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

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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:

Type of Institution	**Number**
Commercial bank	13
Building Societies	5
Savings bank (POSB)	1
Total Banking institutions	**19**
Other Operational Institutions Under the Supervision of Reserve Bank	
Credit-only microfinance institutions	183
Deposit-taking Microfinance Institutions	8
Development Financial Institutions	4
Total Other Institutions	195
Total Number of Institutions	**214**

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 dues 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:

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

The eight-variable model is stated as follows:

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

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:

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

Where:

Day Sales in Receivables Index (DSRI): Accounts $Receivables_t$ /$Sales_t$*Number of Days / Accounts $Receivables_{t-1}$/$Sales_{t-1}$*Number of Days (Beneish, 1999).

Gross Margin Index (GMI): [$Sales_{t-1}$ – $COGS_{t-1}$)/$Sales_{t-1}$] / [$Sales_t$ – $COGS_t$)/$Sales_t$] (Beneish, 1999).

Asset Quality Index (AQI): [1 – ((Current $Assets_t$ + $PP\&E_t$)/Total $Assets_t$)] / [1 – ((Current $Assets_{t-1}$ + $PP\&E_{t-1}$) / Total $Assets_{t-1}$)] (Beneish, 1999).

Sales Growth Index (SGI): $Sales_t$ / $Sales_{t-1}$ (Beneish, 1999).

Depreciation Index (DEPI): $Depreciation_{t-1}$/$PP\&E_{t-1}$ +$Depreciation_{t-1}$ / $Depreciation_t$/($PP\&E_t$ + $Depreciation_t$ (Beneish, 1999).

Selling, General, & Admin. Expenses Index (SGAI): SG&A $Expense_t$/$Sales_t$ / SG&A $Expense_{t-1}$/$Sales_{t-1}$ (Beneish, 1999)

Leverage Index (LVGI): [Current $Liabilities_t$ + Total Long-term Debt/Total $Assets_t$] / [(Current $Liabilities_{t-1}$ + Total Long-term $Debt_{t-1}$) / Total $Assets_{t-1}$] (Beneish, 1999).

Total Accruals to Total Assets (TATA): (Income from Continuing $Operations_t$ – Cash Flow from $Operations_t$) / 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

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

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**

Descriptive Statistics

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

Source: *authors compilation*

Following Figure 2, DSRI (mean 0.979) and SGI (mean 0.95 6) 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

Abdulla, M. (2011). An empirical analysis on the practice and determinants of risk disclosure in an emerging capital market: The case of United Arab Emirates. University of Portsmouth. In Press; 2011.

Abdullahi, R. & Mansor, N. (2015). Fraud Triangle Theory and Fraud Diamond Theory. Understanding the Convergent and Divergent for Future Research. International Journal of Academic Research in Accounting, Finance and Management Science, 5(4), pp. 38-45

Aghghaleh, S.F, Mohamed, Z.M, and Rahmat,M.M. (2016). Detecting Financial Statement Frauds in Malaysia: Comparing the Abilities of Beneish and Dechow Models, Asian Journal of Accounting and Governance 7: 57–65 (2016) ISSN 2180-3838 (http://dx.doi.org/10.17576/AJAG-2016-07-05)

Akra, R. M., & Chaya, J. K. (2020). Testing the effectiveness of Altman and Beneish models in detecting financial fraud and financial manipulation: Case study Kuwaiti stock market. International Journal of Business and Management, 15(10), 70–81.

N.H. Anh, N.H. Linh (2016). Using the M-score Model in Detecting Earnings Management: Evidence from Non-Financial Vietnamese Listed Companies, VNU Journal of Science: Economics and Business, Vol. 32, No. 2 (2016) 14-23

Anning, A. A., & Adusei, M. (2020). An analysis of financial statement manipulation among listed manufacturing and trading firms in Ghana. Journal of African Business. DOI: 10.1080/15228916. 2020.1826856.

Beneish, M. (1999). The detection of earning manipulation. Financial Analyst Journal, 55(5), 24–36.

