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Application of Forensic Tools to Detect Fraud: The Case of Toshiba

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Introduction

References to fraudulent financial statements (FFS) have increased in frequency in the last several years. FFS primarily consists of manipulating elements by overstating assets, sales and profit or by understating liabilities, expense or losses (Charalambos T., 2002). "The auditor has a responsibility to plan and perform the audit to obtain reasonable assurance about whether the financial statements are free of material misstatement, whether caused by error or fraud"-SAA 99 and SAS 113. However, during the past several years, financial and accounting fraud has appeared in the headlines of mainstream news worldwide. Although accounting fraud is not a new phenomenon, recent cases involve much larger sums than previously (Clements, 2016). The present study tests the effectiveness of three popular forensic tools in detecting FFS by Toshiba Corporation from 2008–2014. The three tools are the Beneish Model, the Altman Z-Score and Benford's Law. The comparison of the results and discussion of the tools' relative effectiveness provide direction for investigators about the selected tools' effectiveness for detecting FFS.

Every tool has its advantages and limitations. By using only one forensic tool to detect fraud, an auditor cannot adequately judge the financial statements of any corporation. This study highlights the weaknesses of the selected forensic tools as well as their areas of application. Thorough application of these tools to Toshiba's financial statements revealed that the three tools did not give the same results. In addition, it was not possible to use them with the same input.

The present study's focus was to detect fraud in the financial statements of Toshiba Corporation of Japan during seven years, from 2008–2014, as evidence exists that fraud took place in the company during those years. To detect the fraud, the selected forensic tools were applied to Toshiba's financial statements for the sample period. The study compared the results of the three tools, discussed their limitations and suggested which was best for the purpose. To our knowledge, no prior research has used all three forensic tools in one study, particularly not in the case of Toshiba.

Toshiba's Fraud

Toshiba Group is a widely-acclaimed Japanese-based company with ¥10.12 billion in business market capitalisation. The organization, which has a 140-year history, had been undertaking an orderly, ¥152 billion (USD$1.2 billion) expansion of benefits over the course of the 2008 to 2014 budgetary years. The FFS surfaced after examinations prompted the renunciation of the organization's main eight administrators, including the CEO, who assumed full responsibility for the misrepresentation (The Economist, 2015).

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About the Company

Toshiba Group includes Toshiba Corporation, which has 598 combined auxiliaries, with main operations in Energy and Infrastructure, Community Solutions, Healthcare Systems and Services, Electronic Devices and Components and Lifestyle Items and Services. Toshiba Group's products are manufactured and sold worldwide. As of March 31, 2015, the organization'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).

This paper is organised as follows: next section presents a review of the selected forensic tools. Then, the paper describes the study's methodology. Next, it presents and discusses the study's results. Finally, the paper presents conclusions and suggestions.

Literature Review

Detecting FFS

Ultimately, the prevention and detection of FFS is not only the responsibility of internal and external auditors but the collective responsibility of all stakeholders in an organisation. According to a report from the Central Audit Quality (CAQ, 2010), if corporate executives exchange information, inconsistencies in financial reporting will be brought to the fore, and the opportunity to perpetrate FFS will be curbed. However, rapid asset growth, increased cash needs and external financing all increase the likelihood of fraud (Christopher et al., 2008).

Per research by Beasley et al., (1999), FFS frequently involves the overstatement of revenues and assets. Intentional misstatement in financial statements is noted much more frequently in revenues than is misappropriation of assets. Beasley et al., noted that on an overall, cumulative basis, the average fraud was USD$25 million, and the median fraud was USD$4.1 million. In addition, Cynthia. H (2005) expressed a similar opinion on preventing and detecting manipulated financial statements, noting that detecting FFS using normal audit procedures is extremely difficult, not only for auditors but for all stakeholders. There are three main reasons for this, according to Fanning et al., (1998). First is, a lack of knowledge concerning the characteristics of fraud management. Second is, auditors lack the experience necessary to detect manipulated financial statements. Third is, managers derive new techniques to mislead auditors and investors.

Fraud is very common currently. Of the various types of fraud, financial fraud causes huge losses, not only to investors but for 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. There are various methods for detecting FFS. The models selected for this study were the Beneish Model, the Altman Z-Score and Benford's Law.

