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Using the Beneish M-score Model to Detect Financial Statement Fraud in the Microfinance Industry in Ghana

Nicholas Adoboe-Mensah[1], Hussein Salia[2]*, Emmanuel Budu Addo[3]

[1]Department of Accounting, University of Professional Studies, Accra, Ghana, [2]Department of Accounting, School of Business, Heritage Christian University College, Accra, Ghana, [3]Gulf of Guinea Commission, Luanda, Angola.

*Email: saliahussein@gmail.com

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ABSTRACT

The paper sought to investigate the effect of corporate earnings manipulation on microfinance institutional failures in Ghana. The researchers employed a quantitative investigative technique to analyse data obtained from the Bank of Ghana (BOG) on microfinance companies covering 8-year intervals. Beneish M-scores model was used to analyse the sampled data. The study found a link between earnings manipulation and business failures in the Microfinance Sector of Ghana. It found the M-score model as an effective tool for uncovering early warning signs associated with corporate earnings management, thus, averting many negative repercussions related to the practice. The research findings are based on data obtained only from the microfinance industry of Ghana over an 8-year period. Reasons behind earnings manipulation could not be deduced from the research conclusions. A qualitative inquiry must be considered in future studies to explain the reasons for this phenomenon. Collecting and analysing data from more than one sector and across other geographical boundaries may enhance the applicability of the findings in other jurisdictions. This paper provides some recommendations that help early detection of fraud in the microfinance industry. The research focuses on a sector where data is very sensitive and confidential, hence, highly prone to fraud but hardly researched. It, therefore, adds to the scanty literature on fraud in this part of the economy.

Keywords: Beneish Model, M-score, Earnings Management, Fraud, Microfinance
JEL Classifications: C39, C52, G21, G33, G39

1. INTRODUCTION

Poverty reduction is one of the main targets of the sustainable development goals (SDGs) per the United Nations Agenda 2030 and also in the Agenda 2063 of the African Union. Given the importance of poverty reduction in achieving the SDGs, the United Nations (2014), set an annual global target of five to seven trillion United States dollars as the financial resources required to achieve this target. It was also estimated that less-developed nations would require between 3.3 trillion and 4.5 trillion dollars annually to guarantee food security and support the development of basic infrastructure, education, health, and climate change mitigation and adaptation (Gambetta et al., 2021; United Nations, 2014). Yet governments' actual revenue in Sub-Saharan Africa is often far from these targets. Ghana for instance recorded a 9.4% of GDP budget deficit in 2021 (Ofori-Atta, 2022).

It is on record that 1.4 billion people worldwide survive on less than one United States dollar per day, occasioned by extreme poverty as well as financial and social exclusion (World Bank 2009a, 2009b; Alimukhamedova, 2013). Unsurprisingly, scholars have established a direct link between poor saving culture and perversive poverty rates (Adnan and Kumar, 2021; World Bank 2009a, 2009b). Consequently, most emerging nations have a high-level unbanked population due to the high levels of extreme poverty. Besides, traditional banks in emerging markets are expected to link economically active and indigenous households to financial and non-financial services to achieve the expected level of accelerated economic development. But these institutions are ineffective in achieving this objective (Odoom et al., 2019; Boateng et al., 2015; Adnan and Kumar, 2021).

Therefore, the emergence of microfinance Institutions (MFIs) is not only expected to solve the challenges associated with the supply of credit and related financial services to low-income earners (Adnan and Kumar, 2021) but also enhance savings culture and standard of living (Alimukhamedova, 2013; Yaidoo and Vishawanatha, 2018). In other words, MFIs are now offering financial and non-financial products to entities not prioritised by traditional financial institutions. In effect, the operations of MFIs can eventually reduce global poverty when properly applied. Consistent with the preceding claim, Lieberman et al. (2020) revealed that microfinance schemes have grown from a niche service in some countries around the world to a significant global source of financing for the poor, the unbanked, and other groups previously excluded from conventional banking services. Lieberman et al. (2020), further established that nearly 200 million individuals patronise microfinance services worldwide, the majority of whom are from less-developed economies.

