Detecting probable manipulation of financial statements. Evidence from a selected Zimbabwe Stock Exchange-Listed bank

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Keywords

Jel Classification
M41, M49.

Abstract

Purpose: The study used the Beneish M Score to discover probable financial statement manipulation by a selected Zimbabwe Stock Exchange-listed bank.

Research methodology: The Beneish M Score eight variable statistical model was applied to secondary data of the selected bank from 2011 to 2018. The model utilizes ratios in distinguishing between manipulators and non-manipulators, with a yardstick measure of -2.22. Results greater than -2.22 classify the organization as a financial statements manipulator with less than -2.22 classify it as a non-manipulator.

Results: The M score model detected manipulation for the years 2011 (-0.74), 2013 (-1.84), and 2015 (-2.19), which are greater than the benchmark of -2.22. The years 2012 (-3.17), 2014 (-2.46), 2016 (-3.07), 2017 (-2.80) and 2018 (-2.42) reveal the bank as a non-manipulator as these values are less than -2.22.

Limitations: The Beneish M score statistical model was modeled for manufacturing companies. The study sought to test the M Score’s applicability in the banking sector and it was restricted to the selected bank for the years 2011 to 2018.

Contribution: The Beneish M score is a valuable model for users of issued annual financial statements to guard against earnings manipulation. Stakeholders rely on audited financial statements, believed to be free from manipulation, yet companies fold up with unqualified audit opinions contained in published financial statements. The study validates the Beneish M score statistical model for detecting manipulation in published annual financial statements in Zimbabwe, where there is limited research on earnings manipulation.
1. Introduction

According to Zimstat (2022), Zimbabwe's population stood at 15,178,957 as at 20 April 2022. The economy is highly informal with more 5.7 million people working in the Small to medium enterprises (Mangudya, 2017). Zimbabwean economy has faced a myriad of challenges such as exchange rate volatility, high inflation with periods of hyperinflation, the usage of multiple exchange rates and increased informality as companies fail with little job opportunities for the thousands of graduates in various fields churned out by universities. Debt levels are unsustainable as the country battles to make payments to the International financial institutions. According to the world bank (2022), external debt stands at 76% of gross domestic product in 2022. The continued depreciation of the local currency, punitive interest rates (200%) reduce consumption and negatively impact investment. Real Gross domestic product was 3.4% in 2022 from 5.8% in 2021. World bank (2022) advances Real Gross domestic product growth to be 3.6% in the years 2023 and 2024.

1.2 The Composition Of The Banking Sector In Zimbabwe

The banking sector composition is as follows:

<table>
<thead>
<tr>
<th>Type of Institution</th>
<th>Number</th>
</tr>
</thead>
<tbody>
<tr>
<td>Commercial bank</td>
<td>13</td>
</tr>
<tr>
<td>Building Societies</td>
<td>5</td>
</tr>
<tr>
<td>Savings bank (POSB)</td>
<td>1</td>
</tr>
<tr>
<td><strong>Total Banking institutions</strong></td>
<td><strong>19</strong></td>
</tr>
<tr>
<td>Other Operational Institutions Under the Supervision of Reserve Bank</td>
<td></td>
</tr>
<tr>
<td>Credit-only microfinance institutions</td>
<td>183</td>
</tr>
<tr>
<td>Deposit-taking Microfinance Institutions</td>
<td>8</td>
</tr>
<tr>
<td>Development Financial Institutions</td>
<td>4</td>
</tr>
<tr>
<td>Total Other Institutions</td>
<td>195</td>
</tr>
<tr>
<td><strong>Total Number of Institutions</strong></td>
<td><strong>214</strong></td>
</tr>
</tbody>
</table>