The Beneish Model

The Beneish Model is a mathematical model created by Professor Messod Daniel Beneish, who formulated several analysis ratios with variables to identify the occurrence of financial fraud or the tendency to engage in earnings manipulation. The model's variables are constructed from the data in the organization's financial statements and, once computed, they create an M-Score, which shows the degree to which earnings have been manipulated. The model's efficiency has been tested by various researchers. Muntari M (2015) used the model on Enron Corporation and found that the company's FFS could have been recognized as early as 1997, significantly before it petitioned for insolvency in 2001. Normah Omar et al., (2014) applied the Beneish Model and Ratio Analysis to Megan Media Holdings Berhad (MMHB), finding that the company manipulated its earnings. Its operating-efficiency ratios showed that the company recorded fictitious revenue, proving that the Beneish Model can detect FFS. Drabkova (2014) tested five of the many statistical and mathematical models available for FFS detection: the Beneish M-Score Model, the TATA - Total Accruals to Total Assets in the t-period, Three Jones Nondiscretionary Accruals, and the Altman Z-Score Model. The results showed that the Altman and Beneish Models were able to identify the financial health of the selected case study. Many researchers have applied the Beneish Model to the popular corporate scandals of WorldCom and Enron Corporation to identify their financial statement manipulations. Joost (2010) applied the Beneish M-Score and Logit Score models to WorldCom, and the results showed that the status of this company as a going concern should have been changed to that of a clean concern. Using these statistical models, Joost concluded that WorldCom depended significantly on external financing, implying that this need for credit may have been the reason for the company's earnings manipulations.

However, certain studies show that the Beneish Model is not the ultimate detector of fraud. The ratios used in the model can only help to flag the problematic areas for auditor review. In a study by Cynthia (2005), they did not prove to be consistent indicators of problems. In addition, Ugochukwu (2015) compared use of the Beneish Model's eight-variable and five-variable versions on relevant items in the financial reports of 11 selected manufacturing companies in Nigeria for the period from 2008–2013. The results showed that the five-variable version appeared to be more effective in predicting genuine, existing risks of material misstatement. A study conducted by Amoa (2014) applied both the Altman and Beneish models to FFS by Anglo Gold Ashanti and found that the Altman Model was more efficient at both predicting bankruptcy and detecting FFS than the Beneish Model. The Beneish Model found no financial statement manipulation in the company, whereas the Altman Model found four financial distresses the firm had gone through during the years investigated.

Similarly, a recent study by Edmond (2016) noted that the Beneish M-Score and the Altman Z-Score both detected FFS in Enron Corporation in 1998, 2000, and 2001. Both models were used to analyse data retrieved from Enron Corporation's annual reports, and each displayed flaws. Both 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. This can result in differing predictions of a company's default risk and earnings manipulations.

The Beneish M-Score is like Altman Z-Score except that the M-Score focuses on assessing the degree of profit control as opposed to deciding when an organization may reach bankruptcy. Few studies have tried to apply two statistical models, but of those that have, most have used the Beneish Model as one of the two models used. Nooraslinda et al., (2013) compared the use, process and application of Benford's Law and the Beneish Model in detecting accounting fraud, concluding that both techniques appeared to have benefits in detecting and preventing fraud.

Altman's Z-Score

Altman's Model has been used in various industries to predict bankruptcy, and researchers have also used it to detect FFS. According to Altman (1968), his model correctly predicts financial failure for ninety-five percent of firms one year prior to their demise. Two years prior to insolvency, accuracy decreases to seventy-two percent, and three years out, to fifty-two percent. In addition, a study by Hawariah et al., (2014) found that Z-Scores, which measure the probability of bankruptcy, are sufficient to detect FFS. They compared Z-Scores to 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. A study conducted by Charalambos (2013) used Z-Scores and other techniques on published data from seventy-six firms, finding that Z-Scores can detect FFS. Charalambos found that Z-Scores classified the entire sample with accuracy rates of more than eighty-four percent, and their general indicators were associated with the FFS in the selected firms.

Mehta et al., (2012) found the Z-Scores model had a high probability of detecting FFS in a sample company. The Altman Z-Score model includes the following variables: 1) the ratio of Inventory to Sales; 2) the ratio of Total Debt to Total Assets; 3) the ratio of Net Profit to Total Assets; and 4) financial distress (the Z-Score). The researchers found that the model efficiently predicted variables, with an overall accuracy of 81.28%. In general, the indicators entered in the model were associated with the firm's FFS. Per the results, companies with high Inventories with respect to Sales, high Debt with respect to Total Assets, low Net Profit with respect to Total Assets and low Z-Scores were more likely to misrepresent their financial statements.

Gnyana (2015) applied Altman's Z-Score to predict corporate bankruptcy in five selected fast moving consumer goods (FMCG) companies during five years, from 2011–2015.The author concluded that by applying the Z-Score and selecting liquidity ratios, investors can use the model to analyse the financial positions of companies. The Z-Scores of all selected FMCG companies for the years in question showed sound financial positions. In addition, the study suggested that companies should regularly estimate their Z-Scores when strategizing to improve their financial positions.