Beidleman, C. R. (1973). Income smoothing: The role of management. The Accounting Review, 48(4), 653-667.

Bhavani, G., & Amponsah, C. T. (2017). M-score and Z-score for detection of accounting fraud. Accountancy Business and the Public Interest, 68-86.

Changunda, K.G. (2022). The fall of Kingdom-Afro Asia Bank-Lessons Learnt. Accessed 12 Decemebr 2022 from: hhtps://satrupbiz.co.zw/the-fall-of-kingdom-afro-asia-bank-lessons-learnt/.

Ching, H.Y., Gerab, F., (2017). Sustainability reports in Brazil through the lens of signaling, legitimacy and stakeholder theories. Soc. Responsib. J. 13, 95–110. https:// doi.org/10.1108/SRJ-10-2015-0147

Connelly, B.L., Certo, S.T., Ireland, R.D. and Reutzel, C.R. (2011), "Signaling theory: a review and assessment", Journal of Management, Vol. 37 No. 1, pp. 39-67.

Cynthia, H. (2005). Analysis ratios for detecting Financial Statement fraud. ACFE Fraud Magazine

Dechow, P. M., W. Ge, C. R. Larson, and R. G. Sloan (2011). Predicting material accounting misstatements. Contemporary Accounting Research 28 (1): 17-82.

Dionne, G.; Ouederni, K. (2011) Corporate risk management and dividend signaling theory. Financ. Res. Lett. 2011, 8, 188–195

Drábková, Z. (2014). Possibilities of identifying manipulated financial statements. In The International Scientific Conference INPROFORUM, České Budějovice

Durana, P., Blazek, R., Machova, V., & Krasnan, M. (2022). The use of Beneish M-scores to reveal creative accounting: Evidence from Slovakia. Equilibrium. Quarterly Journal of Economics and Economic Policy, 17(2), 481–510.

Dye R. (1988). Earnings management in an overlapping generations model. Journal of Accounting Research. 1988; 26:195-235.

Easton PD, Zmijewski ME (1989). Cross-sectional variation in the stock market response to accounting earnings announcements. Journal of Accounting and Economics, 11:117-141.

Franceschetti, B.M., Koschtial, C. (2013). Do bankrupt companies manipulate earnings more than the nonbankrupt ones? Journal of Finance and Accountancy, 12, 1-22

Golec, A (2019). Effectiveness of the Beneish Model in Detecting Financial statement manipulations. Doi:https://doi.org/10.18778/0208-6018.341.10

Goranova, M., Alessandri, T. M., Brandes, P., & Dharwadkar, R. 2007. Managerial ownership and corporate diversification: A longitudinal view. Strategic Management Journal, 28: 211-225

Gyawali, S. (2021). Does Model Reflect on Reality? Exploring Beneish M Score on Selected Private Commercial Banks in Nepal. *Journal of Nepalese Business Studies*, *14*(1), 18–28.

Harrington, C. (2005). Formulas for Detection: Analytical Ratios for Detecting Financial Statement Fraud. Association of Certified Fraud Examiners. Fraud Magazine.

Helbig, E (2016). Detecting Accounting Fraud- The Case of Let's Gowex SA. Associaciao Catalana de Comptabilitati Direccio.

Holda, A (2020). Using the Beneish M Score model: Evidence from non-financial companies listed on the Warsaw Stock exchange. Investment Management and Financial innovations, 17(4), 389-401.

IASB (2018). Conceptual Framework for Financial Reporting. IFRS Foundation.

ICAEW (2005). Agency Theory and the Role of Audit, London: Audit Quality.

ICAEW (2020). Fraudulent financial reporting: fresh thinking.

International Standard on Auditing 240 (2009). The Auditor's Responsibilities Relating to Fraud in an Audit of Financial Statements. IAASB

International Standard on Auditing 315 (2019). Identifying and Assessing the Risks of Material Misstatement Through Understanding the Entity and Its Environment. IAASB

Jensen, M. C. & Meckling, W. H. (1976). Theory of the firm: Managerial Behaviour, Agency costs, and Ownership Structure. Journal of Financial Economics, Volume 3, pp. 305-360.