**Source:** Reserve Bank of Zimbabwe (2022)
Shoko (2013) disclosed that twenty listed firms were being investigated for falsifying their financial statements. Zimbabwe has witnessed a spectacular banking sector collapse, notably Royal Bank. Musarurwa and Farawo (2015) advanced the case that the Royal Bank collapsed due to the manipulation of company financial records. The bank recorded liabilities as shareholder loans as well as loans and advances recorded as notes and coins. Trust Bank collapsed in 2015 due to imprudent banking practices and operations without sound administrative accounting practices. The bank faced liquidity constrictions, working capital challenges, and depositor funds misapplication (Shumba, 2013). Tetrad Investment Bank collapsed due to a lack of return on investment, and shareholders complained about a lack of audited financial accounts with their license withdrawn in 2014. Interfin Bank Limited collapsed due to inadequate capitalization, chronic liquidity, and income generation challenges. Its intermittent collapse was due to non-performing loans from the acquisition of CFX Bank. Changunda (2022) articulates that Afrasia closed shop on February 14, 2015, due to its inability to meet capital adequacy requirements as set by the Reserve Bank of Zimbabwe with the bank experiencing liquidity and financial mismanagement challenges. In February 2013, the Barbican Bank license was revoked. According to Musariri (2015), the bank had inadequate risk management and management information systems, making it difficult to mitigate risk as well as poor corporate governance structures, and inexperienced management. This posed liquidity challenges and long-term non-performing assets were funded through short-term liabilities. The bank diverted to speculative activities to keep afloat with rapid expansion funded by depositors’ funds. Barbican bank adopted creative accounting by concealing losses through the creation of fictitious assets, understating expenses and liabilities, under-providing for non-performing loans, and falsifying transactions to conceal undercapitalization. The level of non-performing loans was exorbitant as a result of weak underwriting and monitoring due to poor corporate governance practices. Insider loans were not charged interest and were written off without approval. Profits recorded by the bank are revealed to have emanated from the revaluation of assets. Dividends were declared from unrealized profits on non-
current assets. The bank failures therefore negatively impacted investors’ and depositors’ perceptions of accountability, business ethics, and transparency in the banking sector.

This study found that the use of the Beneish M Score model to identify financial statement manipulation in Zimbabwe’s banking system has not been adequately researched, as evidenced by the paucity of such information. Consequently, the goal of this study is to close the knowledge gap that currently exists. This study adds to the body of knowledge by evaluating the model’s usefulness in identifying financial statement manipulation in Zimbabwe’s financial services industry. The following describes how the paper is constructed: it appraises literature associated with the study and presents the methodology adopted in obtaining study findings, which are presented and discussed before the study culminates with a conclusion that has recommendations.

2. Literature review

2.1 Agency Theory

In 1976, Jensen and Meckling presented the theory. It provides insight into agency relationships and, therefore, economic contractual relationships between the principal and agent. To this effect, top management’s (an agent’s) prerogatives may not be congruent with the shareholder’s (principal’s) interests, as is the premise of the agency theory. This is because the agent’s performance is determined by perceived rewards as a result of meeting financial goals or targets set by the principal. Management may commit financial statement fraud due to perceived pressure (Abdullahi & Mansor, 2015). Compliance with requirements for external financing or concealing poor performance to reap financial rewards could be examples of perceived pressure. Perceived opportunity may contribute to financial statement fraud due to weak internal control and poor governance (Abdullahi & Mansor, 2015). Due to information asymmetry between the principal and agent, the opportunity may arise. Critical decision-making information that is at the disposal of
the management (agent) may be utilized to accomplish desired objectives and maximize agent interests at the expense of the shareholders (ICAEW, 2005). According to the ICAEW (2005), an external audit can reinforce trust between management and shareholders. In line with the agency theory, financial reports should be scrutinized by an external auditor to ensure transparency.

