.96, –2.73, –2.83 and

–2.87, per the five-variable one) as depicted in table 1 did not demonstrate that the organisation was involved in material misstatements in any of the years examined. However, based on the individual scores, Days Sales Receivable Index (DSRI), there was an increase in DSRI in 2010, 2012 and 2013. This indicates that the percentage of accounts receivables to sales increased in these years. But in 2014, there was a slight decrease from 2013, that is, from 1.105 to 0.964. It can be concluded that the inflated revenue from the previous year reduced in the current year.

GMI: Sales to cost of goods sold was almost the same from 2010 to 2014. The values of Gross Margin Index (GMI) for the years 2008 and 2009 are same (approximately) and in 2010 slightly it has come down but thereafter it was almost the same from 2011 till 2014.

AQI: This was greater than 1.0, which signifies a reduction in asset quality. However, Toshiba's AQI for the 7 selected years never crossed the manipulators mean of 1.254.

SGI: The scores of SGI were inconsistent over the selected study years of Toshiba. In the year 2008, it was 1.079; but in 2009 and 2010, there was a fall in SGI. It reached to 1.135 by the end of 2014.

DEPI: The results illustrate an increase in the values of the depreciation index right from the years 2008 to 2014. This is only one variable that exceeded the mean index of 1.077, which confirmed the entry in the manipulators category by 1.0767. This indicates that a growth in income is a result of a decreasing depreciation. The value of this index clearly depicts that there is an earning manipulation in Toshiba for the selected years of study.

SGAI: The trend in SGAI discloses that the years 2008, 2009, 2012 and 2013 crossed the 1.0 standard of the Beneish model. This indicates that there was an increase in sales and general and administrative expenses, and the administrative efficiency of Toshiba should be suspected. But it is observed that there was a decrease in the year 2014 to 0.984.

LVGI: The one important indicator is leverage index. This variable shows the relationship between outside liabilities in the form of long-term and short-term (Debts) to total assets. An increase in the leverage index clearly indicates that the company is prone to earnings manipulation. According to the above results, the years 2012 and 2009 crossed 1.0 and they resulted as 1.123 and 1.024. For the rest of the years, this variable was stable.

TATA: Total accruals to total assets is useful in finding out the income from continuing operations and cash flows from operations. Except in the year 2009, with 0.003, for all the other years, this variable showed negative values. This indicates that the company is not receiving any other sources of profits except the main income source.

The application of the Beneish model to Toshiba's financial statements indicated that the company is not manipulating its earnings. This model categorises companies into two groups: non-manipulators and manipulators by using the aforementioned benchmarks. The calculation for the last two columns in Table 2 represents the Beneish model benchmarks.

Table 2 Toshiba Corporation-Benchmarking with the Beneish Model

Variables	**Mean (Eight Variables)**	**Non-manipulators**	**Manipulators**
Day's Sales Receivable Index	1.0305	1.031	1.465
Gross Margin Index	1.0099	1.041	1.193
Asset Quality Index	1.0128	1.039	1.254
Sales Growth Index	0.9992	1.134	1.607
Depreciation Index	1.0767	1.001	1.077
Sales, General and Administrative Expenses Index	0.9926	1.054	1.041
Leverage Index	0.9951	0.018	0.031
Total Accrual to Total Assets	–0.0453	1.037	1.111

This has been tested with the results of Toshiba in this study. Toshiba Corporation scored very close values to manipulators in only one out of the eight variables, that is, DEPI**.** The situation takes even a near-complex dimension as a closer consideration of the individual indicators of the DEPI, GMI, AQI, SGI, SGAI and TATA variables to the eight-factored variables version, except for the DEPI (1.077 against 1.0767 benchmark), which appears to disagree with the 'risks of material misstatement red flags' earlier indicated.

Results and Analysis of the Empirical Application of the Altman Z-Score Model to Toshiba Corporation

The Z-score for the year 2008 was 1.970, which indicates that the firm was not going to be bankrupt within the next 2 years. This study's second null hypothesis, H0 (2), is rejected. Finally, it is proved that *the Altman Z-score can be used effectively in the detection of fraud in the financial statements of organisations.*

The Z-score results for the year 2008 of this current study is not evidencing the material misstatements, but all other years, 2009–2014, indicated that Toshiba was not sound and would not continue in the market for long. The lower Z-scores, 1.237, 1.641, 1.799, 1.596, 1.541 and 1.567, respectively, showed that the chances of the company filing for bankruptcy were very high. However, the following is an analysis of the individual scores, and results are presented in Table 3.