Despite the fact that Altman's Z-Score is easy to apply and includes various financial ratios, it has been criticized for not incorporating all the important financial ratios. In addition, the model was built based on accrual-basis balance sheets and income statements and does not take into account cash-flow information. Stepanyan (2014) highlighted a new angle in Altman's Z-Score Model in his research on the bankruptcy chances of seven large US airlines, using Z-Scores for six consecutive years. He noted that over the past thirty years, many tests have found Altman's bankruptcy prediction model to be roughly eighty to ninety percent accurate in predicting corporate default two years prior to bankruptcy filing.

Benford's Law

The Big Four accounting firms use Benford's Law to conform to the fraud-detection recommendations in the Financial Statements of the Statement of Auditing Standards No. 99, which highlights the importance of Benford's Law to assessing the possibility of financial misstatement. The first author to thoroughly research and recommend Benford's law was Nigrini. According to Nigriniet et al., (1997), Benford's Law can test the authenticity of lists of numbers by comparing their actual and expected digital frequencies. The non-conformity of the results can indicate FFS in a company.

However, some studies in the literature are cautious about the effectiveness of Benford's Law in detecting fraud. A study conducted by Hayes (2012) found Benford's Law useful as an early indicator of the possibility of FFS and possibly of use as a warning sign of bankruptcy. In addition, the study found that Benford's Law alone cannot detect FFS and that deviations from Benford's Law can cause an analyst to question the validity, accuracy or completeness of the numbers. However, Benford's Law can still be an appropriate method to detect the possibility of fraud. It is a different way of looking at numbers. In conjunction with other audit tools, it can help auditors minimize the expectation gap by increasing their chances of finding fraud and can help companies' bottom lines by finding inefficiencies and errors. In addition, Benford's Law improves sampling so auditors can concentrate on fraudulent or otherwise suspicious areas (Gogi Overhoff, 2011). Durtschi et al., (2004) noted that Benford's Law has been promoted as a simple, effective tool for detecting fraud. They cited an actual example in which Benford's law succeeded in identifying fraud in a volume of accounting data. In addition, they noted that digital analysis based on Benford's Law is most effective and that there are areas where auditors should exercise attention. The study indicated that certain limitations to the law. Likewise, Etteridge et al., (1999) cautioned that a data set that, when tested, does not conform to Benford's Law may show only operating inefficiencies or flaws in accounting and reporting systems, rather than fraud.

Need and Significance of the Study

According to the American Institute of Certified Public Accountants SAS No.82 (1997) and the U.S. Government Accountability Office (2004), there are two types of financial misstatements. First are financial misstatements due to FFS. Second are misstatements resulting from employee fraud or defalcation. Fraudulent financial reporting frequently involves the overstatement of revenues and assets (Beasley et al., 1999). Financial analysts, investors and management have developed various forensic indices to aid forensic accountants in assessing the probability of earnings manipulation. Each tool/model has its flaws and impediments to 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. After thorough examination of the literature, the present case study chose three statistical techniques: the Beneish Model M-Score (both five- and eight-variable), the Altman Z-Score and Benford's Law. The reasons for the selections included popularity, usage and applicability. First, a list of thiryt-six fraud-investigation techniques was developed using common fraud and forensic-accounting texts (Albrecht et al., 2015).Most of these tools and techniques are common in practice and used not only for fraud detection but other purposes as well.

The present study tested the abilities of the three selected models to detect FFS in Toshiba Corporation, the most recent of the large accounting and financial statements scandals. Although the Toshiba scandal involved years from 2008–2014, the study's scope was from 2004–2014. This study contributes to filling the gap in the available literature on the application and effectiveness of forensic tools in detecting FFS. To our knowledge, no prior research has used all three forensic tools in one study, particularly not in the case of Toshiba.

The Objectives of the Study

1. To test the efficacy of the Beneish M-Score, the Altman Z-Score and Benford's Law in detecting FFS in Toshiba Corporation.

2. To compare the results of the three tools and suggest which is most useful to the present purpose.

Hypothesis Development

Based on the above objectives, the following three hypotheses were developed regarding the three tools.