2.2 Signaling theory
Signal theory embraces four elements constituting the signaler, signals, receiver, and feedback. Signaler consists of managers (Goranova et al, 2007) and directors (Miller and Triana, 2009). The signaler communicates information to stakeholders that reduce information asymmetry in relation to the firm's performance in a manner beneficial to the firm. Signals entail the flow of information which can be positive or negative with the organization deciding whether to communicate this to stakeholders (Connelly et al, 2011). Ching and Gerab (2017) postulate that information asymmetry is reduced when organizations send signals to stakeholders through sustainability reporting. Taj (2016) advances disclosure practices to signal sound financial stability, climate change commitment, transparency, and stakeholder engagement as a vehicle for information symmetry reduction. Receivers are outsiders lacking information concerning signals, but need this information as it is pertinent to their decision-making. Receivers comprise potential investors and current shareholders (Kang, 2008). Feedback is a consequence of signalers' and receivers' interaction. Dionne and Ouedemi (2011) suggest firm value and performance are enhanced by positive signals compared to negative signals that influence the stock price as well as demand for entity output (products). The signaling theory advances managers' manipulation of earnings to express the prospects of the entity as it publishes financial statements that are used as a signaling mechanism. Therefore, management may be engaged in earnings management by signaling their performance. Additionally, according to the signalling perspective, shareholders may occasionally demand earnings management. Beidleman (1973), and Easton and Zmijewski (1989) state shareholders advocate for earnings
management in order to reduce the cost of capital through smoother, more predictable income streams. Dye (1988) suggests unwavering and anticipated income streams will inspire potential investors’ perception of firm value.

2.3 Beneish M Score

Beneish (1999) developed the M Score model for detecting earnings manipulation.

The five-variable model is stated as follows:

\[ M = -6.065 + 0.823 \times DRSI + 0.906 \times GMI + 0.593 \times AQI + 0.717 \times SGI + 0.107 \times DEPI \]

The eight-variable model is stated as follows:

\[ M = -4.840 + 0.920 \times DRSI + 0.528 \times GMI + 0.404 \times AQI + 0.892 \times SGI + 0.115 \times DEPI - 0.172 \times SGAI - 0.327 \times LVGI + 4.697 \times TATA \]

Days sales in receivables index (DSRI) inconsistent receivables increasing in comparison with sales suggests revenue inflation (Beneish, 1999). To measure the adjustments made to receivables that are consistent with the adjustments made to sales, DSRI is utilized.

Gross margin index (GMI). A GMI of 1 suggests weakened gross margins, hence greater susceptibility to manipulating earnings (Beneish, 1999). GMI is a metric used to determine how closely a GMI from one year to the next compares to a review from that year.

Asset quality index (AQI). An AQI greater than 1 implies increased intangibles or deferred costs, which could be associated with the manipulation of earnings (Beneish, 1999). The AQI is a metric for comparing the total assets of the current year to those of the previous year. An increase in AQI indicates that new expenditures are being capitalised to prevent their elimination from the statement of comprehensive income and to preserve profit. (Harrington, 2005).

Sales growth index (SGI). Growth does not entail manipulation though in some instances growth companies are shown to have a greater propensity to manipulate
financial statements. Sales from the current year are contrasted with sales from the previous year using SGI. The current-year sales total is measured using SGI. Companies with high growth rates, according to Harrington’s observations from 2005, are highly motivated to perpetrate fraud when the trends turn. A prospective growth rate above a particular percentage in such circumstances may give rise to suspicion (Pustylnick, 2009).

Depreciation index (DEPI). When the DEPI value exceeds 1, it indicates that the asset’s rate of depreciation has reduced, which could indicate that the asset’s useful life has been revised or that the company has switched to an income-increasing technique (Beneish, 1999). With depreciation expenses taken into account, DEPI is a statistic used to compare the value of the company’s PPE in the current year to that in the previous year.

Sales, general, and administrative expenses index (SGAI). A disproportionate upsurge relating to sales translates into negative projections for the entity (Beneish, 1999). SGAI is a statistic used to contrast the current year’s expenses with those from the previous year. A disproportionate increase in revenue sends the wrong message about the company’s future prospects, according to Beneish (1999). A disproportional increase in SGAI, according to Lev and Thiagarajan (1993), is a warning indicator concerning the future potential of the company. A positive correlation suggests that there is a chance of manipulation.

Leverage index (LVGI). Current and non-current debt is matched with the current and non-current assets relating to current and preceding years (Beneish, 1999). The company’s LVGI is determined using the ratio of total debt to total assets for the current year divided by the ratio for the prior year. If the company’s leverage ratio has increased and it has taken on more debt to fund its operations over the time being considered, the LVGI will be greater than 1.