Table 3 Altman Z-score of Toshiba for the years 2008 to 2014

	Variables	**2014**	**2013**	**2012**	**2011**	**2010**	**2009**	**2008**
X1	Working Capital / Total Assets	0.0689	0.0688	0.0591	0.056	0.0501	-0.0637	-0.0095
X2	Retained Earnings/ Total Assets	0.0737	0.1041	0.1029	0.1025	0.0689	0.0725	0.1305
X3	EBIT/Total Assets	0.035	0.0308	0.0308	0.0424	0.0129	-0.045	0.0514
X4	M.V of Equity/Total Liabilities	0.3579	0.3996	0.3362	0.4023	0.4517	0.1813	0.488
X5	Sales / Total Assets	1.0514	0.9719	1.0786	1.2071	1.1712	1.2526	1.3365
	Z-.Score	**1.567**	**1.541**	**1.59694**	**1.7991**	**1.64137**	**1.23794**	**1.97022**

Table 4 Altman Z- Score of Toshiba for the years 2008 to 2014

	Variables	2014	2013	2012	2011	2010	2009	2008
X1	Working Capital / Total Assets	0.0689	0.0688	0.0591	0.056	0.0501	-0.0637	-0.0095
X2	Retained Earnings/ Total Assets	0.0737	0.1041	0.1029	0.1025	0.0689	0.0725	0.1305
X3	EBIT/Total Assets	0.035	0.0308	0.0308	0.0424	0.0129	-0.045	0.0514
X4	M.V of Equity/Total Liabilities	0.3579	0.3996	0.3362	0.4023	0.4517	0.1813	0.488
X5	Sales / Total Assets	1.0514	0.9719	1.0786	1.2071	1.1712	1.2526	1.3365
	Z-.Score	1.567	1.541	1.59694	1.7991	1.64137	1.23794	1.97022

X_1: As shown in Table 4, low Z-score results indicated the proportion of working capital to total assets, which was either negative or low for every one of the years analysed, a conceivable pointer that the organisation had liquidity issues. This part of the Z-score model shows liquidity issues that build the likelihood of insolvency. The qualities were somewhat enhanced throughout the years, except for 2008 and 2009, which had negative results, –0.0095 and –0.0637, separately. From 2010 to 2014, the outcomes—0.0501, 0.056, 0.0591, 0.0688 and 0.0689—separately, were basically steady. The outcomes in 2013 and 2014 were precisely the same.

X_2: This ratio highlights the fact that the profits were used to cover the accumulated losses incurred in prior years. Nonetheless, low values of the ratio of retained earnings to total assets generally indicate low profitability. From 2011 to 2013, the values for this variable, 0.103, 0.103 and 0.104, respectively, were stable.

X_3: In the year 2009, the value of this ratio was negative at –0.045. The results for all the other years were positive and stable.

X_4: Except that there was a decrease in 2009, the Z-score of this ratio, that is, 0.813, for all other years was stable.
X_5: In 2013, the value for this variable decreased slightly to 0.9719, indicating a decreased effectiveness of asset use to generate revenue. In 2008, the result was 1.3365, the highest value during the 7 years studied.

Statistical Analysis Results of the Beneish and Altman Models on Toshiba's FFR

Table 5 presents the mean values, standard deviations, independent sample *t*-test and *p*-values of the ratios of Toshiba Corporation from 2008 to 2014. This was done in favour of the proposed hypothesis restated as follows:
H0 (3) = The ratios used in the Beneish (M-score) model and the Altman (Z-score) model are not efficient in the detection of FFR.