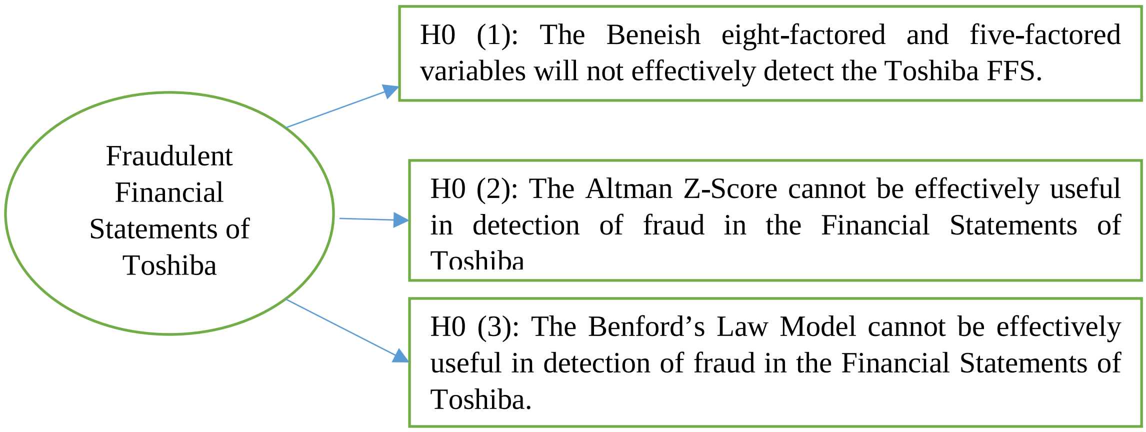


Figure 1: Hypotheses of the study

Methodology

- Apply the Beneish Model with both five- and eight-factor variables to Toshiba's financial statements.
- Apply the Altman Z-Score to Toshiba's financial statements.
- Apply Benford's Law to Toshiba's financial statements.
- Analyse each of these applications. Each of the three tools has a different procedure for application. The methodologies of the tools are discussed below.

The Beneish Model

The Beneish M-Score is a mathematical model with two versions, one with five variables and one with eight variables, both of which can identify financial fraud in earnings manipulations. The Beneish Model has been acclaimed as being more sophisticated than ratio analysis (Cynthia, 2005; Roxas, 2011; Ugochukwuet et al., 2013). Aside from the high comprehensibility they maintain, the eight-variable and five-variable versions of the model are both quite simple for auditors to use (Beneish et al., 2008). The model incorporates the recommended ratio and trend analysis common among preparers of financial statements, financial analysts and fraud examiners by comparing the relationships between key financial-statement items for signs of earnings manipulation (Ugochukwu et al., 2015). The Beneish Model is similar to the Altman Z-Score Model, except that it does not predict bankruptcy.

Steps for application of Beneish Model

1. Calculate the eight variables or the five variables of the M-Score Model.

2. Enter the variables used into the model equation to calculate the M-Score. The present study used Microsoft Excel to do this.

3. After calculating the M-Score and getting the results, categorize the company as a manipulator if the M-Score >-2.22.

Then, the variables shown in Table I were applied to the function of the M-Score: The equation for calculating the M-Score using eight variables is as follows.

M-Score = -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).

Table I: Beneish (1999) and Rationale of the Variables

Variable	Full Form	Description	Rationale
DSRI	Days Sales in Receivables Index	(Net Receivables$_t$ / Sales$_t$) / Net Receivables$_{t-1}$ / Sales$_{t-1}$)	This variable measures how accounts receivables as a percentage of sales have changed compared to the previous year. This variable is useful to capture distortions in accounts receivables that initiate from an inflated revenue.
GMI	Gross Margin Index	[(Sales$_{t-1}$ - COGS$_{t-1}$) / Sales$_{t-1}$] / [(Sales$_t$ - COGS$_t$) / Sales$_t$]	This variable compares the gross margin i.e sales to cost of goods sold between the previous year and the current year
AQI	Asset Quality Index	[1 - (Current Assets$_t$ + PP&E$_t$ + Securities$_t$) / Total Assets$_t$] / [1 - ((Current Assets$_{t-1}$ + PP&E$_{t-1}$ + Securities$_{t-1}$) / Total Assets$_{t-1}$)]	This variables indicates the relationship between the non-current assets other than PPE and the total assets.
SGI	Sales Growth Index	Sales$_t$ / Sales$_{t-1}$	This variable compares sales between two consecutive years. An increase in sales in the current year compared to previous year indicates that the company in the current year is doing good or not. But growth companies always have chances of manipulations in their earnings
DEPI	Depreciation Index	(Depreciation$_{t-1}$/ (PP&E$_{t-1}$ + Depreciation$_{t-1}$)) / (Depreciation$_t$ / (PP&E$_t$ + Depreciation$_t$))	This variable indicates that growth in income as a result of declining depreciation could have changes of earning manipulations
SGAI	Sales, General and Administrative Expenses Index	(SG&A Expense$_t$ / Sales$_t$) / (SG&A Expense$_{t-1}$ / Sales$_{t-1}$)	Higher sales and administrative expenses indicate a decrease in administrative efficiency and influence firms to engage in financial misstatements
LVGI	Leverage Index	[(Current Liabilities$_t$ + Total Long Term Debt$_t$) / Total Assets$_t$] / [(Current Liabilities$_{t-1}$ + Total Long Term Debt$_{t-1}$) / Total Assets$_{t-1}$]	This variable indicates the relationship between long term debt and current liabilities to total assets. Increase in leverage could make a company prone to earnings manipulation
TATA	Total Accruals to Total Assets	(Income from Continuing Operations$_t$ - Cash Flows from Operations$_t$) / Total Assets$_t$	This variable is useful to capture accounting profits which are not real and are not supported by profits at hand

The equation for calculating the M-Score using five variables excludes SGAI, LEVI and TATA, which were found not to be significant to the original Beneish Model. The equation for calculating it is as follows.