In Ghana, microfinance activities are mostly savings-based. They often operate as Rural and Community Banks, Savings and Loans Companies, Credit Unions, financial non-governmental organisations, and mobile savings collectors, - also known as “Susu” operators in Ghana. As indicated by Asiama and Amoah (2018), the MFCs sector has been growing at an average of twenty to thirty per cent annually, providing services to an estimated 15% of Ghana’s total population. Whilst Asiama and Amoah (2018) perceived MFIs as the focal point for small and medium-scale enterprises for mobilising capital, Odoom et al. (2019) described MFIs as a pivot around which financially disadvantaged entities turn to finance their businesses. The two observations suggest that services by MFIs are critical to breaking the poverty yoke, which is the target of both the UN Agenda 2030 and the African Union Agenda 2063. However, the continuous existence and effective operations of MFIs in Ghana are significantly influenced by the nature of trust and confidence depositors have in these schemes.

Unfortunately, a substantial number of microfinance companies continue to collapse every year in Ghana due to financial irregularities and related factors. For example, in the first quarter of 2013, approximately thirty microfinance companies collapsed in Ghana because of their inability to support financial obligations. Later that same year, an additional twenty became insolvent because of financial irregularities (Odoom et al., 2019). To curtail this worrying phenomenon, the Bank of Ghana placed all forms of microfinance companies under a regulatory structure (Odoom et al., 2019). The Central Bank has the sole mandate to revoke the license of a specialised deposit-taking institution if it is insolvent or is likely to become insolvent within the next 60 days (Bank of Ghana, 2016). Despite these measures by the Bank of Ghana (BoG), the microfinance sector in the country continue to grapple with fraud, insolvency, and institutional failures. Considering the vital role the negative impact their failures have on individual customers and the general economy, there is a dire need to establish mechanisms that will help stakeholders identify and prevent the likely collapse of these institutions, thus, ensuring their growth and sustainability.

One way to prevent MFCs from bankruptcy is by utilising predictive business models. Predictive models estimate the probability of a business entity going bankrupt in the short to medium term. While several predictive models can be used for this purpose, this study focused on the Beneish M-score model. Unfortunately, distinguishing a failing financial institution from a sound one is still a major global concern for the investing public, regulators and policymakers.

Previous literature on corporate failure predictions in financial institutions focused on regions other than Sub-Saharan Africa (Arena, 2008; Cole et al., 2021; Gambetta et al., 2019, 2021). Moreover, the rare studies conducted on Ghana were either concentrated in the banking sector (Agyemang and Agalega, 2014; Boateng et al., 2015; Yaidoo and Vishawanatha, 2018) or on the role of credit defaults of borrowers on the collapse of microfinance companies (Asiama and Amoah, 2018; Ayayi and Peprah, 2018; Bank of Ghana, 2016). To the best of our knowledge, this is the first study to adopt the Beneish model (M-scores) to predict the likely collapse of microfinance companies in Ghana.

The collapse of MFIs negatively impacts the lives of many individuals, corporate institutions and the economy of Ghana as a whole. It has been observed that financial irregularities alone account for about thirty percent of the failure of microfinance companies (Odoom et al., 2019). It is therefore most appropriate to develop solutions that incorporate early warning signs so that future catastrophes resulting from financial irregularities and related matters can be averted.

This quantitative study examined whether MFI earnings are manipulated and whether there exists any relationship between earnings manipulation and MFIs failures. It finally tested the reliability of the M-Score model as an optimal tool for predicting the failure of MFIs. The following hypotheses were tested:

- H_1. Published financial statements of MFIs are not manipulated prior to their failure
- H_2. There is no relationship between earnings manipulation and the failure of MFIs
- H_3. The M-score model is statistically insignificant in optimal predicting MFIs failure.

In testing the established hypotheses (H_1-H_3), the paper adopted the Beneish M-score model. The M-score method is suitable for determining whether a corporate entity’s financial statements are manipulated (Warshavsky, 2012; Al-Manaseer and Al-Oshaibat, 2018; Erdoğan and Erdoğan, 2020; Saha, 2022). Unlike other multivariate analyses such as the Z-score model, which emphasises general corporate financial distress, the M-score allows researchers to deploy specific variables to probe the relationship between financial statements irregularities and a firm’s demise (MacCarthy, 2017; Odoom et al., 2019). As an integrated approach, the M-score model has been credited for enabling users to detect possible fraud cases based on the financial statements of companies. This is possible because the model allows various segments of a company's performance to be examined simultaneously (Aris et al., 2013). Beneish et al. (2013) emphasised that companies with high probability of earnings manipulation are more likely to report low returns in the future compared to those with low exposure to earnings manipulations.