Total accruals to total assets (TATA). It seeks to establish the magnitude of discretionary policies that management adopts that convert to manipulation of
earnings (Beneish, 1999). TATA is used to calculate the change in the working capital ratio for accounts other than cash and accounts with reduced depreciation. A common indicator of TATA's growth is that the financial accounts contain fabricated goodwill and amortisation data.

According to Beneish (1999), the M score correctly identifies manipulators in 76% of sampled cases, while only 17.5% of cases are classified as non-manipulators. Franceschetti and Koschtial (2013) to detect the manipulation of small businesses adopted Beneish M Score. According to the research, companies that are close to bankruptcy do not manipulate earnings, and the likelihood of insolvency is quite low. Nwoye et al. (2013) propose the Beneish M Score as a crucial model and tool for auditors’ ability to detect financial statement fraud. The Beneish M score was determined to be a powerful tool in fraud detection with a low error rate (Anh and linh, 2016). Aghghaleh, Mohamed, and Rahmat (2016) utilized the M Score to detect financial statement fraud and identified 73.17% of cases as manipulators from a Malaysian context. Kamal, Sellar, and Ahmad (2016) support the usage of the M score as a forensic tool in detecting fraudulent financial reporting as the model detected 14 of 17 companies as having manipulated their financial statements. According to Repousis (2016), in a sample of 25468 Greek companies, 33% engaged in earnings manipulation using the Beneish M Score in 2011 and 2012. According to Tahmina and Naima (2016), the inflation of intangible assets was detected as an earnings manipulation scheme in relation to financial statements published in Bangladesh. According to Maccarthy (2017), the M score forecast of earnings manipulation must be complemented with the Altman Z Score for forensic accounting investigation. In textile companies in Bangladesh, receivables, cash and accruals were key ways to manipulate earnings and misstate financial information (Sakib, 2019). Manufacturing companies in Ghana and trading corporates were determined to have been involved in financial manipulation on the basis of the Beneish M Score (Anning and Adusei, 2020). The fraud diamond analysis and the Beneish M Score were utilised by Umar, Partahi, and Purba (2020) to identify the premise for fraud.
They came to the conclusion that financial stability, auditor replacement, nature, and industry rationalisation all have an effect on financial statement fraud.

Durana, Blazek, Machova, and Krasnan (2022) discover the M score five and eight ratio models accurately predict financial reporting fraud. Bhavani and Amponsah (2017) posit the Beneish M score and Altman Z score models as inefficient in the identification of financial statement fraud in their research based on Toshiba. Kukreja et al. (2020) discovered the M score to be weaker than the Z score in their Comscore analysis in the American continent. Lotfi & Chadegani (2017) articulate the inappropriateness of the M Score model in fraud detection; hence, new models are needed based on their research of Tehran Stock Exchange listed companies. According to Mantone (2013), the M score can accurately detect fraud hence an effective tool for unearthing financial statement fraud for forensic investigators.

2.4 Empirical literature review

Akra and Chaya (2020) advance the M score as a forensic tool that can be utilized in the detection of financial statement fraud. According to Nyakarimi (2022) In Kenya, Tanzania, and Uganda, certain banks have been found to be engaged in earnings management, with 79.4% of Kenyan banks, 83.3% of Tanzanian banks, and 70% of Ugandan banks being found to be non-manipulators. Paolone and Magazzino (2014) stated that 51.4% of Italian firms are involved in earnings management upon application of the Beneish M score. Shakouri, Taherabadi, Ghanbari, and Jamshidinavid (2021) propose DRSI, GMI, AQI, DEPI, and TATA as being fundamental in detecting financial statement fraud. Talab, Ali, and Flayyih (2018) discover that 65.2% of the Iraq Stock exchange listed banks are involved in earnings management utilizing the Beneish model. Using the M score, Repousis (2016) states that 33% of companies in Greece are engaged in earnings manipulation. Interest income and balances with other financial institutions are postulated by Khatum, Ghosh, and Kabir (2022) as manipulation items in the study of DSRI variables. Gyawali (2021) concludes that 4 out of 16 commercial banks in Nepal manipulated income and there
was no evidence that supported financial statement fraud in the Nepalese financial institutions using the M Score.