M = –6.065 + 0.823 * DSRI + 0.906 * GMI + 0.593 * AQI + 0.717 * SGI + 0.107 * DEPI

According to Beneish (1999), an M-Score greater than -2.22 indicates that the company is involved in FFS.

The Altman Z-Score

In 1968, Edward Altman developed a bankruptcy-prediction model using Multiple Discriminant Analysis (MDA). The Z-Scores that it generates can be used to predict the potential of bankruptcy two years prior to the actual filing.

Steps to use the Altman Z-Score

1. Calculate all five variables in the Z-Score Model.

2. Enter all of five variables into the model's equation and calculate the Z-Score. The present study used Microsoft Excel to do this.

3. After calculating the Z-Score and getting the results, categorize the selected company per the benchmark standards of the Z-Score, which are given below.

Z-Score Benchmark Standards

Financially sound if greater than	2.99
Caution required if between	2.77–2.99
Likely to go bankrupt within two years if between	1.8–2.7
Likelihood of bankruptcy is high if below	1.88
Average for non-bankrupt companies	5.02
Average for bankrupt companies	-0.29

Table II: Altman Z-Score and Rational of the variables

Variable	Description	Rationale
X1	Working Capital / Total Assets	This component in the Z-score model that reflects liquidity, and the low value of this ratio may indicate that the company has liquidity problems which increase the possibility of the filing for bankruptcy.
X2	Retained Earnings/ Total Assets	This reflects profitability and the company's ability to accumulate and reinvest earnings. The low value of this ratio may suggest that the company had difficulties accumulating earnings due to losses or small profits.
X3	EBIT/Total Assets	Earnings before interest and taxes to assets that reflects the operating efficiency before tax and financial leverage effects. In other words, this ratio represents the ROA measure.
X4	M.V of Equity/Total Liabilities	This component of the Z-score model that considers security price fluctuations and represents the relation between market value of equity and total book value of liabilities. The ratio shows how market assesses the firm's profitability and risk. Market value of the equity is defined as the market value of all common and preferred stock outstanding.
X5	Sales / Total Assets	Low value of this ratio bespeaks low effectiveness of assets utilization to generate revenue.

Then, the variables shown in Table II were applied to the function of the Z-Score as follows. These Z-Scores, which combine five financial ratios of a publicly traded firm, are generated using the formula below.

Z-Score = 1.2 X1+ 1.4X2+ 3.3 X3+ 0.6 X4+ 1.0 X5.

Benford's Law

According to research by Nigrini (1997), the original Benford's Law included 5 tests in the areas of accounting and auditing. The model converts digits into calculations, which is why it is also called the Digits test. The five tests are: First Digit, Second Digit, First Two Digits, First Three Digits, and Last Two Digits. Each test has its own purpose. Both the First and Second Digit tests are high-level tests used to check the general reasonableness of data. They identify only identify obvious anomalies. To get efficient, effective results, the input data must be massive. Using less data does not enable comparison of patterns.

In the present study, Toshiba's financial statements for 2007 through 2014, years during a known period of fraud, were obtained from the company's website, providing a sufficient volume of data to enable comparison of patterns. A similar study conducted by Haynes (2012) compiled six years of data from three U.S. municipalities and found non-conforming results, suggesting that Benford's Law can be used to find financial misstatements.

Although Benford's Law might not accurately detect fraud, it can still indicate the possibility of fraud. Non-conformities to Benford's Law are red flags indicating possible irregularities, thereby directing an auditor's attention to the financial statements that merit further attention. The following steps were taken to analyse Toshiba's financial statements using Nigrini's rules (1997).

Steps to use Benford's Law

1. Perform digital analysis of each data set using a software program called NigriniCycle.xlsx, which is an Excel program created by Nigrini.

2. Analyse the numbers from Toshiba's published, comprehensive annual financial reports.

3. Compile the numbers for all seven years to get sufficiently massive data.

4. Omit numbers such as page numbers, dates, the numbers of notes, references to time (e.g., depreciation over ten years or ninety-day notes).