Also, many scholar-practitioners have commended the Beneish M-score model for its ability to guide institutional investors and regulators to promptly uncover potential manipulation of corporate financial statements (MacCarthy, 2017; Nugent, 2003). Similarly, recent researchers (Ayu et al., 2020; Siekelova et al., 2020; Svabova et al., 2020) regarded the results produced from the M-score model as an effective guide for avoiding costly litigation and reputational damage to many stakeholders including auditors and financial analysts. Apart from the aforementioned justifications, the research extends the literature on the fraud triangle.

The next sections of the paper are organized as follows. Section 2 presents a brief review of the relevant literature. In section 3, the data source, empirical strategy and research techniques employed are discussed. The fourth section discusses the research findings. Finally, Section 5 provides research conclusions with recommendations to aid corporate actions and future studies.

2. LITERATURE REVIEW

The core objective of every profit-oriented organisation is to maximize the total returns on investment. For this and other reasons, corporate managers strive to assure investors that their investments are safe and secured. As a result, firms usually adopt different strategies – ethical and sometimes unethical – to achieve their goals. This study focused on one of such unethical schemes, specifically financial statement manipulations, which often leave many investors with zero or negative returns.

2.1. Corporate Earnings Manipulation

The impacts of the Asian financial crisis of 1997-1998, the Enron and WorldCom scandal in the USA of the early 2000 s and the Parmalat Finanziara shock in Italy in 2005, though nearly two decades ago, are still fresh in the minds of accountants, regulators and the investing public. The scandals left an indelible mark on the investment industry globally. From these financial scandals, it emerged that companies might manipulate their financial transactions to conceal fiduciary failures, extreme conflicts of interest, and excessive compensations (KPMG, 2006; MacCarthy, 2017).

Corporate results manipulation is usually done using "creative" and high-risk accounting techniques to conceal certain critical off-balance sheet activities (Deloitte, 2008). In Africa, the financial scandals that resonate are the reported N40 billion (approximately US$308 million) scandal in Nigeria (Ademola et al., 2017) and the 140% increase in fraud losses to GH¢61 million (approximately US$10.5 million) in 2021 over the previous year's figure in the financial sector of Ghana (Bank of Ghana, 2022).

Sadly, companies that entertain fraudulent practices are less likely to succeed. Fraud can thus cause corporate failure and jeopardise the wealth and livelihoods of stakeholders. Fraud can be explained as any form of misconduct intended to deceive, and indeed deceive the victim to act upon it, resulting in a financial loss to the victim of fraud (Rezaee, 2005; Wang et al., 2010; Murphy et al., 2009; Kranacher et al., 2011; Murphy, 2012; Asmah et al., 2019). The fact that manipulation of a financial statement is intended to induce the victim to act to their detriment, which ordinarily they would not do when given full disclosure, is fraud. The Fraud Triangle model is widely used for financial statement analysis. Its effectiveness has been confirmed by several scholars (Cressey, 1973; Omar et al., 2014; Romney and Steinbart, 2018). The model as illustrated in Figure 1 helps to expound on the possible causes of financial statement manipulations by corporate managers.

2.2. Fraud Triangle and Factors Influencing Financial Statements Manipulations

Cressey's (1973) seminal work on the theory of fraud outlined three elements in every fraud case. These elements are pressure, opportunity, and rationalization. Romney and Steinbart (2018) in a related study elaborated on Cressey's three elements with additional triangles (Figure 1).

