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The Beneish model as a fraud control measure in Zimbabwean state-owned enterprises

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ABSTRACT

Research purpose: The research purpose of the study was to determine the effectiveness of the Beneish model as a fraud control measure for Zimbabwean state-owned enterprises (SOEs).

Design/methodology/approach: This study adopted a triangulation research approach. Statistically tested, quantitative data from financial statements were validated with the qualitative data derived from Auditor General (AG) reports on Zimbabwean SOEs, and reported fraud issues from newspaper articles on Zimbabwean SOEs.

Research findings: The findings revealed that the Beneish model is effective in detecting and preventing fraud, and can be used as an early indication of fraud in the financial statements of Zimbabwean SOEs. This can assist the AG, internal and external auditors, anti-corruption agencies, forensic accountants, and certified fraud examiners with early identification of possible fraud in the financial statements, and will reduce the fraud impact, since faster detection and prevention can potentially minimise financial losses.

Policy implication: Fraud indicators (red flags) from the Beneish model can be used as an early indication of potential fraud in the financial statements of Zimbabwean SOEs. This helps the AG, external and internal auditors, anti-corruption agencies, forensic accountants, and certified fraud examiners to identify red flags in the financial statements, earlier. Curbing fraud losses can potentially improve the performance of Zimbabwean SOEs.

Originality: Fraud control measures from the Beneish model's red flag fraud indicators are expected to add value in curbing the occurrence of fraud in Zimbabwean SOEs.

Key words

Beneish model; control measure; fraud; red flags; state-owned enterprise; Zimbabwean

1 INTRODUCTION

State-owned enterprises (SOEs) fulfil a pivotal function in economic growth, infrastructural development, and provision of basic amenities of any country, however, despite this important function, it is involved in fraudulent activities in many countries **(**Agence Française de Développement 2022:1; Owusu, Koomson, Alipoe & Kani 2021). Similarly, Zimbabwean SOEs play a major role in providing basic amenities and services, and are also expected to contribute towards the national gross domestic product, employment creation, reduction of inequality, and poverty alleviation (Zimbabwe Coalition on Debt and Development 2023:2; World Bank 2017:2020:6). Nevertheless, in Zimbabwean SOEs, widespread fraud and irregularities present, and some Zimbabwean SOEs are reluctant to disclose the fraud information (Mazikana & Mabenge 2023:3; Newman, Tshuma & Sitsha 2023:86-87; Mthombeni, Nyamudzodza, Sifile, Manuere & Siziba 2021:3).

The Auditor General (AG) of Zimbabwe has highlighted recurring fraud and irregularities in the audit reports of Zimbabwean SOEs, and this has resulted in Zimbabwean SOEs losing millions of United States Dollars (USD) annually, attributable to fraud (Chikono 2023; Mazikana & Mabenge 2023:3; Newman *et al.* 2023:86; Office of the Auditor-General Zimbabwe [OAGZ] 2015-2024; Mthombeni *et al.* 2021:3). This has hampered the ability of Zimbabwean SOEs to expand (Newman *et al.* 2023:86). The question, of specific

concern the public, is why these fraudulent activities are not being detected, whilst the resources just go to waste (Newman *et al*. 2023:87). Fraud can be controlled through prevention, detection and investigation (Repousis, Lois & Veli 2019). Fraud control can be executed by identifying symptoms and signs of fraud, referred to in this paper as red flag fraud indicators (Ratmono, Darsono & Cahyonowati 2020). The Beneish model is recommended as a well-established control measure for preventing and detecting fraud in organisations, using the M-Score, and eight variables as red flag fraud indicators (Siregar, Lores, Sari, Sagala & Saragih 2023:623 & 625).

2 LITERATURE REVIEW

2.1 The concept of fraud

It has been reported that "fraud" involves intentional manipulations and falsification practices intended to acquire a financial or non-financial benefit (Oranefo & Egbunike 2021:71). Fraud reduces both the assets and reputation of organisations (Siregar *et al*. 2023:623). Reduction of assets via fraud can compromise service delivery by SOEs to the citizens of the country (OAGZ 2023:48; Baloyi & Beyers 2019:25). Also, reduction of assets through fraud will result in financially burdens to the organisation, and harm the organisation's reputation by undermining the quality and efficiency of resources and operation of the organisation, and the integrity of the top management in charge of managing assets in the organisation (Husin, Mohamed, Sultan, Saruji & Nauli. 2023:395). Fraud also leads to bankruptcy of organisations (Hasibuan, Muda & Erwin. 2022:270). The indulgence in such unethical practices is often in contravention of existing laws and policies, at both government and organisations (Oranefo & Egbunike 2021:71). As a result, the illegal act of fraud harms an organisation and benefits the perpetrator (Siregar *et al*. 2023:623).

2.2 Financial statement fraud

"Financial statement fraud" is an action that involves deliberate misrepresentation of the financial position by an employee of an organisation (Association of Certified Fraud Examiners [ACFE] 2024:103; Hasibuan *et al.* 2022:271; Erdoğan & Erdoğan 2020:176). Financial statement fraud is performed by neglecting truthful disclosure in the financial statements, to deceive those concerned with using the financial statements (ACFE 2024:103; Hasibuan *et al.* 2022: 271; Erdoğan & Erdoğan 2020:176). Financial statement fraud is committed through changes of accounting records; destruction of records; issuing falsified source documents and then transferring that false organisational transaction data to financial statements; alteration of records in order to change the financial results; and fictional recordings by performing operations contrary to the principle of periodicity (ACFE 2024:103; Wells 2011, cited by Siregar 2023:624; Hasibuan *et al*. 2022:271; Göçen 2010, cited by Erdoğan & Erdoğan 2020:177; Rezaee & Riley 2009:4). Financial statement fraud is prevalent within SOEs (Inayah & Chariri 2024:21), and the occurrence of financial statement fraud damages the reputation of organisations and its management (Fathmaningrum & Anggarani 2021).

2.3 Beneish model

The theoretical framework of this study was underpinned by the Beneish model. The Beneish model, with its eight variables, is the latest and most detailed tool that can be used for detecting fraud from the financial statements (Achmad, Ghozali & Pamungkas. 2022:13; Hasibuan *et al.* 2022:271; Sabău, Mare & Safta. 2021:2). The Beneish model ratios are used to detect fraud in the financial statements of a company, from one year (t) to the previous year (t-1) (Siregar *et al.* 2023:625). The Beneish M-score, which is the result of the calculation, indicates that, if the value or score is more than -2.22, the company is classified as a manipulator; if it is equal to -2.22, it is classified as a grey company; and if it is less than -2.22, it is classified as a non-manipulator (Siregar *et al*. 2023:625; Hasibuan *et al*. 2022:271). If the value of the M-score is equal to -2.22 (grey company) or less, it is classified as a non-manipulator (Dimitrijević & Danilović 2017, cited by Đorđević, Mitić & Vučurević. 2025:5). A grey company does not have a significant amount, or the amount of fraud is not sufficient to be declared as a manipulator company (Siregar *et al.* 2023:629). If the indication is that it is a grey company, the internal and external auditors, and fraud examiners should conduct a more thorough investigation including expanded analytical procedures and increased scrutiny of key transactions, to determine the true nature of the financial reporting.

2.4 The Beneish M-score and eight variables as fraud red flag indicators

Eight variables, i.e., DSRI (days' sales in receivables index); GMI (gross margin index); AQI (asset quality index); SGI (sales growth index); DEPI (depreciation index); SGAI (sales general and administrative expenses index); LVGI (leverage index); and TATA (total accruals to total assets), are applied by the model (Alam 2022:2-4; Valaskova & Fedorko 2021:4; Wall Street Mojo 2019; Buljubasic & Halilbegovic 2017:253). As aforementioned, the Beneish ratio's eight variables are measured by using data from a specified year (t) and data from the previous year (t-1) [Siregar *et al.* 2023:623]. Certain results from the ratios are fraud red flag indicators, i.e., an unnatural increase in accounts receivable; deteriorating gross margins; decrease in gross profit and assets; increased growth in sales; an increase in accruals; and abnormal changes in demand and asset quality (Valaskova & Fedorko 2021:3; Svabova, Kramarova, Chutka & Strakova 2020:490; Beneish 1999). The Beneish model extracts the financial statement data, to indicate potential fraud red flags (Buljubasic & Halilbegovic 2017:253; Beneish 1999). The M-score model, as an integrated approach, enables users to detect possible fraud cases, based on the financial statements (Adoboe-Mensah, Salia & Addo 2023:48). This is possible, as the Beneish model allows various segments of financial statements to be examined simultaneously (Aris, Othman, Arif, Malek & Omar 2013).