Holda (2020) states the M score eight variable models accurately identified manipulators and non-manipulators in Poland. The Beneish M-score model can be used as a forensic accounting tool to spot fraud in financial accounts because it generates more findings than assessments of other fraud detection methods (Ozcan, 2018; Akra & Chaya, 2020).

Kaur, Sharma and Khanna (2014) investigated 332 companies from the Indian market from 2011 to 2013 utilising the M score and discovered than that M score is superior to the Modified Jones model in detecting earnings management. Mahama (2015) posits that users of financial statements could have utilised the M score to detect earnings management at Enron early in 1997. Cornell University students identified Enron’s earnings manipulation using the M Score at a time when financial analysts failed to detect the manipulation of earnings at Enron in 1998 with the entity later filing for bankruptcy in 2001 (Newstex Global Business, 2016). Mehta and Bhavani (2017) adopted the M score, Altman Z Score and Benford’s law from their study of Toshiba Corporation of Japan from 2008 to 2014 and postulate that all these techniques were crucial in unearthing fraud but could not pinpoint the exact area from which the fraud took place. Omar, Koya, Samisi and Shafie (2014) applied the model to Megan Media Holdings Berhad in Malaysia and the M score was effective in detecting financial statement fraud. Dechow, Ge, Lavson and Sloan (2011) modified the M score and produced the F score that is used to detect misstatements, and to this extent identifying 51.4% which is less than the M score.

Durana, Blazek, Machova, and Krasnan (2022), using the indicator of creative accounting, found that both the parameter (eight ratios and five ratios) of the Beneish model were able to find and predict the fraudulent behaviour of financial reporting. Samuel (2022), using the banking sector of East Africa as a sample, proved that the Beneish model result divided the sample group into likely manipulator and
nonlikely manipulation with accuracy. Ramirez-Orellana et al. (2016) discover aggressive accounting practices in Spanish enterprises as entities manipulated daily sales and total accruals on total assets using the M score. Golec (2019) advanced the Beneish M score unearthed fraud in Polish companies. Ofori (2016) articulates the Beneish M Score and the Altman Z Score accurately detected fraudulent financial reporting in Enron in the years 1998, 2000 and 2001. Bhavani and Amponsah (2017) utilised the Altman Z Score and the Beneish M score in their research of Toshiba between 2008 and 2014 and posit the Beneish M Score failed to discover fraud whilst Altman Z score to a certain extent was able to reveal distress in the inconsistent financial statements. Nwoye, Okoye and Oraka (2013) elucidate the five variable Beneish M Score as crucial in discovering material misstatements in their research on Nigerian manufacturing firms from 2008 to 2013. According to Cynthia (2005), the Beneish M Score could not consistently unearth fraudulent financial reporting. Drabkova (2014) tested the Beneish M Score, Altman Z Score and Jones non-discretionary accruals models. The results reveal Altman Z score and Beneish M Score as crucial in assessing the financial condition of organizations. Kukreja, Gupta, Sarea and Kumaraswamy (2021) postulate Beneish M Score as less predictable in fraud detection than Altman Z Score in their research of Comscore Inc. of the United States of America. Helbig (2016) employed the Beneish M Score and Altman Z Score in the investigation of Lets Gowex SA in Spain and recommends the usage of the two models as forensic tools to unearth fraud. Mavengere (2015) advanced Altman Z score and Beneish M score models as effective in unearthing possible bankruptcy as well as earnings manipulation.