Kamal, M. E. M., Salleh, M. F. M., & Ahmad, A. (2016). Detecting financial statement fraud by Malaysian public listed companies: The reliability of the Beneish M-Score model. Jurnal Pengurusan (UKM Journal of Management), 46

Kang, E. 2008. Director interlocks and spillover effects of reputational penalties from financial reporting fraud. Academy of Management Journal, 51: 537-555.

Kaur, R., Sharma, K., & Khanna, A. (2014). Detecting earnings management in India: A sectorwise study. European Journal of Business and Management, 6 (11), 11-18.

Khatum, A., Ghosh, R and Kabir, S (2022). Earnings manipulation behavior in the banking industry of Bangladesh: the strategical implication of Beneish M-score model. Arab Gulf Journal of Scientific Research, Emerald Insight

Kukreja, G., Gupta, S. M., Sarea, A. M., & Kumaraswamy, S. (2020). Beneish M-score and Altman Z-score as a catalyst for corporate fraud detection. Journal of InvestmeCompliance, 21(4), 231-241. https://doi.org/10.1108/JOIC-09-2020-0022

Lev, B. & Thiagarajan, S.R. (1993). "Fundamental information analysis", Journal of Accounting Research, vol. 31, no. 2, pp. 190-215.

Lotfi, N & Chadegani, A. (2017). Detecting Corporate Financial Fraud using Beneish M-Score Model, International Journal of Finance and Managerial Accounting, Vol.2, No.8, Winter 2017.

Maccarthy, J. (2017). Using Altman Z-score and Beneish M-score models to detect financial fraud and corporate failure: A case study of Enron corporation. International Journal of Finance and Accounting, 6(6), 159–166. https://doi.org/10.5923/j.ijfa.20170606.01

Mahama, M. (2015). Detecting corporate fraud and financial distress using the Atman and Beneish models. International Journal of Economics, Commerce and Management, 3(1), 1-18.

Mangudya, J.P. (2017). Re-Igniting SME Development in Zimbabwe: Learning from Global Experiences, Harare: Reserve Bank of Zimbabwe.

Mantone, P. S. (2013). Using analytics to detect possible fraud: Tools and techniques. Hoboken, New Jersey: John Wiley & Sons, Inc. ISBN: 978-1-118-71598-7

Mavengere, K. (2015). Predicting corporate bankruptcy and earnings manipulation using the Altman Z-score and Beneish M score. The case of Z manufacturing firm in Zimbabwe. International Journal of Management Sciences and Business Research4 (10), pp. 8–14 2226- 8235)

Mehta, A., and Bhavani, G. (2017). Application of forensic tools to detect fraud: the case of Toshiba. Journal of forensic and investigating accounting, 9 (1), 692-710.

Miller, T., & Triana, M. D. C. (2009). Demographic diversity in the boardroom: Mediators of the board diversity— firm performance relationship. Journal of Management Studies, 46: 755-786

Musarurwa, D and Farawo, T (2015). Shocking rot at Royal Bank. Retrieved 24 October 2022, from: https://www.sundaymail.co.zw/shocking-rot-at-royal-bank.

Musariri (2020). Mthuli And The Fall of Barbican Bank. Accessed 12 December- 2022 from: https://www.zimeye.net/2020/06/30/mthuli-and-the-fall-of-barbican-bank-limited/

Nermeen F. (2014). Theories and determinates of voluntary disclosure. Accounting and Finance Research. 3(1).

Nyakarimi, S (2022). Probable earning manipulation and fraud in the banking sector. An empirical study from East Africa. Cogent Economics and Finance, 10(1), 2083477.

Nwoye, U.J., Okoye, E.I. & Oraka, A.O. (2013). Beneish Model as effective complement to the application of SAS No. 99 in the conduct of Audit in Nigeria. Management and Administrative Sciences Review 2(6): 640-655.

Ofori, E. (2016). Detecting corporate financial fraud using Modified Altman Z-score and Beneish M-score. The case of Enron Corp. Research Journal of Finance and Accounting 7(4): 59-65.