Once the variables are constructed from the data in the financial statements, it is computed to create an M-score, that shows the degree or extent of fraud (Aris *et al.* 2013:4). Handoko and Anindita (2019:6868), and Svabova *et al.* (2020) explained that, if the M-score is

more than -2.22, fraud is suspected to have been committed; and if the M-score is smaller than -2.22, it is suspected that fraud has not been committed. The Beneish model's financial reporting fraud rate is equal to the M-score, and it describes the extent to which the financial statements have been manipulated (Shakouri, Taherabadi, Ghanbari & Jamshidinavid 2021:41; Svabova & Blazek 2021:4). Empirically, organisations with higher M-scores have a higher tendency to commit fraud (Tarjo & Herawati 2015:926). Hence, fraud is committed by playing with financial numbers in a manner that results in the intentional misrepresentation of disclosures in financial statements, as a way of deceiving others (Shakouri *et al.* 2021:41). The Beneish M-score model detects fraud and it provides more results than any other measure of fraud detection tools (Khatun, Ghosh & Kabir. 2022).

The Beneish model's eight variables, processed as red flag fraud indicators, are described as follows:

2.4.1 DSRI: Days' sales in receivables index

The ratio of day's sales in the receivables index during the last year (t) is compared to the year before (t-1). Any disproportionate increases in receivables relative to sales, may signify a red flag fraud indicator (Beneish 1999:10). A DSRI greater than 1 suggests that receivables are growing faster than sales this is a potential red flag fraud indicator that denotes aggressive accounting tactics, such as recognising revenue prematurely (Fajasy 2025; Ibadin & Ehigie 2019:54; Beneish 1999:10).

2.4.2 GMI: Gross margin index

The ratio of GMI during the last year (t) is compared to the year before (t-1). Any value greater than 1 signifies that margins have deteriorated and indicates a red flag fraud indicator. This signals poor prospects, that may be ascribed to fraudulent activities (Beneish 1999:10). Declining or rapidly increasing gross margins may be a potential red flag fraud indicator that a company is more likely to engage in fraud, in order to make its financial performance appear better than it actually is (Fajasy 2025; Ibadin & Ehigie 2019:54-55; Beneish 1999:10).

2.4.3 AQI: Asset quality index

The ratio of AQI during the last year (t) is compared to the year before (t-1). An AQI greater than 1 indicates that an organisation has potentially increased its involvement in cost deferral (Beneish 1999:10). Accounting Tools (2025) explained "cost deferral" as a cost that had already been incurred, but which will not be charged to expenses until a later reporting period; it appears on the financial position as an asset; and the reason for deferring recognition of the cost as an expense is that the item has not yet been consumed. The cost deferral can be a red flag fraud indicator. Also, an AQI greater than 1 indicates that non-current assets, such as goodwill, intangibles, and other items with uncertain long-term value are growing as a percentage of total assets, compared to the previous year. This increase in the proportion of assets with uncertain future benefits may indicate a potential red flag for fraud (Fajasy 2025; Ibadin & Ehigie 2019:55; Beneish 1999:10).

2.4.4 SGI: Sales growth index

The ratio of SGI during the last year (t) is compared to the year before (t-1). A value greater than one, increases the probability of fraudulent activities and can be a red flag fraud indicator (Beneish 1999:11). When an entity with high sales growth also scores poorly on other variables in the Beneish model, it can be a significant red flag for potential financial statement fraud (Fajasy 2025; Ibadin & Ehigie 2019:55; Beneish 1999:11).

2.4.5 DEPI: Depreciation index

The rate of depreciation is year t-1 / year t. If this value exceeds 1, the rate at which assets are depreciated has slowed. The changes in the rate of depreciation can be a red flag fraud indicator (Beneish 1999:11). This places the spotlight on assets that may have been misappropriated, as the changes by management of revising the estimates of assets' useful life upwards or adopting a new income method can be due to fraud. The DEPI captures potential manipulation of depreciation, to inflate earnings. This can be a potential red flag fraud indicator, as increasing the estimates of assets useful lives slows down the recognition of expenses and artificially boosts its reported income (Fajasy 2025; Ibadin & Ehigie 2019:55; Beneish 1999:11).

2.4.6 SGAI: Sales, general and administrative expenses index

The ratio comprises SGAI to sales in year t / SGAI to sales in year t-1. A disproportionate increase in sales against general and administration expenses can be a red flag fraud indicator (Beneish 1999:11). The SGAI captures potential manipulation of SG&A expenses, to boost earnings. A disproportionate increase in sales compared to SG&A expenses is a potential red flag fraud indicator, that denotes that sales are overstated (Fajasy 2025; Ibadin & Ehigie 2019:55; Beneish 1999:11).

2.4.7 LVGI: Leverage index

The ratio of total debt to total assets in year t is relative to year t-1. A value greater than 1 indicates an increase in leverage (Beneish 1999:12). Being increasingly leveraged is a potential red flag fraud indicator, as a company may be more predisposed to manipulate its earnings to meet obligations or maintain access to capital (Fajasy 2025; Ibadin & Ehigie 2019:55; Beneish 1999:12).

2.4.8 TATA: Total accruals to total assets

The reason for including TATA into the Beneish model, is to determine fraud on financial information based on increase in revenue or decrease in expense, or vice versa, within the framework of accrual basis (Aghghaleh, Mohamed & Rahmat 2016:60). In this TATA context, if non-cash working capital increases or decreases dramatically, it is a red flag for a potential fraud (Aghghaleh *et al* 2016:60).

The computation of total accruals as changes in working capital accounts, other than cash and depreciation on total assets, can produce estimates of a company's income and expenditure activities (Soepriyanto, Meiryani, Ikhsan & Rickven 2022:13). In

this context, if the accrual value is too high, it is a red flag for a potential fraud (Soepriyanto *et al*. 2022:13). High total accruals indicate that the cash portion of the profits generated is low, and indicate a possible fraud in the form of an overstatement of profit (Soepriyanto *et al.* 2022:13). A higher TATA ratio suggests that the company is deferring expenses, so as to artificially inflate earnings (Faster Capital 2025). Deferring expenses can be executed by depreciating or amortising assets over a longer period than appropriate this lessens the amount recorded as expenses in the current period and places some of the expense in later periods (Oyedokun 2018:13). These fraudulent actions raise the profit figure in the current period, however, performing the action in reverse results in fraudulent activities, as it can beperformed to lower the profit figure, in order to reduce a tax liability (Oyedokun 2018:13).

The Beneish model expects a strong positive association between accruals (less cash) and the higher likelihood of manipulation (Beneish 1999:12). Generating large accruals(accounting profits without corresponding cash profits) is a potential red flag fraud indicator, that a company is more likely to be engaging in fraud. Higher positive accruals (signifying less cash) indicate a greater red flag of fraud (Fajasy 2025; Ibadin & Ehigie 2019:55; (Paolone & Magazzino 2014:256; Beneish 1999:12). If the TATA ratio is unusually high, auditors and fraud examiners must lodge further investigations into the accounts of the organisation (Faster Capital 2025).

2.5 Benefits of the use of Beneish model in detecting fraud in SOEs

According to the Beneish model, the financial reporting fraud rate is equal to the M-score (Shakouri *et al.* 2021:41). The existence of a high-level probability of financial statement falsification, indicates the presence of other fraudulent activities in the operations of the organisation (Lehenchuk, Valinkevych, Hrytsak & Vyhivska 2022:9; Hołda 2020:393). The model, in practice, would point to an organisation that should be subjected to a further detailed investigation, as the model indicates that manipulation may have occurred (Hołda 2020:399). Therefore, accountants and auditors must analyse the Beneish model variables of numerous years of financial statement data, to obtain a vivid picture of any other fraudulent activities (Gabrielli & Medioli 2019:78; Li *et al.* 2018:83). To identify a trend of fraud, it is recommended to analyse financial statements for five reporting periods (Aris *et al.* 2013:729).