5. Omit numbers that were sub-totals or totals that did not convey any new information. For example, subtotals of total current assets or total current liabilities can be omitted. Since these subtotals and totals are the sums or differences between items and do not reflect any new information, they cannot be manipulated.

6. To assess each digit test's conformity to Benford's Law, a test called the Mean Absolute Deviation (MAD) is used, as per NigriniCycle.xlsx. By referring to a range of MAD values, which is given on a table, the results can be evaluated for conformity to Benford's Law to indicate the degree of possible fraud. The higher the MAD value, the larger the difference between the actual and expected values and the higher the chances of fraud.

The other benchmark for conformity used in this model is the Z-Statistic, which is automatically generated after the test is conducted. Per GogiGogi Overhoff (2011) that the Z-Statistic of Benfod's law measures the size of the deviations between the expected and the actual values. The larger the Z-Score (commonly 1% at 2.58, 5% at 1.96, or 10% at 1.65), the less likely it is that the result is due to chance. According to Benfod's law, after analysing the test results the conclusions will be given in the following order.

Digits	Range	Conclusion
First Digits	0.000 to 0.006	Close Conformity
	0.006 to 0.012	Acceptable Conformity
	0.012 to 0.015	Marginally Acceptable Conformity
	Above 0.015	Non-Conformity
Second Digits	0.000 to 0.008	Close Conformity
	0.008 to 0.010	Acceptable Conformity
	0.010 to 0.012	Marginally Acceptable Conformity
	Above 0.012	Non-Conformity

Analysis

The Beneish Model

Table III shows that Toshiba's overall M-Score results for 2008–2014 are less than the benchmark of -2.22, signifying that, overall, Toshiba was not manipulating earnings in the years under review. Although Toshiba's FFS for 2008–2014 has been proved by the Japanese government and various authorities with access to the evidence, the Beneish Model did not detect this fraud. Using the eight-variable version of the model, whose outcome was comparatively weighed against that of the five-variable version, the present study did not detect a possible risk of material misstatement in Toshiba's published figures/financial data for the years examined. As Table III shows, the M-Score indicators for 2008–2014 (-2.75, -2.50, -2.76, -2.83, -2.58, -2.49 and -2.58, according to the eight-variable model and -3.02, -2.75, -2.93, -2.96, -2.73, -2.83 and -2.87, according to five-variable one) did not indicate that the company was involved in material misstatement in any of the years studied.

Table III: **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	1.16	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	0.96	0.898	1.123	0.989
Total Accurals to Total Assets	-0.046	-0.022	-0.058	-0.07	-0.083	0.003	-0.042
Beneish M Score , 8 Variable Version	-2.58	-2.49	-2.58	-2.83	-2.76	-2.5	-2.75
Beneish 5 Variable Version	-2.87	-2.83	-2.73	-2.96	-2.93	-2.75	-3.02

However, the following is an analysis of the individual scores.

DSRI: DSRI is above 1.0 in the years of 2010, 2012, and 2013, indicating that the ratio of Accounts Receivables to Sales increased in these years. In 2014, there was a slight decrease from 2013, from 1.105 to 0.964, indicating that the previously inflated revenue was reduced in the current year.

GMI: The ratio of Sales to Cost of Goods Sold remained almost the same from 2010–2014. The GMI values for 2008 and 2009 were approximately the same, and thereafter, GMI values were almost same from 2010–2014.

AQI: This was lesser than 1.0, signifying a reduction in Asset Quality. However, Toshiba's AQI for the seven selected years never crossed the crucial mean of 1.254.

SGI: These scores were inconsistent over the seven years studied. In 2008, SGI was 1.079, but in 2009 and 2010, it fell, reaching 1.135 by the end of 2014.

DEPI: These results indicated an increase in value of the Depreciation Index from 2008–2014. This is the only variable that exceeded the mean index of 1.077, barely crossing the threshold that indicates possible manipulation, which is 1.0767. The increases indicated growth in income that was the result of decreasing depreciation. The value of this index clearly depicted earnings manipulations by Toshiba for the years studied.

SGAI: The trend in SGAI crossed the 1.0 standard of the Beneish Model in 2008, 2009, 2012, and 2013, indicating increased in Sales and General and Administrative Expenses, which should raise suspicion about Toshiba's administrative efficiency. However, in 2014, the SGAI decreased to 0.984.

LVGI: The most important indicator is the Leverage Index. This variable showed the relationship among outside liabilities in the form of both long-term and short-term liabilities to total assets. An increase in the Leverage Index clearly indicated that the company was prone to earnings manipulation. In 2009 and 2012, it exceeded 1.0, reaching 1.024 and 1.123, respectively. In all other years, this variable was stable.