2.2.1. Perceived pressure

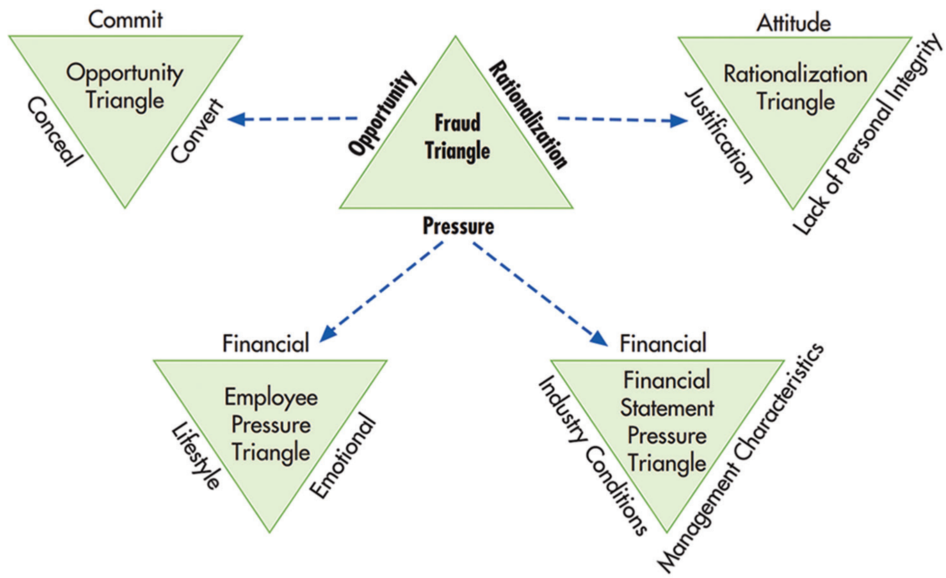
Romney and Steinbart (2018) identified pressure as one of the key elements leading to fraud. Cressey (1973) defined pressure as a non-shareable fiscal need that can emanate from employees or financial statement preparation. It is the result of individual financial needs and pressure on corporate managers to show good financial performance. As noted by Romney and Steinbart (2018), industrial factors such as changes in regulatory requirements, intense competition, declining margins, and significant tax changes are the root causes of financial statement pressures.

An example of the pressure situation can be inferred from Enron's demise. The Chief Executive Officer, Kenneth L. Lay, is on record to have promoted many unethical tactics, including portraying a healthy state of the company's affairs in a misleading manner. According to Bratton (2002), as cited in MacCarthy (2017), the management of Enron had engaged in many illegal measures that won battles against protected energy monopolists, spent copiously on politics, and adopted a market-to-market accounting method to enable it to report USD 1.41 billion pre-tax profit in 2002 financial year. In other words, Enron management was pressured to conceal the then factual financial position of the company.

2.2.2. Perceived opportunities

Internal control lapses are the main sources of opportunity for fraud perpetrators. Other factors such as poor management attitude to sanctioning perpetrators to serve as a deterrent can also create opportunities for perpetrators. Dorminey et al. (2010) and Romney and Steinbart (2018) in their studies highlighted, among others, poor training, lack of willpower to prosecute perpetrators of fraud; management override of internal controls, ineffective anti-fraud programs, unclear line of authority, and a weak ethical culture as the leading factors that enable fraud to flourish. Without opportunities, fraud perpetrators will find it impossible to commit it or conceal their actions and escape being sanctioned (Cressey, 1973; Brockner et al., 1986; Asmah et al., 2019). For instance,

Figure 1: Fraud triangle model



Source: Romney and Steinbart (2018)

in the case of Enron, the board of directors permitting the Chief Financial Officer to use his private firm as auditors and consultants at the same time was a clear case of extensive conflict of interest (Dibra, 2016; MacCharty, 2017). This position also compromised the independence of the auditors and made it impossible for them to execute their professional duties with the requisite objectivity. The lapse then created the opportunity for several fraudulent activities to be perpetrated but not reported.

2.2.3. Rationalisation

These are the excuses by fraud perpetrators to justify their illegal conduct. Rationalisation involves reconciling fraudulent behaviour with the generally accepted belief of morality and trust. (Asmah et al., 2019; Cressey, 1973). In this way, fraud perpetrators view their acts or behaviour as "okay." Most fraudsters justify their illegal acts as acceptable by deploying tactics that project them as trustworthy to preserve their personal integrity (Dorminey et al., 2010; Omar et al., 2014; Romney and Steinbart, 2018; Asmah et al., 2019).

2.3. Criticism of the Fraud Triangle Theory

The fraud triangle theory has provoked many criticisms from scholars. It is tagged as being a one-dimensional psychological analytical tool that fails to fully evaluate the perpetrator (Albrecht et al., 2009; Asmah et al., 2019). The theory minimises the emphasis on specific issues regarding collusion and management override (Lokanan, 2015) and organisational culture (Donegan and Ganon, 2008), which could aid and reward the perpetrators' actions. For this reason, Murphy and Dacin (2011) called for the theory to be re-examined because some fraudsters need no rationalisation to commit fraud.