As the model's eight variables are associated with the existence of fraud in the financial statements, it can help external and internal auditors, and fraud examiners to flag possible problem areas in the financial statement (Aghghaleh *et al.* 2016:61; Aris *et al.* 2013:4). This model can estimate public financial information and this analysis technique can be used as an early detection for parties who use financial statements in making decisions (Beneish 1999). Therefore, the model can be used as an early indicator of potential fraud existence (Khaksari, Shoorvarzi, Mehrazeen & Massihabadi. 2024:95; Tarjo & Herawati 2015:925). This assists external and internal auditors and fraud examiners to identify flags of possible problem areas of fraud in the financial statement, early (Khaksari *et al*. 2024:95; Aghghaleh *et al.* 2016:61; Omar *et al.* 2014:186). In that way, the attention is directed to the problem areas of accounts and items, that should be further investigated, in detail, and timely legal action is enabled (Khaksari *et al.* 2024:95; Buljubasic & Halilbegovic 2017:261).

It is suggested that the Beneish model effectively improves the likelihood of the AG, internal and external auditors, anti-corruption agencies, forensic accountants, and certified fraud examiners, to detect fraud in the financial statements (Aghghaleh *et al.* 2016:61; Omar *et al.* 2014:186; Nwoye, Okoye & Oraka 2013:644). The fraud can be detected with less difficulty, by using the Beneish model, as the variables of the model can track the accounting alterations in financial statements caused by the fraud (Omeir, Vasiliauskaite & Soleimanizadeh. 2023:337, 342). Auditors can use Beneish's ratios to help execute the International Standard on Auditing (ISA) 240 requirements to perform audits, to be reasonably assured that financial statements are free from material misstatement, owing to fraud (Omar *et al.* 2014:186). The International Auditing and Assurance Standards Board (IAASB), and the International Federation of Accountants (IFAC) with ISA 240 outlined the auditor's responsibility to consider fraud and error in an audit of financial statements (IAASB n.d.; IFAC 2025). According to IAASB (n.d.) and ISA 240 (IFAC 2025:169), the auditor is required to 1. identify and assess the risks of fraud, from the financial statements; 2. design and perform audit procedures to address the risks of material misstatement, due to fraud.

The Beneish M-score model could be utilised by auditors as a time- and cost-efficient tool in the financial statement audit (Buljubasic & Halilbegovic 2017:261; Aris *et al.* 2013:4).

Since auditors are essential role players in detecting fraud (Achmad *et al.* 2022:13), the Beneish model's statistical techniques can provide the auditor with a method of detecting fraud, by identifying red flags (Aris *et a*l. 2013:5). The Beneish model can assist auditors when gathering audit evidence, as the use of the model's statistical techniques can strengthen the audit evidence, by collecting detailed audit evidence concerning fraud (Omeir *et al*. 2023: 342; Achmad *et al.* 2022:13; Tugui & Georgescu 2005:3).

The most difficult issue facing the auditing profession is the absence of auditing procedures that can provide absolute assurance in detecting all fraudulent financial reporting (Knežević, Mitrović & Cvetković 2019:98; Nwoye *et al*. 2013:2). The auditor is responsible for obtaining reasonable assurance that the financial statements are free from material misstatement, whether caused by fraud or error (Willoughby 2022; Knežević *et al.* 2019:98). These limitations thus suggest the need for additional effective, analytical audit procedures, for the effective detection of fraud (Safta, Achim & Borlea, 2020:95; Nwoye *et al.* 2013:2; Spathis 2002). It has been suggested that auditors need the Beneish model to effectively complement the various analytical audit procedures performed during an audit assignment (Safta *et al.* 2020:95; Nwoye *et al.*

2013:2; Harrington 2005). The Beneish model is now being taught at universities, globally, and has become an accepted tool in detecting fraud in organisations (Aghghaleh *et al.* 2016:61). It is apparent that, for auditors and fraud examiners, it is less expensive, effective, and easier to detect fraud using the Beneish model as a tool (Elkhaldi, Flayyih, Ali & Mohammd 2021:126,130-131). The Beneish model, as a fraud detection tool, is proven for its popularity, simplicity, powerfulness, and reliability (Safta *et al.* 2020:96). Therefore, auditors and fraud examiners should review the financial documents with regard to each Beneish model variable indicator (Elkhaldi *et al.* 2021:132). The Beneish model can be an effective guide for avoiding costly litigation and reputational damage to auditors (Adoboe-Mensah *et al.* 2023:49) e.g., litigation resulting from failure to detect potential fraud or red flags. In the United States of America, courts have ruled that an auditor's failure to recognise evidence of potential fraud red flags uncovered during the audit—may be sufficient to establish auditor-liability (Blythe 2021:5). Therefore, the Beneish model can assist auditors and financial analysts in conducting comprehensive corporate financial disclosure analyses (Elkhaldi *et al.* 2021:131).

According to ISA 700, the auditor is required to issue an audit report at the end of the audit assignment, expressing their opinion. However, according to Xu (2019:69), the Beneish model can be used to test the quality of the audit report. The International Accounting Standards Board (IASB) framework for the preparation and presentation of financial statements, describes that the management of an entity has the primary responsibility for preparing and presenting the entity's financial statements. However, according to Xu (2019:69), the Beneish model can be used to measure the quality of the financial statements, prepared by management.

3 AIM AND OBJECTIVES OF THE RESEARCH STUDY

The aim of the research was to test the effectiveness of the Beneish M-scores, and Beneish eight variables red flag fraud indicators as a fraud control measure in Zimbabwean SOEs. The researchers employed quantitative data analytical methods, via statistical testing of the Beneish M-scores and Beneish model's eight variables-procedures, as red flag fraud indicators.

3.1 The objectives of the study

The objectives of the study was

1. to perform a Beneish model assessment, establishing its reliability as a fraud control to identify red flag fraud indicators in Zimbabwean SOEs and, if the model was found to be effective, it would be recommended as an effective fraud control measure; 2. to perform a document assessment so as to identify procurement irregularities and examples of asset misappropriation experienced by Zimbabwean SOEs by scrutinising comments, major highlights, and risks of issues of fraud and irregularities, reported by the OAGZ in respect of Zimbabwean SOEs; and 3. to execute a triangulation analysis on statistically tested quantitative data derived from Zimbabwean SOEs' audited financial statements, qualitative data from the OAGZ's reports, and newspaper articles.

4 METHODOLOGY

This study's population comprised 153 Zimbabwean SOEs, i.e., all Zimbabwean SOEs that were audited by the AG from 2015 to 2023. The researchers adopted the near-census method, which was applied to the Zimbabwean SOE population. A census is a method in which data are collected on every member of a group or "the population" (Annenberg Learner 2019:4; Bansal 2008:1). The applicability of the near-census method was that it enabled the researchers to consider the SOEs with the most fraud and irregularity issues, and those without issues of fraud and irregularities, as highlighted in the AG reports from 2015 to 2023. The researchers also focused on Zimbabwean SOEs reported on in state-owned newspapers, with reference to issues of fraud and irregularities. This study adopted a triangulation research approach. Statistically tested quantitative data, derived from the financial statements, was validated with the qualitative data from AG reports on Zimbabwean SOEs, and fraud reported in newspaper articles. The data was quantified from the only publicly available, audited financial statements, of 64 Zimbabwean SOEs, from 2015 to 2023, and anonymous, alphabetical lettered names were given to each of the SOEs—in order to ethically research the Beneish model, as a reliable tool to identify fraudulent and non-fraudulent Zimbabwean SOEs. The researchers used the documentation method as its data collection method, since the data required for the research was secondary data. The documentation method is a data collection method that is conducted by collecting and studying relevant secondary data (Handoko & Anindita 2019:6867). The document analysis data were collected from 1. the OAGZ's reports on Zimbabwean SOEs; the 2. audited financial statements of Zimbabwean SOEs; and3. Zimbabwean SOEs' reported fraud issues, from state-controlled newspaper articles.