3. Research Methodology

The study adopted the Beneish M Score eight variable model, which is stated as:

$$M\text{-score} = -4.840 + 0.920 \times DSRI + 0.528 \times GMI + 0.404 \times AQI + 0.892 \times SGI + 0.115 \times DEPI - 0.172 \times SGAI - 0.327 \times LVGI + 4.697 \times TATA \text{ (Beneish, 1999)}$$

Where:
Day Sales in Receivables Index (DSRI): \( \frac{\text{Accounts Receivables}_t}{\text{Sales}_t} \times \frac{\text{Number of Days}}{\text{Accounts Receivables}_{t-1}/\text{Sales}_{t-1}} \times \frac{\text{Number of Days}}{\text{Accounts Receivables}_{t-1}/\text{Sales}_{t-1}} \) (Beneish, 1999).

Gross Margin Index (GMI): \( \frac{[\text{Sales}_t - \text{COGS}_t]}{[\text{Sales}_{t-1} - \text{COGS}_{t-1}]} / \frac{\text{Sales}_t - \text{COGS}_t}{\text{Sales}_{t-1}} \) (Beneish, 1999).

Asset Quality Index (AQI): \( \frac{[1 - ((\text{Current Assets}_t + \text{PP&E}_t)/\text{Total Assets}_t)]}{[1 - ((\text{Current Assets}_{t-1} + \text{PP&E}_{t-1}) / \text{Total Assets}_{t-1})]} \) (Beneish, 1999).

Sales Growth Index (SGI): \( \frac{\text{Sales}_t}{\text{Sales}_{t-1}} \) (Beneish, 1999).

Depreciation Index (DEPI): \( \frac{\text{Depreciation}_{t-1}}{\text{PP&E}_{t-1}} + \frac{\text{Depreciation}_t}{\text{PP&E}_t + \text{Depreciation}_t} \) (Beneish, 1999).

Selling, General, & Admin. Expenses Index (SGAI): \( \frac{\text{SG&A Expense}_t}{\text{Sales}_t} / \frac{\text{SG&A Expense}_{t-1}}{\text{Sales}_{t-1}} \) (Beneish, 1999)

Leverage Index (LVGI): \( \frac{[\text{Current Liabilities}_t + \text{Total Long-term Debt}/\text{Total Assets}_t]}{[\text{Current Liabilities}_{t-1} + \text{Total Long-term Debt}_{t-1}] / \text{Total Assets}_{t-1}] \) (Beneish, 1999).

Total Accruals to Total Assets (TATA): \( \frac{(\text{Income from Continuing Operations}_t - \text{Cash Flow from Operations}_t)}{\text{Total Assets}} \) (Beneish, 1999).

Secondary data was collected from 2011 to 2018 from bank X’s published audited annual financial statements. Bank X offers consumer and investment banking (commercial banking, advisory services, custodial services, mortgage finance, micro finance, equities trading, and reinsurance services) and insurance services with a wide branch network in Zimbabwe. The M Score values were computed in Microsoft Excel to determine whether or not the bank manipulated its financial statements as well as using descriptive analytical tools.

The M score interpretation is as follows:

M Score < -2.22. This implies the company is not an earnings manipulator.
M Score > -2.22. This implies the company is an earnings manipulator.

4. Results and discussions

Secondary data from the ZSE-Listed bank from 2011 to 2018 was subjected to the M Score 8 variable model.

The results are summarized in figure 1 below:

**Table 1: M Score results**

<table>
<thead>
<tr>
<th>YEARS</th>
<th>CONSTANT</th>
<th>DSRI</th>
<th>GMI</th>
<th>AQI</th>
<th>SGI</th>
<th>DEPI</th>
<th>SGAI</th>
<th>TATA</th>
<th>LVGI</th>
<th>M SCORE</th>
</tr>
</thead>
<tbody>
<tr>
<td>2011</td>
<td>-4.84</td>
<td>0.81</td>
<td>0.60</td>
<td>1.04</td>
<td>1.47</td>
<td>0.12</td>
<td>0.16</td>
<td>0.56</td>
<td>0.33</td>
<td>0.74</td>
</tr>
<tr>
<td>2012</td>
<td>-4.84</td>
<td>1.06</td>
<td>0.49</td>
<td>0.16</td>
<td>0.71</td>
<td>0.10</td>
<td>0.18</td>
<td>-0.32</td>
<td>0.35</td>
<td>-3.17</td>
</tr>
<tr>
<td>2013</td>
<td>-4.84</td>
<td>1.13</td>
<td>0.55</td>
<td>0.40</td>
<td>0.76</td>
<td>0.12</td>
<td>0.17</td>
<td>0.54</td>
<td>0.33</td>
<td>-1.84</td>
</tr>
<tr>
<td>2014</td>
<td>-4.84</td>
<td>1.20</td>
<td>0.43</td>
<td>0.62</td>
<td>0.65</td>
<td>0.11</td>
<td>0.18</td>
<td>-0.10</td>
<td>0.35</td>
<td>-2.46</td>
</tr>
<tr>
<td>2015</td>
<td>-4.84</td>
<td>0.85</td>
<td>0.51</td>
<td>0.39</td>
<td>1.13</td>
<td>0.12</td>
<td>0.17</td>
<td>0.14</td>
<td>0.32</td>
<td>-2.19</td>
</tr>
<tr>
<td>2016</td>
<td>-4.84</td>
<td>0.85</td>
<td>0.50</td>
<td>0.48</td>
<td>0.92</td>
<td>0.10</td>
<td>0.26</td>
<td>-0.49</td>
<td>0.33</td>
<td>-3.07</td>
</tr>
<tr>
<td>2017</td>
<td>-4.84</td>
<td>0.99</td>
<td>0.49</td>
<td>0.45</td>
<td>0.85</td>
<td>0.12</td>
<td>0.18</td>
<td>-0.35</td>
<td>0.33</td>
<td>-2.80</td>
</tr>
<tr>
<td>2018</td>
<td>-4.84</td>
<td>0.95</td>
<td>0.51</td>
<td>0.24</td>
<td>1.16</td>
<td>0.12</td>
<td>0.17</td>
<td>-0.05</td>
<td>0.34</td>
<td>-2.42</td>
</tr>
</tbody>
</table>

*Source: author’s compilation*

In order to ascertain the likelihood that the chosen bank distorted or not its financial accounts between 2011 and 2018, the research uses the Beneish M Score. The results revealed that the bank manipulated its earnings for the years 2011 (-0.74), 2013 (-1.84), and 2015 (-2.19) as the M score values were greater than the benchmark of -2.22. The years 2012 (-3.17), 2014 (-2.46), 2016 (-3.07), 2017 (-2.80) and 2018 (-2.42) reveal the bank as a non-manipulator as these values are less than the -2.22 benchmark. The results are in agreement with Akra and Chaya (2020), Nyakarimi (2022), Paolone and Magazzino (2014), Talab, Ali, and Flayyih (2018), and Repousis (2016) that validate the usage of the Beneish M score as a beneficial model in the detection of earnings manipulation in published financial statements.
Table 2: Descriptive statistics

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>DSRI</td>
<td>8</td>
<td>.805</td>
<td>1.200</td>
<td>.97938</td>
<td>.142789</td>
</tr>
<tr>
<td>GMI</td>
<td>8</td>
<td>.430</td>
<td>.600</td>
<td>.51000</td>
<td>.049281</td>
</tr>
<tr>
<td>AQI</td>
<td>8</td>
<td>.160</td>
<td>1.040</td>
<td>.47250</td>
<td>.269431</td>
</tr>
<tr>
<td>SGI</td>
<td>8</td>
<td>.650</td>
<td>1.470</td>
<td>.95625</td>
<td>.278051</td>
</tr>
<tr>
<td>DEPI</td>
<td>8</td>
<td>.097</td>
<td>.120</td>
<td>.11275</td>
<td>.009513</td>
</tr>
<tr>
<td>SGAI</td>
<td>8</td>
<td>.160</td>
<td>.260</td>
<td>.18375</td>
<td>.031595</td>
</tr>
<tr>
<td>TATA</td>
<td>8</td>
<td>-.490</td>
<td>.560</td>
<td>-.00863</td>
<td>.396594</td>
</tr>
<tr>
<td>LVGI</td>
<td>8</td>
<td>.320</td>
<td>.350</td>
<td>.33500</td>
<td>.010690</td>
</tr>
<tr>
<td>Valid N (listwise)</td>
<td>8</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Source: authors compilation