Despite the criticisms, the theory has provided comprehensive knowledge of some key factors that stimulate fraudulent actions. It has helped corporate managers understand that fraud is most likely to occur when fertile ground is created by corporate managers. Such grounds include pressurizing the staff and creating the opportunity to commit and conceal fraudulent action for the perpetrator's personal benefit. Being able to justify fraudulent acts to retain personal integrity is also a motivator.

Conversely, fraud is unlikely to occur in organizations where there is an intense corporate governance culture. In such an instance, management often ensures that pressure on employees is reasonable. Minimal opportunity is also allowed for individuals to conduct the fraudulent act because there are strong internal controls, and high moral standards are practised as a culture.

The theory has, therefore, received general acceptance and usage. MacCarthy (2017) observed that the association of certified fraud examiners were the first to adopt the fraud triangular model because of its perceived benefits, followed by the American Institute of certified public accountants for the application of the Statement on Auditing Standards No. 99.

Nevertheless, the fraud triangular model alone is incapable of predicting a business entity going into bankrupt in the short to medium term with high degree of probability. Hence, relevant and tested M-model used to uncover fraudulent practices in the corporate world by scholars (MacCarthy, 2017; Nwoye et al., 2012; Omar et al., 2014; Repousis, 2016) has been adopted by this study. The following sections, therefore, discuss the research methodology used by the paper to identify the predator variables and further establish the empirical model to complement the effort being made in the field of fraud research.

3. METHODOLOGY

The paper's objective is achieved using a quantitative investigative approach to inquiry based on the Beneish M-score model research. According to Valaskova and Fedorko (2021), the Beneish model utilises several financial ratios of a given business entity to determine the probability that reported earnings had been manipulated.

The approach used in this paper is akin to that of earlier scholars (Al-Manaseer and Al-Oshaibat, 2018; Erdoğan and Erdoğan, 2020; Saha, 2021), as it allows the sample variables to be investigated over a representative interval without interfering with those variables. This segment discusses the data sources and the justification for employing the Beneish M-score model research.

3.1. Data and Data Sources

The paper relied on annual secondary data from the Bank of Ghana (BOG) between 2013 and 2020, primarily gathered by the research department of the Bank. The BOG is the sole licensee and regulator of the activities of MFIs in Ghana (Bank of Ghana, 2018; Odoom et al., 2019). In addition, the research department of the BOG is well recognised for being able to collect, analyse and publish valid and dependable information, and as such, appears to be the most authoritative source of data for this exercise. Moreover, three hundred and forty-seven (347) MFIs and ten (10) indigenous banks had their operating licenses revoked between 2014 and 2018 due to insolvency (Bank of Ghana, 2018). In all, four hundred and twenty-four (424) microfinance companies' data fell within the interval of study. However, 254 met Yamane's (1973) criterion at a 95% confidence level and accordingly formed the bases of the final analyses. In other words, the data ultimately used for this study was 254 MFIs – comprising those that (i) had ceased operations or liquidated (ii) had licenses revoked, or (iii) were undergoing restructuring processes.

3.2. Independent Variables and Empirical Model

This subsection describes the independent variables used to calculate the M-score and determine Beneish M-score model. In this paper, we used three key sources for choosing endogenous variables. First, we relied on signals identified by past scholars. The general presumption is that corporate earnings manipulations are more likely when firms' future prospects are poor (Beneish, 1999; Omar et al., 2014; Repousis, 2016; Veganzones et al., 2023). We also considered the variables based on companies' cash flows and accruals (Healy, 1985; Jones, 1991; and Beneish, 1999). Then, we selected our remaining variables based on positive theory research, which adopts contract-based incentives as reasons for earnings management (Watts and Zimmerman, 1986).

Consequently, the eight explanatory variables selected are: The daily sales and receivable index (DSRI), gross margin index (GMI), assets quality index (AQI), sales growth index (SGI), depreciation index (DEPI), expenses index (SGAI), total accrual to total assets index (TATA), and leverage index (LVGI), These are generally accepted as being fair explanatory variables for predicting corporate earnings manipulations (Beneish, 1999; MacCarthy, 2017; Nwoye et al., 2012; Omar et al., 2014; Repousis, 2016). The selected variables for establishing the M-score model are consistent with the results from recent studies (Adu-Gyamfi, 2020; Anning and Adusei, 2022).