Table 5 Statistical properties of Beneish and Altman analysis

BENEISH MODEL (M-SCORE)					**ALTMAN MODEL (Z-SCORE)**				
	Mean	**SD**	***t*-test**	***p*-value**		**Mean**	**SD**	***t*-test**	**P-value**
Day's Sales Receivable Index	1.031	0.132	20.717	0.002	Working Capital/ Total Assets	0.038	0.050	1.723	0.136
Gross Margin Index	1.010	0.133	20.162	0.011	Retained Earnings/Total Assets	0.094	0.023	10.913	0.012
Asset Quality Index	1.013	0.067	40.152	0.002	EBIT/ Total Assets	0.023	0.032	1.865	0.111
Sales Growth Index	0.999	0.086	30.847	0.001	MV of Equity/ Total Liabilities	0.374	0.099	9.949	0.013
Depreciation Index	1.077	0.211	13.500	0.001	Sales/ Total Assets	1.153	0.126	24.174	0.010
Sales, General and Administrative Expenses Index	0.993	0.056	47.305	0.001					
Leverage Index	0.995	0.069	38.356	0.001					
Total Accruals to Total Assets	0.955	0.046	22.402	0.001					

This hypothesis is useful for testing the efficiency of ratios under two models in the detection of FFR. This is tested through the "*p*-value" at 5% level of significance with the help of SPSS.

This analysis provides an understanding of the statistical characteristics of ratios in both types of models. The *t*-test results of this study suggest that Beneish model ratios has strong variation between the groups compared with Altman model ratios. Similarly, the mean difference from the independent ratios are more in the Beneish model than in the other. The *p*-values of both models at 5% level of significance are less than (<0.05), which indicates that the ratios were related and efficient in detecting the fraudulent financial statements of Toshiba. Hence, the H0 (3) hypothesis has been rejected with a strong evidence at 5% level of significance, proving that the variables may be helpful in predicting fraudulent financial statements.

CONCLUSION

The primary objective of this study was to examine the efficacy of the Beneish M-score and the Altman Z-score in detecting FFR by Toshiba Corporation as a case study. This study found that the hypothesis of the Beneish model is not effective in detecting FFR of Toshiba. The five-variable version of the model on the same financial data showed results that were slightly lower than those of the eight-variable model. These results strengthens the hypothesis by further supporting that there was no material misstatement in Toshiba's financial statements. These results are consistent with those of a similar study conducted by Karikari et al. (2014) on AngloGold Ashanti. These authors used the Beneish M-score, the Altman Z-score and Benford's law on the selected company, and the results of the Beneish model did not indicate financial distress, but those of the Altman Z-score and Benford's law did. The current study's null hypothesis regarding the Altman Z-score was rejected, proving that the Altman Z-score was effective in detecting FFR of Toshiba. These results are consistent with those of studies conducted by Hawariah Dalniala, Amrizah Kamaluddina, Zuraidah Mohd Sanusia and Khairun Syafiza Khairuddin (2014); Mehta Ujal, Patel Amit, Patel Hiral and Purohit Rajan (2012); and Charalambos (2002). These authors found that Z-scores that measured the probability of bankruptcy were effective at detecting FFR. The present study found that unlike the Beneish M-score, the Altman Z-score was very effective in identifying FFR.

RECOMMENDATIONS

One of the objectives of this current study was to suggest which of the two tested forensic tools is more useful for detecting FFR. The results of the present study support using more than one forensic tool to detect FFR because each model has its own limitations. To apply the Beneish model variables, one must consider the financial statements in the objective organisation's money-related issues. The model's outcomes will be more exact when the extent of the study is over 5 years and the money-related qualities in the budgetary proclamations are substantial. The Beneish model is a probabilistic model, so it will not distinguish control with 100% precision (Beneish et al., 1999). The consequences of the present study boost that announcement, demonstrating that this model neglected to distinguish the financial misstatements in Toshiba, giving back an M-score of not exactly the limit standard of –2.22.

The Altman Z-score is a statistical tool to utilise and quickly gives a picture of the objective organisation's financial position. The present study found that the Z-score was the most exact model of the three tried. The results of this study found that the Z-score was the most accurate model out of the two tested models. Hence, it can be concluded that all forensic tools are not useful with regard to financial statements. However, the two forensic tools used in the study were useful for indicating red flags regarding the scope of the fraud at Toshiba, although none could pinpoint the exact location or area of the fraud.

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