TATA: Total Accruals to Total Assets is useful for calculating the income from continuing operations and cash flows from operations. In 2009, the TATA was 0.003, but in all other years, this variable had negative values, indicating that the company was not receiving profits from any sources other than their main ones.

Table IV: Toshiba Corporation

Benchmarking with Beneish Model _per Beneish Mean

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 Accurals to Total Assets	-0.0453	1.037	1.111

Applying the Beneish Model to Toshiba's financial statements indicated that the company was not manipulating its earnings. The calculations in the last two columns in Table IV represent the model's findings and categorize the company into one of two groups, non-manipulators and manipulators. As Table IV shows, Toshiba scored close to the threshold for being in the manipulators category in only one variable of the eight used: DEPI. A close consideration of the indicators included in the eight-variable version of the model shows that except for the DEPI, none appear to indicate risks of material misstatement.

Altman Z-Score

In 2008, the Z-Score was 1.970, indicating that the firm was going to go bankrupt within the next two years. Except for 2008, the Z-Scores for all other years, from 2009–2014, indicated that Toshiba was not sound and would not long continue in the market. These 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.

These Z-Scores rightly indicated that the company was not sound financially and they also indicated that there were financial misstatements by Toshiba.

However, the following is an analysis of the individual scores.

X1: As Table V shows, low Z-Score values were conditioned by the ratio of Working Capital to Total Assets, which was either negative or very low for all the years examined, a possible indicator that the company had liquidity problems. This component of the Z-Score model indicates liquidity problems that increase the possibility of bankruptcy. The values improved slightly over the years, except in 2008 and 2009, which had negative results, -0.0095 and -0.0637 respectively. From 2010–2014, the results, 0.0501, 0.056, 0.0591, 0.0688 and 0.0689 respectively were essentially stable. The results in 2013 and 2014 were almost the same.

X2: The ratio of Retained Earnings to Total Assets implied that Toshiba had not been able to accumulate and reinvest profits during the period studied. 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 2011–2013, values for this variable, 0.103, 0.103 and 0.104 respectively were stable.

X3: The ratio of Earnings before Interest and Taxes to Total Assets, which reflects profitability and operating efficiency, was generally low for the years studied, which, again, speaks a low level of operating profitability and operating efficiency before taxes and financial leverage. In other words, this ratio represents the Return on Assets (ROA) measure. Only in 2009 did the variable show a negative value, -0.045; the results for all other years were both positive and stable.

X4: Although in 2009 the result for this variable decreased to 0.1813, for all other study years, the value was stable.

X5: In 2013, the value for this variable decreased slightly to 0.9719, indicating decreased effectiveness of asset use to generate revenue. In 2008, the result was 1.3365, the highest value during the seven years studied.

Table V: **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

Benford's Law

As Table VI shows, the first digit's test for Toshiba's annual financial statement data showed MAD of 0.035757, which exceeded the 0.015 critical values for non-conformity by a wide margin. Figure 2 shows the difference between the actual and expected proportions of first digits from Benford's Law. Since there was overall non-conformity to Benford's Law in the first digit's test, this signals that the data set may have had abnormal duplications and anomalies. This result shows that deviation from the actual and Benford's values was greater than the accepted level of standard. However, the digits 1–8 as given in Table VII of the first digit's test did not return a Z-Statistic higher than 1.96, meaning that the individual differences in the actual and expected frequencies were not significant. The digit 9 returned a Z-Statistic of 2.006, which is higher than 1.96, confirming that there was a manipulation in this digit place. As Table VI shows, the second digits' test showed a MAD of 0.02833, which exceeded the 0.012 critical value for non-conformity by a wide margin. Figure 3 shows the difference in the actual and expected proportions of second digits from Benford's Law. Since there was overall non-conformity to Benford's Law in the second digits' test, this signals that the data set may have had abnormal duplications and anomalies. This result shows that deviation from actual and Benford's values were greater than the accepted level of standard. However, none of the second digits had a Z-Statistic higher than 1.96, meaning that the individual differences in the actual and expected frequencies were not significant. Table VIII shows the actual and Benford's results of the first digits 1–9 and the second digits 0–9.