5 RESULTS AND DISCUSSION

5.1 Quantitative analysis of financial statements from Zimbabwean SOEs

Quantitative data for the Beneish model eight variables were obtained from the audited financial statements of Zimbabwean SOEs, from 2015 to 2023. The researchers collected data from all financial statements of Zimbabwean SOEs that were publicly available at the time of data collection. Due to ethical reasons, no actual names were mentioned in this regression data analysis, and anonymous names were used by assigning alphabetical letters to each Zimbabwean SOE. Table 1 provides clarification as to how the SOE's were identified, per period, and why not all 64 formed part of each period, from 2015–2023, as shown in Table 2 and 3. Table 1 shows the distribution numbers of Zimbabwean SOEs with publicly financial statements available, per financial period.

Table 2 lists Beneish model eight variables data that was collected from Zimbabwean SOEs' audited financial statements, from 2015 to 2023.

Table 1: Distribution of Zimbabwean SOEs with publicly available financial statements, per financial period

Financial Year	Number of Zimbabwean SOEs with publicly available financial statements, per financial period	Comments
2016–2015	6	The financial statements of six Zimbabwean SOEs were publicly available for only the 2016–2015 financial year
2017–2016	4	The financial statements of four Zimbabwean SOEs were publicly available for only the 2017–2016 financial year
2018–2017	5	The financial statements of five Zimbabwean SOEs were publicly available for only the 2018–2017 financial year
2019–2018	5	The financial statements of five Zimbabwean SOEs were publicly available for only the 2019–2018 financial year
2020–2019	6	The financial statements of six Zimbabwean SOEs were publicly available for only the 2020–2019 financial year
2021–2020	17	The financial statements of 17 Zimbabwean SOEs were publicly available for only the 2021–2020 financial year
2022–2021	12	The financial statements of 12 Zimbabwean SOEs were publicly available for only the 2022–2021 financial year
2023–2022	9	The financial statements of nine Zimbabwean SOEs were publicly available for only the 2023–2022 financial year
TOTAL	**64**	

(Source: Own)

Table 2: Beneish model eight variables data from Zimbabwean SOEs

Zimbabwean SOEs (anonymous names used)	DSRI	GMI	AQI	SGI	DEPI	SGAI	TATA	LVGI
2016–2015 FY								
XYZ	1.39	1.00	1.02	1.15	0.90	0.83	-0.03	1.02
TVU	0.13	1.78	1.18	0.56	0.84	1.93	0.17	0.96
HIJ	1.20	1.00	8.01	0.85	1.25	1.16	-0.01	2.12
VVV	1.06	3.19	0.92	0.99	1.17	1.04	-0.05	1.28
BBC	1.26	0.89	1.03	0.80	1.18	2.41	-0.10	0.87
CCD	4.38	0.39	0.92	0.79	0.54	2.50	-0.26	1.46
2017–2016 FY								
SIV	1.29	1.00	1.25	1.11	1.76	0.88	-0.05	0.97
TYY	2.24	1.02	0.08	0.92	0.99	1.24	0.11	1.10
BBF	0.69	0.75	0.98	1.36	0.99	0.63	0.09	0.99
CCE	1.07	-0.96	1.17	2.05	0.96	0.46	-0.13	0.98
2018–2017 FY								
WSN	1.33	1.00	0.64	1.00	0.79	1.03	-0.09	1.11
AAA	1.34	0.01	-0.92	1.00	0.76	1.03	-0.87	1.10
SSS	0.97	-3.98	0.98	1.14	0.75	1.14	-0.61	1.07
ABB	1.70	1.04	1.00	1.11	0.90	1.06	-0.00	1.09
CCG	0.91	0.65	1.10	1.31	0.91	0.68	0.07	0.74
2019–2018 FY								
JRW	0.19	-3.70	0.96	1.14	1.96	1.25	-0.28	0.25
AAC	3.31	1.67	0.97	0.74	0.82	1.67	3.52	8.75
AAP	0.70	0.39	1.00	0.90	4.73	1.07	0.03	0.36
BBG	0.64	0.47	0.95	2.08	0.28	1.62	0.22	0.56
BBS	0.27	0.95	0.91	1.44	1.44	1.88	0.47	0.56
2020–2019 FY								
NNN	0.42	0.10	1.04	1.47	0.76	0.92	4.82	0.92
AAQ	4.15	0.79	1.00	3.11	0.32	1.07	-0.21	0.23
AAR	0.47	0.74	0.94	1.32	1.00	0.77	-0.14	4.10
AAX	0.27	1.44	1.00	0.88	1.39	0.82	-0.02	0.43

continued/

Zimbabwean SOEs (anonymous names used)	DSRI	GMI	AQI	SGI	DEPI	SGAI	TATA	LVGI
2020–2019 FY								
BBD	1.28	1.23	1.03	1.16	5.53	1.34	0.16	0.94
BBQ	0.32	14.17	0.75	0.79	0.48	0.70	-0.40	0.39
2021–2020 FY								
EFG	4.64	1.00	1.01	0.23	0.04	9.28	-0.37	0.77
PQR	0.59	1.00	2.89	1.03	0.38	1.50	0.06	0.93
KDV	0.99	0.64	0.91	1.56	0.90	1.02	0.48	1.58
OMN	0.76	1.00	0.25	1.55	0.45	0.66	0.05	0.53
ABW	1.20	0.72	0.92	1.99	0.27	2.34	-1.60	0.29
CJL	0.85	1.00	-2.56	0.99	1.04	1.01	0.18	0.78
WWW	0.85	1.03	0.97	0.99	1.06	1.01	0.21	0.91
AAD	0.28	1.30	0.68	1.60	1.00	1.27	0.29	0.38
AAE	1.43	0.60	1.00	2.24	3.83	0.67	0.11	1.99
AAN	2.50	0.05	1.04	0.05	0.80	27.0	0.21	1.60
AAS	0.42	-1.81	1.00	0.62	0.59	0.86	-0.09	4.57
BBE	1.77	1.41	1.05	0.11	0.76	1.06	0.15	1.02
BBK	1.04	0.94	1.00	3.24	0.74	0.43	-0.01	0.72
BBN	0.73	0.61	1.00	1.70	0.43	0.54	0.58	0.15
BBR	2.31	1.09	1.00	2.79	2.50	0.91	0.07	0.78
BBT	2.17	5.37	1.05	1.80	1.20	1.33	0.02	1.38
BBV	2.18	0.86	1.00	1.50	0.96	0.84	0.50	0.67
2022–2021 FY								
PPP	0.18	0.71	0.88	1.36	0.66	1.15	-1.12	0.97
TTT	1.64	2.35	1.68	1.37	1.15	1.31	-0.04	1.75
DDD	1.19	0.03	0.93	1.43	0.94	0.11	-2.19	0.72
AAF	0.06	0.91	0.71	1.01	0.01	1.28	0.36	0.37
AAG	0.22	0.32	1.03	2.17	1.52	1.20	0.17	0.36
AAH	1.01	0.74	9.80	0.93	0.03	1.77	0.10	0.83
AAJ	0.49	3.26	1.00	1.38	3.37	1.04	-0.54	1.06
AAT	4.17	6.24	1.36	1.32	0.59	1.60	0.50	0.84
BBH	2.14	0.67	1.02	2.22	1.37	0.79	0.37	0.71
BBJ	2.17	0.67	1.00	2.21	1.32	0.75	0.39	0.66
BBM	1.51	0.80	1.00	9.96	0.19	0.41	0.19	11.9
BBU	0.64	-0.04	0.91	1.47	1.19	1.05	-0.16	0.65
2023–2022 FY								
BBX	0.93	1.10	1.00	1.87	0.98	1.07	0.64	1.12
AAL	0.74	0.88	0.98	0.89	0.80	1.26	0.58	1.17
AAM	0.82	2.16	1.01	2.07	0.09	1.26	0.21	0.82
AAU	0.79	0.36	0.96	10.01	0.97	0.83	0.23	1.27
AAV	0.10	0.83	0.95	2.42	2.03	0.08	0.24	1.14
AAY	0.07	2.85	0.90	2.24	1.57	1.33	-0.13	0.56
AAZ	1.12	-0.68	0.86	8.12	0.66	1.15	-0.16	2.09
BBY	0.17	0.53	0.95	2.51	0.26	0.66	0.26	0.80
BBZ	2.61	-2.83	1.36	3.80	0.03	0.81	0.20	1.29

Table key: FY financial year

(Source: Own processing of data from Zimbabwean SOEs' audited financial statements).