The mathematical formula for each endogenous variable is summarised in Figure 2. For each firm that was included in the final sample, its average score was obtained, weighed separately and evaluated for sensitivity to manipulation. Beneish (1999) and Chadha (2016) recommended that researchers use financial statements data to calculate M-score model for detecting possible manipulations. The M-score model formula adopted for the research has recorded 76% accuracy rate (Omar et al., 2014; Chadha, 2016; Anning and Adusei, 2022) and 73.17% in other instances (Aghghaleh et al., 2016). As such, the approach serves as a reliable tool for this research. Hence, the tested and widely accepted Beneish M-score model formula adopted for this paper is as follows:

$$M = -4.84 + 0.920{*}DSRI + 0.528{*}GMI + 0.404{*}AQI \\ + 0.892{*}SGI + 0.115{*}DEPI - 0.172{*}SGAI \\ + 4.679{*}TATA - 0.327{*}LVGI$$

Where M = Overall Index and the endogenous variables are explained briefly as follows:

3.2.1. DSRI

It determines whether or not variations in receivables are consistent with variations in sales. This is calculated by dividing a firm's days' sales in receivables in current year (represented by t) by days' net receivables in previous year (t-1) (Beneish, 1999; Adu-Gyamfi, 2020; Nyakarimi, 2022). Based on the DSRI, the consistency between a firm's accounts receivable and the related sales can be determined. According to MacCarthy (2017) and Nyakarimi (2022), corporate non-manipulators have DSRI mean value of 1.031, whilst earnings manipulators have a DSRI mean value of 1.465. An upsurge in the index suggests that sales are progressively made on credit relative to cash, meaning the company is facing a cash collection challenge. This evinces that a large increase in DSRI denotes high probability of revenue being inflated by management.