Following Figure 2, DSRI (mean 0.979) and SGI (mean 0.956) have the highest mean values. This implies that the selected bank utilized DSRI and SGI to manipulate its financial statements for the affected years. This is in agreement with Warshavsky (2012), Shakouri, Taherabadi, Ghanbari, and Jamshidinavid (2021), and Khatum, Ghosh, and Kabir (2022) who postulate that banks use DSRI to manipulate earnings. The results also reveal high standard deviations.

The agency theory informs of an information asymmetry between those charged with governance and shareholders due to the access to company-sensitive information that they decide to disclose. Poor performance may lead to the adoption of creative accounting in order to manipulate earnings to meet the company's reported earnings to beat earnings targets as managers pursue personal interests at the expense of the entity they govern. The behavioural effects of the agency theory are revealed in the entity's earnings with a perceived impact on the entity's share price and value of the firms hence luring investors. The findings indicate that the entity manipulated the results of 2011, 2013, and 2015 in order to meet financial targets and stay afloat.
during the cataclysmic period of bank failures that lasted from 2010 to 2015. The findings, therefore, are in agreement with the agency theory.

The research also adopted the signaling theory that advanced managers’ manipulation of earnings to express the prospects of the entity as it publishes financial statements that are used as a signaling mechanism. Therefore, management engaged in earnings management to signal their performance to the various users of financial statements. This is adopted as an attempt to earn and attract greater investments. Directors signal in order to gain more advantages, including a higher reputation and a beneficial effect on the share price as well as the firm’s value. The period between 2011 to 2015 witnessed numerous bank closures due to creative accounting, banks augmenting their income through non-core activities, weak corporate governance structures, and risk management. The selected bank according to the Beneish M Score manipulated its earnings for the years 2011, 2013, and 2015. Many of the collapsed financial institutions within the period had failed to meet the minimum capital adequacy requirements as set by the RBZ and hence manipulated earnings in an attempt to lure investors. This could explain the selected bank’s manipulation of earnings during this calamitous period of bank failures and signal its financial performance.

5. Conclusion

The research sought to identify whether or not the selected bank manipulated its financial statements. The results revealed that the bank manipulated its earnings for the years 2011 (-0.74), 2013 (-1.84), and 2015 (-2.19) as the M score values were greater than the benchmark of -2.22. The years 2012 (-3.17), 2014 (-2.46), 2016 (-3.07), 2017 (-2.80) and 2018 (-2.42) reveal the bank as a non-manipulator as these values are less than the -2.22 benchmark. There is a need for users of financial statements to adopt the Beneish M Score for assessing financial statement manipulation to protect their investments as external audits may fail to detect financial statement manipulation. In many cases, various companies have collapsed
and published accounts with unmodified audit opinions, for example, Enron was audited by Arthur Anderson to its collapse. The FRC has fined big 4 audit firms and others for poor audits and failure to detect misstatements. The Beneish M score is thus a valuable model for uncovering earnings manipulation though it cannot detect corporate bankruptcy. Therefore, there is a need to adopt other analytic tools, such as the Altman Z Score to assess bankruptcy in the year of manipulation. This is necessary to determine the depth of financial statement fraud and whether it leads to the eventual collapse of the firm.

**Limitations:** The Beneish M score statistical model was modeled for manufacturing companies. The study sought to test the M Score's applicability in the banking sector and it was restricted to the selected bank for the years 2011 to 2018.

**Contribution:** The Beneish M score is a valuable model for users of issued annual financial statements to guard against earnings manipulation. Stakeholders rely on audited financial statements, believed to be free from manipulation, yet companies fold up with unqualified audit opinions contained in published financial statements. The study validates the Beneish M score statistical model for detecting manipulation in published annual financial statements in Zimbabwe, where there is limited research on earnings manipulation.
References