Omar, N., Koya, R.K., Sanusi, Z.M. & Shafie, N.A. (2014). Financial statement fraud: A case examination using Beneish Model and Ratio Analysis. International Journal of Trade, Economics and Finance 5(2)

Ozcan, A. (2018). The use of Beneish model in forensic accounting: Evidence from Turkey. Journal of Applied Economics and Business Research, 8(1), 57–67

Paolone, F., & Magazzino, C. (2014). Earnings manipulation among the main industrial sectors. Evidence from Italy. Economia Aziendale Online, 5(4), 253–261

Pustylnick, I. (2009, January 4). Combined Algorithm of Detection of Manipulation in Financial Statements. Retrieved from http://www.ssrn.com/abstract=1422693

Ramirez-Orellana, A., Martinez-Romero, M., Marino-Garrido, T. (2016). Measuring fraud and earnings management by a case of study: Evidence from and international family business. European Journal of Family Business, 7(1-2), 41-53

Repousis, S. (2016). Using Beneish model to detect corporate financial statement fraud in Greece. Journal of Financial Crime, 23(4), 1063–1073.

RBZ (2022). Banking Sector Industry Report for The Quarter Ended 31 March 2022. Accessed 5th April 2023 from: https://www.rbz.co.zw/documents/BLISS/2022/Banking-Sector-Industry---31-March-2022.pdf

Sakib, I. A. (2019). Detection of earnings manipulation practices in Bangladesh. International Journal of Management, Accounting and Economics, 6(8), 616–631.

Shakouria, M.M, Taherabadib. A Ghanbaric .M, Jamshidinavid, B (2021). Explaining the Beneish model and providing a comprehensive model of fraudulent financial reporting(FFR). Int. J. Nonlinear Anal. Appl. Volume 12, Special Issue, Winter and Spring 2021, 39-48 ISSN: 2008-6822 (electronic)

Shoko, J. (2013). Zimbabwe Stock Exchange investigates firms amid fraud fears. Accessed 12th January 2023 from: https://theafricareport.com/5865/zimbabwe-stock-exchange-inestigates-firms-amid-fraud-fears/

Shumba, P. (2013). Trust Bank shut down, again. Accessed 12 December 2022 from : https://www.chronicle.co.zw/trust-bank-shut-down-again/

Tahmina, A., & Naima, J. (2016). Detection and analysis of probable earnings manipulation by firms in a developing country. Asian Journal of Business and Accounting, 9(1), 59–82.

Talab, H.R, Flayyih.H.H, and Ali.S.I.(2018). Role of Beneish M-score Model in Detecting of Earnings Management Practices: Empirical Study in Listed Banks of Iraqi Stock Exchange. International Journal of Applied Business and Economic Research, Vol15.23. ISSN: 0972-7302

Taj, S.A., (2016). Application of Signaling Theory in management research: addressing major gaps in theory. Eur. Manag. J. 34 (4), 338–348. https://doi.org/10.1016/j. emj.2016.02.001.

Tarjo, N., H. (2015). Application of Beneish M-Score Models and Data Mining to Detect Financial Fraud. In Procedia - Social and Behavioral Sciences, 2015, pp. 924-930

Umar, H., Partahi, D., & Purba, R. B. (2020). Fraud diamond analysis in detecting fraudulent financial report. International Journal of Scientific and Technology Research, 9(3), 6638–6646

Warshavsky, M. (2012). Analyzing earnings quality as a financial forensic tool. Financial Valuation and Litigation Expert Journal, 39, 16–20.

Watson A. Shrives P, and Marston C (2002). Voluntary disclosure of accounting ratios in the UK. The British Accounting Review. 2002;34 (4):289-313.

Worldbank (2022). Zimbabwe Overview: Development news, research, data. Accessed 5th April 2023 from: https://www.worldbank.org/en/country/zimbabwe/overview.

Zimstat (2022). 2022 Population and Housing Census Preliminary Results on Fertility. Accessed 5th April 2023 from: https://www.zimstat.co.zw/