The Beneish model eight variables quantitative data for each Zimbabwean SOE in Table 2 were inserted into the Beneish model regression formula, to obtain the M-score for each Zimbabwean SOE:

Beneish model score formula = -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 3 shows the M-score of each Zimbabwean SOE, following the computation of the data from Table 2 into the Beneish model regression formula. In Table 3, M-score < -2.22 indicates a non-manipulator; M-score > -2.22 indicates a manipulator; and M-score = -2.22 indicates a grey company.

Table 3: M-score results for each Zimbabwean SOE

Zimbabwean SOEs (anonymous names used)	**M-score**	**Comment:** M-score threshold value greater than -2.22. This is a red flag fraud indicator.
2016–2015 FY		
XYZ	-2.1085	✓
TVU	-2.5582	X
HIJ	-0.0096	✓
VVV	-1.6226	✓
BBC	-3.1124	X
CCD	-1.5900	✓
2017–2016 FY		
SIV	-2.1302	✓
TYY	-1.3321	✓
BBF	-2.0973	✓
CCE	-2.9587	X
2018–2017 FY		
WSN	-2.8082	X
AAA	-7.6018	X
SSS	-7.9501	X
ABB	-1.7680	✓
CCG	-1.9734	✓
2019–2018 FY		
JRW	-6.5956	X
AAC	13.5548	✓
AAP	-2.4007	X
BBG	-1.1641	✓
BBS	-0.5796	✓
2020–2019 FY		
NNN	19.5117	✓
AAQ	1.3682	✓
AAR	-4.4729	X
AAX	-2.8577	X
BBD	-0.7154	✓
BBQ	1.8795	✓
2021–2020 FY		
EFG	-3.0046	X
PQR	-1.9205	✓
KDV	-0.1748	✓
OMN	-2.1303	✓
ABW	-9.1617	X
CJL	-3.1481	X
WWW	-1.6060	✓
AAD	-1.0649	✓
AAE	-0.6163	✓
AAN	-6.1414	X
AAS	-6.4478	X
BBE	-1.6714	✓
BBK	-0.3639	✓
BBN	0.6954	✓
BBR	0.9569	✓
BBT	1.5731	✓
BBV	1.4480	✓

continued/

Zimbabwean SOEs (anonymous names used)	M-score	Comment: M-score threshold value greater than -2.22. This is a red flag fraud indicator.
2022–2021FY		
PPP	-8.4105	X
TTT	-1.0421	✓
DDD	-12.4713	X
AAF	-1.7721	✓
AAG	-1.4708	✓
AAH	1.1642	✓
AAJ	-3.6976	X
AAT	5.8755	✓
BBH	1.3956	✓
BBJ	1.5173	✓
BBM	3.2090	✓
BBU	-3.5984	X
2023–2022 FY		
BBX	1.2254	✓
AAL	-0.2982	✓
AAM	-0.1826	✓
AAU	6.0233	✓
AAV	-0.7974	✓
AAY	-1.7487	✓
AAZ	1.8679	✓
BBY	-0.9097	✓
BBZ	0.3841	✓

Table key: FY financial year
Indicators of potential fraud, with same consideration of other symbol descriptions:
✓ = Indicators of potential fraud were identified;
X = No indicators of fraud were identified;
❖ = No grey category was identified.
(Source: Own).

From the analysis of the data in Table 3, it could be stated that the M-scores of Zimbabwean SOEs with the anonymous names of HIJ in the period 2016–2015, TYY in the period 2017–2016, ABB in the period 2018–2017, AAC in the period 2019–2018, NNN in the period 2020–2019, BBT in the period 2021–2020, AAT in the period 2022–2021, and AAU in the period 2023–2022 exceeded -2.22 and were the highest in its different periods and, therefore, the Zimbabwean SOE NNN, in the period 2020–2019, had the highest M-score of any Zimbabwean SOE, from 2015 to 2023. It indicated that the extent of fraud in NNNwas higher than any other Zimbabwean SOE in the table, since it had the highest M-score. According to Alam (2022:6), Shakouri *et al.* (2021:41) the higher the M-score value from the M-score threshold value of -2.22, the higher the extent of fraud. From the analysis of the data in Table 3, it was found that no Zimbabwean SOE can be categorized as grey, as no Zimbabwean SOE had a value of -2.22.

Table 4 shows the M-score descriptive statistical analysis for Zimbabwean SOEs.

Table 4: M-score descriptive statistical analysis for Zimbabwean SOEs

M-score variables	Number (N)	Minimum	Maximum	Mean	Standard deviation
DSRI	64	0.060	4.640	1.257	1.070
GMI	64	-3.980	14.170	1.027	2.262
AQI	64	-2.560	9.800	1.163	1.531
SGI	64	0.050	10.010	1.811	1.845
SAGI	64	0.080	27.000	1.621	3.414
DEPI	64	0.010	5.530	1.095	1.005
LVGI	64	0.150	11.900	1.320	1.811
TATA	64	-2.190	4.820	0.115	0.878

(Source: Own 2024-processed data from Zimbabwean SOEs' audited financial statements)

Table 4 shows the period 2015 to 2023's financial years, in respect of the data that was analysed on the 64 SOEs, and that only one set of financial statements were analysed per SOE. Table 4 depicts that SGI was the most common red flag fraud indicator,as denoted by the highest mean of 1.811. The second red flag

fraud indicator was SAGI, that had a mean of 1.621. The third red flag fraud indicator was LVGI, with a mean of 1.320. This implied that the selected Zimbabwean SOEs mainly utilised SGI, SAGI, and LVGI to manipulate its financial statements for fraudulent activities. The lowest red flag fraud indicator was TATA, that had a mean of 0.115. This implied that TATA was not generally used by Zimbabwean SOEs to manipulate financial statements for fraudulent activities.

Table 4 reveals high standard deviations, which are also red flag fraud indicators that quantify the deviation of transactions from the expected value (mean). A Zimbabwean SOE that has a higher standard deviation than any other Zimbabwean SOE, indicated that it differed from the average fraud rate committed by other Zimbabwean SOEs. As the standard deviation was calculated from M-score variables, this indicated the manipulation of financial statements for fraudulent activities. M-score variables capture the effects of manipulation and assumptions that are engaged in by organisations in committing fraudulent activities (Valaskova & Fedorko 2021:3). SAGI had the highest standard deviation of 3.414; the second was GMI, with a standard deviation of 2.262; and the third was SGI, that had a standard deviation of 1.845.