Table VI:

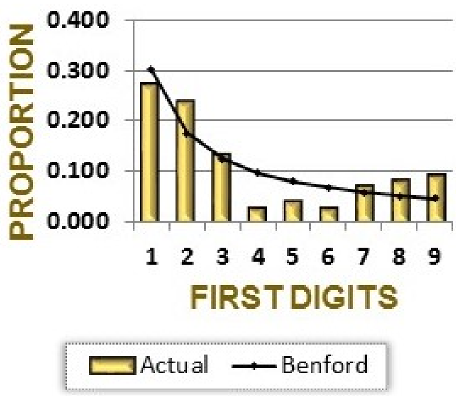
Results of Mean Absolute Deviation (MAD)	
First Digits Test	0.03757
Second Digits Test	0.02833

Table VII: Results of Z-Test

Digit	First Place	Second Place
0		1.889991
1	0.533751	0.503298
2	1.499288	0.638015
3	0.156113	0.161703
4	2.002138	0.383824
5	1.172223	1.305913
6	1.195333	1.240557
7	0.407402	0.061803
8	1.199708	1.049519
9	2.005956	2.04154

Table VIII:

Digits	First Digit Test		Second Digit Test	
	Actual	Benford	Actual	Benford
0			0.1875	0.11968
1	0.27083	0.30103	0.135	0.114
2	0.23958	0.17609	0.083	0.109
3	0.13542	0.12494	0.115	0.104
4	0.03125	0.09691	0.083	0.1
5	0.04167	0.07918	0.052	0.097
6	0.03125	0.06695	0.135	0.093
7	0.07292	0.05799	0.083	0.09
8	0.08333	0.05115	0.052	0.088
9	0.09375	0.04576	0.073	0.085



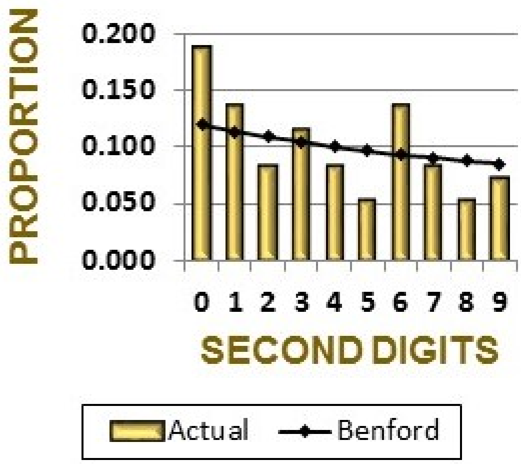


Figure 2: The results of First Digits text from 1-9

Figure 3: The results of Second Digits Test 0-9

Conclusion

The primary of objective of this study was to examine the efficacy of the Beneish M-Score, the Altman Z-Score and Benford's Law in detecting FFS by Toshiba Corporation. The study found that the null hypothesis of the Beneish Model was accepted, meaning that this is model was not effective in detecting FFS at Toshiba. Comparative application of 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, strengthening the study's results 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 (2014) on Anglo Gold Ashanti. The author used the Beneish M-Score and the Altman Z-Score on the selected company, and the results of the Beneish Model did not indicate financial distress, but those of the Altman Z-Score did.

In the present study, the null hypothesis regarding Altman's Z-Score was rejected, meaning that the Altman's Z-Score was useful in detecting FFS by Toshiba. These results are consistent with those of studies conducted by Hawariah et al., (2014), Mehta et al., (2012) and Charalambos (2002). These authors also found that Z-Scores that measured the probability of bankruptcy were effective at detecting FFS. The present study found that unlike to the Beneish M-Score, the Altman Z-Score was very effective in identifying FFS.

In the present study, the null hypothesis regarding Benford's Law was rejected, meaning that Benford's Law was useful in detecting FFS by Toshiba. These results were consistent with those of studies conducted by Gogi Overhoff (2011), Durtschi (2004) and Hayes (2012).

Like any other forensic tool, all three of the models tested have limitations. According to Nigrini (2011), Benford's Law can identify only digits manipulation, and while it can give an indication of the probability of fraud, it cannot give its exact location. The massive volume of input data required by this model increases the possibility that it contains errors.

Discussion and Suggestions

One objective of this research was to suggest which of the three tested forensic tools was most useful for detecting FFS. The results of the present study support using more than one forensic tool to detect FFS, because each model has shortcomings. To apply the Beneish Model variables, one must consider the financial values in the target corporation's financial statements. The model's results will be more accurate when the scope of the study is more than five years and the financial values in the financial statements are large. The Beneish Model is a probabilistic model, so it will not detect manipulation with 100% accuracy (Beneish et al., 1999). The results of the present study support that statement, showing that this model failed to detect the fraud in Toshiba's financial statements, returning an M-Score of less than the threshold value of -2.22.

Altman's Z-Score is very simple to use and rapidly provides a snapshot of the target corporation's financial position. The present study found that the Z-Score was the most accurate model of the three tested. The study's results suggested that all forensic tools are not useful with regard to financial statements. For example, Benford's Law is useful for detecting digits fraud, so it must be applied to the target company's day-to-day transactions, check collections and cancellations and debt collections, rather than to financial statements. However, all three forensic tools used in the study were useful for indicating red flags regarding the scope of the fraud at Toshiba, although none could pin point the exact location or area of the fraud.

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