5.2 Qualitative analysis of AG reports on Zimbabwean SOEs

In order to evaluate fraud in Zimbabwean SOEs and its total prejudice, data was collected by scrutinising comments, major highlights, and the risk of reported issues of fraud and irregularities from the AG reports on Zimbabwean SOEs. The data collected from the OAGZ's reports on SOEs from 2015 to 2023, revealed that fraud and irregularities are regularly recurring and are causing financial prejudice in Zimbabwean SOEs. Table 5 summarises the data findings on Zimbabwean SOEs, from AG reports, for the period 2015 –2023. The data from Table 5 were matched with the data from Table 3 —presented in Section 5.3 —using triangulation analysis. The following table key applies:X = no issues were reported;

✓ = issues were reported;

* = the AG report did not quantify the monetary value;

** = the AG report did not quantify the monetary value or specify the type of asset.

Table 5: Overall summary table of frauds —procurement irregularities and asset misappropriation — financial prejudice in Zimbabwean SOEs from the AG reports

SOE	CGF issues	Procurement irregularities	Asset misappropriation	Others
2015				
PF	✓	(Goods were lost after issuing goods without verifying proof of payment).	X	X
CAAZ	✓	USD13 624 202 (payment above the contract price).	• Dump truck • Two Toyota Hilux vehicles	X
ZINARA	✓	USD2 419 511 (payment vouchers were reported missing).	Tolling assets	X
NSSA	✓	X	USD 2 244 375	X
ATZ	✓	X	• Two Mitsubishi L200's • One Toyota D4D • Concrete mixer • Lightning plant • Double-edged log sheet	X
HHC	✓	X	**	X
2016				
ZINARA	✓	USD2 342 956 (no supporting documents for the expenditure & missing payment vouchers).	X	X
GMB	✓	USD1 545 219 (failing to comply to informal tendering procedures).	X	X
TIMB	✓	USD7 083 242 (non-compliance with State Procurement Board procedures).	X	X
ZACC	✓	USD442 717 (no supporting documents for trade payables & irregular transactions).	X	X
ZYC	✓	USD32 616 (payment vouchers without supporting documents).	X	X
CMED	✓	USD1 096 440 (no tendering process was executed).	X	X
JM	✓	USD44 692 (non-delivery of goods after prepayments).	X	X
NRZ	✓	USD1 444 093 (non-delivery of goods after prepayments).	X	X

continued/

SOE	CGF issues	Procurement irregularities	Asset misappropriation	Others
2016				
MCH	✓	USD57 454 (failure to solicit three quotations as required).	X	X
SHT	✓	USD14 189 (payment made without being authorised).	X	X
NSSA	✓	X	USD3 419 000	X
ZEC	✓	X	• 10 Electric generators • Three computer monitors	X
PGH	✓	X	USD277 743	X
2017				
CAAZ	✓	USD397 328 (purchases made without being authorised & non-delivery of goods after prepayments).	X	X
ZINARA	✓	USD1 379 532 (payments made without tender processes).	X	X
ZPWMA	✓	USD1 710 (unauthorised expenditure).	X	X
SRC	✓	USD65 109 (payments made without proper authorisation and documentation).	X	X
NAC	✓	USD12400 (competitive bidding procedures were not performed).	X	X
AZ	✓	USD16 128 066 (no tender approval by the State Procurement Board & no creditors' reconciliations between suppliers' statements and the underlying accounting records & no supporting documents for expenses incurred).	USD8 378 109	X
ZETDC	✓	USD1 764 038 (non-delivery of goods after prepayments).	X	X
ZPC	✓	USD520 241(non-delivery of goods after prepayments).	X	X
POSB	✓	USD7 955 (payment for training services that were never rendered).	X	X
SHT	✓	USD9 100 (lacking supporting documents for procurement expenditure made).	X	X
2018				
ZETDC	✓	USD4 9000 000 (non-delivery of goods after prepayment).	X	X
ZPC	✓	ZAR 196 064 (non-delivery of goods after prepayment).	ZAR196 064	X
GMB	✓	USD1 088 382 (fraudulent purchases and forged depot-to-depot transfer documents).	X	X
AZ	✓	USD4 552 982 (payments made to suppliers but suppliers had not acknowledged these payments & long-outstanding deposits made to suppliers without clarifying the purpose of these payments).	X	X
EM	✓	USD49 846.87 (no supporting documentation for procured goods).	X	X
ZPC	✓	USD66 989 (non-delivery of goods after prepayment).	X	X
ZYC	✓	X	Three laptops	X
EM	✓	X	• Plant & machinery • Cell phones & accessories • Office equipment • Motor vehicles • Assets disposed of without supporting documents	X

continued/

SOE	CGF issues	Procurement irregularities	Asset misappropriation	Others
2018				
ZMDC	✓	X	• Office chairs • Office equipment • Lawnmower • Laptops	X
2019				
GMB	✓	USD1 000 000 (overpayment of goods).	X	X
SEC	✓	*	X	X
ZCDC	✓	USD352 068 (non-delivery of goods after prepayments).	X	X
ZETDC	✓	USD1 293 654 (payment for incorrect goods).	X	X
MMCZ	✓	X	USD2 075	X
PT	✓	X	Two motor vehicles	X
2020				
HS	✓	ZWL20 177 (prepayments made before invoices, goods and services were received).	X	X
NPC	✓	ZWL54 600 (no procurement due diligence procedures, lack of segregation of duties, as the same person was responsible for both delivery notes and confirmation of receipt of goods) & (the procurement from a supplier was completed without required documents).	X	X
ZCDC	✓	* (failing to prepare creditors' reconciliations in a timely manner).	X	
TIMB	✓	X	Four laptops	X
NRZ	✓	X	**	X
ZUPCO	✓	X	**	X
ZIPAM	✓	X	• 487 Padded blue chairs • Four-drawer office desks • Four brush cutters • Two Pro desktop PCG4FF • Three tea urns • Two chest freezers • One plate stove • Eight water dispensers • Three 48 kg lpg Cylinders • One convection oven • One gas stove burner with oven	X
2021				
NB	✓	* (no Procurement Management Unit & not obtaining at least three competitive quotes).	X	X
ZINARA	✓	USD48 652 (procurement contracts were signed after the delivery of goods and services).	X	X
ZINARA	✓	ZWL3 418 000 (tender was awarded to supplier without contract & price changes during delivery of goods resulting in overstatement).	X	X
ZSEC	✓	ZWL756 250 (failing to seek at least three competitive quotes).	X	X
ATZ	✓	* (procured from unregistered suppliers without providing reasons).	X	X
ATZ	✓	* (purchase orders were raised after the delivery of goods).	X	X
PT	✓	* (no timely reconciliations between the prepayments account and subsequent deliveries) & (contracted suppliers who failed to deliver after prepayments were made).	X	X

continued/

SOE	CGF issues	Procurement irregularities	Asset misappropriation	Others
2021				
CCH	✓	ZWL4 474 488 (no reconciliations between creditors' balances and creditors' statements & payments made were not recognised in the supplier ledgers).	X	X
NUST	✓	ZWL31 188 (failure to solicit three competitive quotes from reputable suppliers).	X	X
ZEC	✓	X	**	X
MPC	✓	X	Accessories of diamond drilling rig	X
MCH	✓	X	ZWL1 832 538 254	X
2022				
TIMB	✓	ZWL1 700 000 (non-delivery of goodsfollowing prepayments).	X	X
TIMB	✓	USD50 500 (non-delivery of goodsfollowing prepayments).	X	X
ZACC	✓	ZWL353 472 (no supporting documents for validating procurement expenditure).	X	X
PF	✓	USD64 282 (delivered goods to a new customer without receiving payment, resulting in lost goods where the customer could not be located).	X	
ZPC	✓	* (splitting of procurement orders to circumvent financial thresholds for determining the appropriate procurement method).	X	X
ZUPCO	✓	ZWL290 000 000 (no evidence to support the procurement expenditure).	X	X
AEHPC	✓	* (no Procurement Management Unit) & (no solicitation for at least three quotations was performed for the procurement of goods and services).	X	X
PCZ	✓	* (failed to issue vouchers for goods received and acknowledge receipt of goods procured).	X	X
UZ	✓	* (default of creditors' reconciliations, resulting in discrepancies between what was confirmed by suppliers and what was recorded in books of UZ).	X	X
ZIPAM	✓	* (quotations were solicited for the revaluation of PPE instead of inviting suppliers to submit bids, as required by the Procurement Act).	X	X
ZSM	✓	ZWL278 420 (no action to recover a refund due to a breach of contract, after supplier supplied old goods instead of new goods).	X	X
ZNSA	✓	X	**	X
GMB	✓	X	*	X
ZACC	✓	X	Five vehicles	X
ZEC	✓	X	• One CPU HP Compaq dx23000 • Two keyboards HP • One laptop HP ProBook 4540s • Three modem Sahara 56k USB • 18 gas cylinders 3kg • Two generators	X
IL	✓	X	**	X
CHE	✓	X	ZWL60 600 000	X
USF	✓	X	Six laptops	X
UBH	✓	X	*	X
UZ	✓	X	ZWL3 909 318	X
SIRDC	✓	X	• Seven furniture desk • One laptop	X

continued/

SOE	CGF issues	Procurement irregularities	Asset misappropriation	Others
2023				
ZERA	✓		SAP transaction without description in the ledger ZWL 6 700 000	
NSSA	✓	* (no assessment of estimated procurement values, which exceeded financial thresholds when short-listing firms & no issue of public notice inviting expressions of interest & no evidence that members of the Evaluation Committee declared any conflicts of interest during the evaluation of shortlisted firms & all procurement records for selected tenders were missing & not preparing an Annual Procurement Plan for the year).	X	X
ZNBWCB	✓	* (quotations were being used as receipts or invoices for payments & instances of duplicate invoices for transactions, and some payments were processed without proper approval).	X	X
FC	✓	* (minutes of procurement evaluation proceedings were not being recorded, contrary to the requirements of the Procurement Act).	X	X
NCC	✓	* (not soliciting for at least three quotations & no comparative schedule analyses were conducted for the procurement of goods and services).	X	X
CMED	✓	USD119 361 (non-delivery of goodsfollowing prepayments).	X	X
GE	✓	* (continued to transact with suppliers after its contracts had expired).	X	X
IDCZ	✓	* (procured despite goods not being included in the approved budget & finance department was not represented on the tender evaluation committee & the price variation exceeded the threshold stipulated by the Procurement Act).	X	X
MMCZ	✓	* (non-delivery of goods following prepayments).	X	X
PZL	✓	* (members of the procurement evaluation committee did not declare their interest when evaluating bids).	X	X
PF	✓	* (prepayment for the goods was made & the goods were not delivered and the contract was cancelled and no refund for the prepayment was received from the supplier).	X	X
TLO	✓	* (a supplier was contracted for an indefinite periodcontrary to the requirements which recommends that the contract period be specified).	• 20 pieces of IT equipment • 37 pieces of furniture and fitting equipment	X
WF	✓	USD96 306 (no supporting documents for work-in-progress disbursements).	X	X
POST	✓	USD1 200 000 (non-delivery of goodsfollowing prepayments).	X	X
AHPCZ	✓	ZWL133 530 (no supporting documents for procurement expenditure).	X	X
CCZ	✓	ZWL144 700 000 (no supporting documents for the procurement expenditure).	X	X
SEC	✓	ZWL23 300 000 (no documentation showing approval and explanations for procurement expenditures).	X	X
ZYC	✓	ZWL2 059 630 (no invoices, payment vouchers and quotations as supporting documents).	X	X

continued/

SOE	CGF issues	Procurement irregularities	Asset misappropriation	Others
2023				
DPC	✓	* (several unauthorised POS swipe card purchase transactions were executed, and various employees shared the same security PIN code as the POS swipe card).	X	X
NBS	✓	USD7 800 000 (prepayment for the construction of housing units and the contractor failed to construct and deliver housing units & partially completed housing units with structural defects & land was compensated following arbitration and the value of land was lower, resulting in a loss).	**	X
UBH	✓	ZWL137 400 000 (no supporting documents for procurement expenditure).	ZWL1 7 39 500 000	X
MTB	✓	* (not performing creditors' reconciliations).	X	X
MSU	✓	* (payment of salaries to an employee who had since left the employment).	X	X
NUST	✓	ZWL44 900 000 (prepayment made based on quotations only, which were not supported by invoices).	X	X
SHT	✓	* (non-submission of annual budget for approval to the parent Ministry for its financial year, as required).	**	X
UZSF	✓	ZWL15 600 000 (prepayments to suppliers without invoices).	X	X
UZFT	✓	USD204 685 (non-delivery of goodsfollowing prepayments).	X	X
ZNSA	✓	ZWL7 000 000 (non-delivery of goodsfollowing prepayments).	• 100 tablets • One motor vehicle	X
ZPWMA	✓	* (non-delivery of goods following prepayments).	X	X
ZMC	✓	* (non-delivery of goods following prepayment).	X	X
PCZ	✓	ZWL8 700 000 (non-delivery of goodsfollowing prepayment).	X	X
SMEDCO	✓	USD59 900 (non-delivery of goods after prepayment).	X	X
LSU	✓	ZWL22 600 000 (non-delivery of goodsfollowing prepayments).	X	X
ZERA	✓	* ZWL6 700 000 (transactions recorded without descriptions in SAP system computer ledger).	X	X
AFC	✓	X	• 80 disc ploughs • 10 combine headers	X
EHPCZ	✓	X	**	X
MDPCZ	✓	X	• One leather sofa • 10 chairs with steel frame and padding	X
SLF	✓	X	Cash	X
ICH	✓	X	ZWL53 500 000	X
CUT	✓	X	**	X
ZSM	✓	X	• Fuel • Donations	X
NMMZ	✓	X	*	X

(Source: Adapted from OAGZ 2015-2023)

The data presented in Table 5, shows the total prejudice of Zimbabwean SOEs, attributed to fraud. From the data, it was noted that fraud that involve procurement irregularities and asset misappropriations are increasing in Zimbabwean SOEs, and are causing financial prejudice in Zimbabwean SOEs.

5.3 Validation using triangulation analysis

The validation of the quantitative data (section 5.1.1) and qualitative data (section 5.1.2) was performed via triangulation analysis.

The findings of the quantitative data (Table 3) were linked to the findings of the qualitative data (Table 5), to determine the Zimbabwean SOEs where fraud was detected using the Beneish model, and was confirmed by the AG report. During the course of this research, the actual names of SOEs were initially matched, however, following completion of the write-up of this paper, only the names of Zimbabwean SOEs in Table 2 and 3 were changed to anonymous monikers, for ethical reasons.

5.3.1 AG reports: FY 2015 and 2016

The qualitative data from AG reports for 2015 and 2016 FY, is outlined in Table 5. The SOE CAAZ exhibited issues of procurement irregularities and asset misappropriation, according to AG reports. Quantitative data for the period 2016–2015 FY, as outlined in Table 3, validated the qualitative data. This data was validated, as presented in Table 3, with CAAZ anonymous moniker (XYZ)'s M-scores exceeding -2.22, and fraud suspected to have been committed, since the M-score is more than -2.22. These results validated the effectiveness of fraud red flag indicators of the Beneish model, and that it can be used as a fraud control measure in Zimbabwean SOEs.

5.3.2 AG reports: FY 2020 and 2021

The qualitative data from AG reports for 2020 and 2021 FY, is outlined in Table 5. With regard to the SOEs TIMB and ZSEC, issues of procurement irregularities and asset misappropriation were reported by the OAGZ. Quantitative data for the period 2021–2020 FY, as outlined in Table 3, validated the qualitative data. This data was validated as presented in Table 3, with TIMB anonymous moniker (PQR) and ZSEC anonymous moniker (BBT) their M-scores exceeding -2.22, and fraud thus suspected to have been committed, as the M-score is more than -2.22. These results validated the effectiveness of fraud red flag indicators of the Beneish model, and that it can be used as a fraud control measure in Zimbabwean SOEs.

5.3.3 Periods 7 and 8 of AG reports: FY 2022 and 2023

The qualitative data from AG reports for 2022 and 2023 FY, is outlined in Table 5. The SOE DPC exhibited issues of procurement irregularities and asset misappropriation, according to reports by the OAGZ. Quantitative data for the period 2023–2022 FY, as outlined in Table 3, validated the qualitative data. This data was validated as presented in Table 3, with DPC anonymous moniker (AAV)'s M-scores exceeding -2.22, and fraud suspected to have been committed, as the M-score is more than -2.22. These results validated the effectiveness of fraud red flag indicators of the Beneish model, and that it can be used as a fraud control measure in Zimbabwean SOEs.

5.3.4 Newspaper articlesreporting on Zimbabwean SOE issues of fraud

The cases of fraud, confirmed by news articles, were linked with the findings of the Beneish model from Table 3. The cases were analysed by using the Zimbabwean Herald newspaper. The Herald newspaper is a Zimbabwean state-owned and the largest daily newspaper, hence, why it was used to collect fraud issues, in this validation of the quantitative data from the Beneish model on Zimbabwean SOEs. For ethical reasons, Zimbabwean SOEs implicated in issues of fraud by the newspaper articles, were anonymised via the assignment of alphabetical letters.

News Article 1: 2016 Fraud case. The relevant news article of 2016 reported that the audit on the operations of Zimbabwean SOE VVV revealed endemic fraud. VVV was losing millions of dollars through fraud, involving the misappropriation of assets and procurement irregularities (Gumbo 2016a). Quantitative data for the period 2016–2015 FY, as outlined in Table 3, validated the qualitative data from the newspaper article. In Table 3, VVV's M-scores exceeds -2.22, thus fraud was suspected to have been committed, as the M-score is more than -2.22. These results validated the effectiveness of fraud red flag indicators of the Beneish model, and that it can be used as a fraud control measure in Zimbabwean SOEs.

News Article 2: 2017 Fraud case. The selected news article of 2017 reported that Zimbabwean SOE TYY was prejudiced of millions of dollars, through fraud involving the misappropriation of assets and procurement irregularities (Gumbo 2016b). Quantitative data for the period 2017–2016 FY, as outlined in Table 3, validated the qualitative data from the newspaper article. In Table 3, TYY's M-scores exceeded -2.22, thus fraud was suspected to have been committed, since the M-score is more than -2.22. These results validated the effectiveness of fraud red flag indicators of the Beneish model, and that it can be used as a fraud control measure in Zimbabwean SOEs.

News Article 3: 2021 Fraud case. This news article reported fraud at Zimbabwean SOE PQR involving abuse of a loan facility scheme by PQR to a certain company, in 2021. The loan was granted through fraudulent means, with a loan value of USD397 739.51, for three years. No efforts were made to recover the loan, that accrued to USD539 650.50 by 2024, with interest (Dembedza 2024). Quantitative data for the period 2021–2020 FY, as outlined in Table 2, validated the qualitative data from the newspaper article. In Table 3, the M-scores of PQR exceeded -2.22, thus fraud was suspected to have been committed, as the M-score is more than -2.22. These results validated the effectiveness of fraud red flag indicators of the Beneish model, and that it can be used as a fraud control measure in Zimbabwean SOEs.

6 RECOMMENDATIONS

The recommended fraud control measures for Zimbabwean SOE are stipulated in Table 6.

Table 6: Fraud red flag indicators of Beneish model as fraud control measures for Zimbabwean SOEs

Ser	Fraud control measures
1.	Zimbabwean SOEs should apply the Beneish model's eight variables' procedures to identify red flag fraud indicators.
2.	The internal- and external audit functions, and fraud examiners should monitor the Beneish eight variables fraud indicators and follow up on suspected fraud red flags.
3.	Financial statements and management accounts can be used on a quarterly basis to identify the Beneish eight variables fraud indicator threats, rendering it unnecessary to await the annual financial statements figures at the end of the year, in order to detect fraud. This will reduce fraud velocity, as faster detection and prevention lower fraud losses.
4.	The Beneish model can be used as an early indication of fraud red flags in the financial statements of Zimbabwean SOEs. This helps internal- and external auditors, and fraud examiners to flag possible fraud issues in the financial statement, promptly.
5.	If the M-score indicator is greater than -2.22, it signals a red flag fraud indicator that the SOE is suspected to have committed fraud, and if the M-score indicator is smaller than -2.22, it signals that the SOE is not suspected of having committed fraud. A grey category is signalled if the M-score is equal to -2.22.
6.	The presence of a high level of probability of falsification and fraudulent financial statements indicates (red flag fraud indicator) and also shows the existence of other fraudulent activities in the functioning SOEs.
7.	The Beneish model shows Zimbabwean SOEs' standard deviations, which is also a red flag fraud indicator that quantifies the deviation of transactions from the expected value (mean). A Zimbabwean SOE with a higher standard deviation than any other Zimbabwean SOE, is an indication that it differs from the average fraud rate committed by other Zimbabwean SOEs. Since the standard deviation is calculated from M-score variables, this indicates the manipulation of financial statements for fraudulent activities.
8.	The Beneish model's statistical techniques assist auditors when gathering audit evidence, as its use can strengthen the audit evidence by collecting detailed audit evidence concerning fraud.
9.	The management of an entity has the primary responsibility for preparing and presenting the entity's financial statements. As a fraud control measure, the Beneish model can be used to measure the quality of the prepared financial statements, by management.
10.	The M-score that shows the existence of a high-level probability of financial statement falsification—indicates the presence of other fraudulent activities in the operations of the enterprise. The model, in practice, will point to an enterprise that should be subjected to a further, detailed investigation.
11.	To obtain a vivid picture and trends of any other fraudulent activities using the Beneish model variables, accountants, auditors, and fraud examiners must analyse financial statements for five reporting periods.

(Source: Own)

7 CONCLUSIONS

Based on the findings, it was concluded that SGI was the most common red flag fraud indicator in Zimbabwean SOEs, as indicated by its highest mean. The second red flag fraud indicator was SAGI, and the third red flag fraud indicator, LVGI. This implied that the selected Zimbabwean SOEs mainly utilise SGI, SAGI, and LVGI to manipulate its financial statements for fraudulent activities. The lowest red flag fraud indicator was TATA, implying that TATA was not generally used.

The study's qualitative data findings from AG reports were linked with quantitative data findings, for validation. The M-scores of certain Zimbabwean SOEs, anonymised as AAV, BBT, XYZ and PQR, exceeded -2.22, thus fraud is suspected to have been committed, since the M-score is more than -2.22. The validation of findings showed that the model can be used as a fraud control measure in Zimbabwean SOEs. Based on the findings of statistical calculations of the Beneish M-score, it was concluded that no Zimbabwean SOE can be categorized as "grey", since no SOE had a value equal to -2.22.

The cases of fraud confirmed by newspaper articles were linked with quantitative findings of the Beneish model. Zimbabwean SOEs, anonymised as VVV, TYY and PQR, have issues of fraud, reported in newspapers. Quantitative data findings for Zimbabwean SOEs VVV, TYY, and PQR revealed M-scores exceeding -2.22, thus fraud is suspected to have been committed, in view of the M-Score being more than -2.22. The validation of the findings showed that the model can be used as a fraud control measure in Zimbabwean SOEs.

Furthermore, it could be concluded that the model shows the extent of fraud in Zimbabwean SOEs, as indicated by the M-scores of anonymised SOEs, i.e., HIJ in the period 2016–2015; TYY in the period 2017–2016; ABB in the period 2018–2017; AAC in the period 2019–2018; NNN in the period 2020–2019; BBT in the period 2021–2020; AAT in the period 2022–2021; and AAU in the period 2023–2022, that exceeded -2.22, and were the highest in respective periods. As such, the SOE NNN—in the period 2020–2019—had the highest M-score of any Zimbabwean SOE, from 2015 to 2023. This indicated that the extent of fraud in Zimbabwean SOE NNN is higher than that of any other Zimbabwean SOE.

Additionally, it could be concluded that the Beneish model shows Zimbabwean SOEs' standard deviations, which is also a red flag fraud indicator, that quantifies the deviation of transactions from the expected value (mean). Table 3 reveals high standard deviations—also a red flag fraud indicator, that quantifies the deviation of transactions from the expected value (mean). A Zimbabwean SOE with a higher standard deviation than any other Zimbabwean SOE, is an indication that it differs from the average fraud rate, committed by other Zimbabwean SOEs. As the standard deviation is calculated from M-score

variables, this indicates the manipulation of financial statements for fraudulent activities. SAGI had the highest standard deviation, the second was GMI, and the third, SGI.

It was concluded that fraud red flag indicators from the Beneish model is an effective fraud control measure, and can be used as an early indication of fraud red flags in the financial statements of Zimbabwean SOEs. This helps external auditors, forensic accountants, and certified fraud examiners to promptly flag possible problem areas of fraud in the financial statements.

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