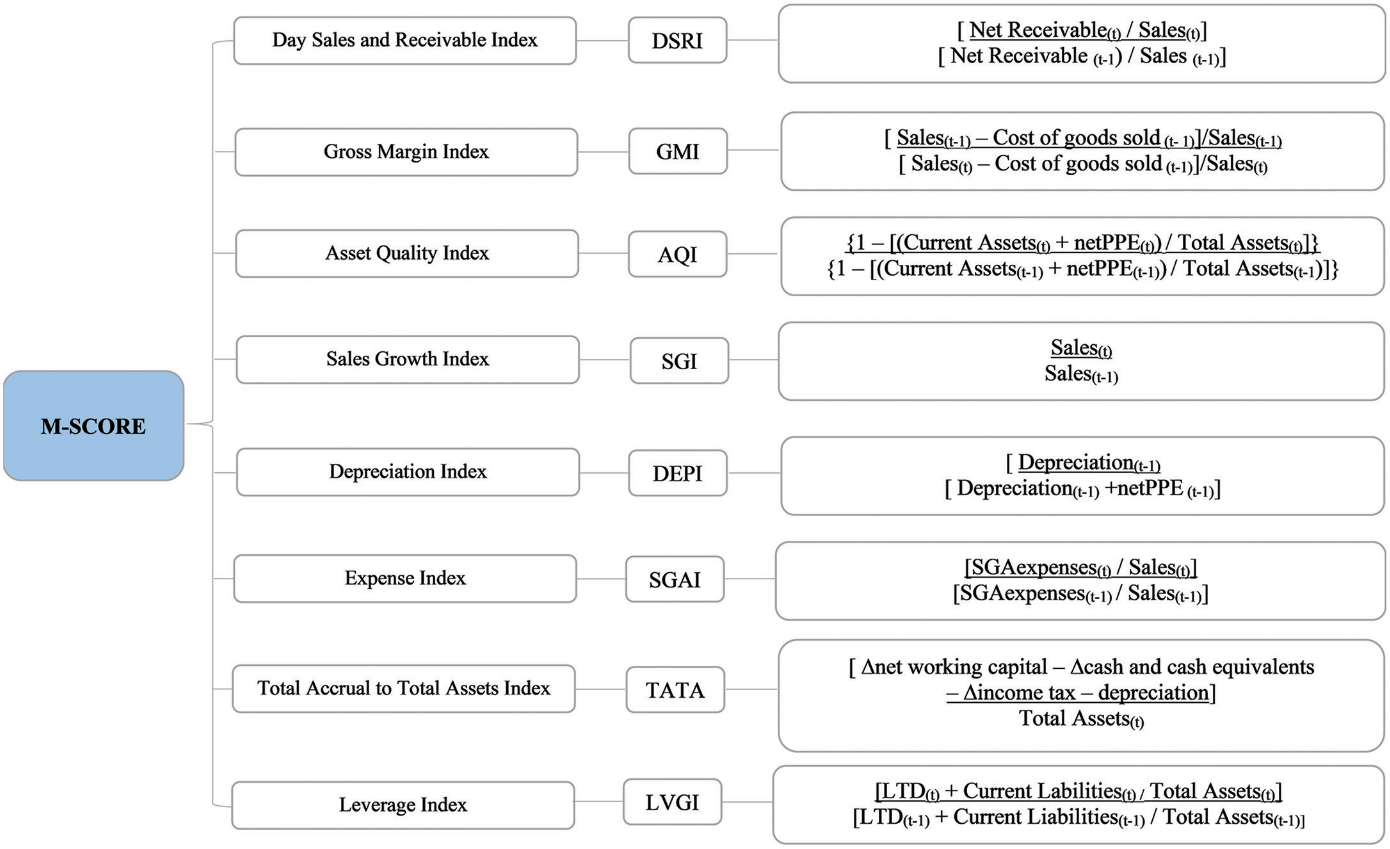
3.2.2. GMI

This index is used to assess whether gross margin, that is, sales less cost of goods sold, has dropped. It is calculated by dividing the gross profit (margin) in the previous year (t-1) by the gross (profit) margin in the current year (t). GMI >1 denotes a deterioration in the entity's gross profit (Beneish, 1999; Nwoye et al., 2012; Repousis, 2016; Nyakarimi, 2022). Harrington (2005) claimed that a GMI score of 1.041 or lower is an indication that the gross profit of the current accounting period is not being manipulated, whereas a score of 1.193 and above signifies a high probability that the gross profit of the company is being manipulated.

3.2.3. AQI

The AQI is the ratio of all non-current assets of a business (excluding plant, property and equipment) to its total assets. It compares the ratio of the assets quality of a firm in the current year (t) to its asset quality in the previous year (t-1) (Beneish, 1999; Nwoye et al., 2012; Repousis, 2016; Adu-Gyamfi, 2020). A rise in this index signifies a drop in asset quality. Beneish (1999) posited that AQI >1 signifies the tendency to capitalise intangibles or expenses, i.e., deferring costs.

Figure 2: Endogenous variables of the M-score model



Source: Beneish et al. (2013)

3.2.4. SGI

This index deals with growth in sales between financial periods. It relates to the ratio of a firm's sales in the current year (t) to sales in the previous year (t-1). SGI mean score of 1.134 signifies non-manipulation of earnings and 1.607 denotes likely manipulation (Beneish, 1999; Nwoye et al., 2012; Repousis, 2016; Adu-Gyamfi, 2020; Nyakarimi, 2022). In other words, higher SGI points to a high probability of corporate earnings manipulation and vice versa. Nevertheless, it is important to emphasise that sales growth in itself does not imply manipulation.

3.2.5. DEPI

This is a measure of the proportion of a firm's depreciation rate in the previous year (t-1) to the corresponding rate in the present year (t). According to Beneish (1999) and Harrington (2005), DEPI >1 implies that the firm's assets are being deliberately depreciated at a slower rate. A decreasing trend gives further credence to the argument that the firm might have either adopted a new method that is income friendly or revised its assets' useful life upwards (Beneish, 1999; Nwoye et al., 2012; Repousis, 2016). The index helps to monitor the likelihood of depreciation rate adjustment being used to report favourable earnings positions.

3.2.6. SGAI

It is a measure of the ratio of a firm's sales, general and administrative expenses in the current accounting year (t) relative to the previous year's value (t-1) (Beneish, 1999; Repousis, 2016; Adu-Gyamfi, 2020). Beneish (1999) observed that a disproportionate increase in the current year's sales over the previous period in excess of 1.001 is an indication of bad future prospects.

3.2.7. TATA

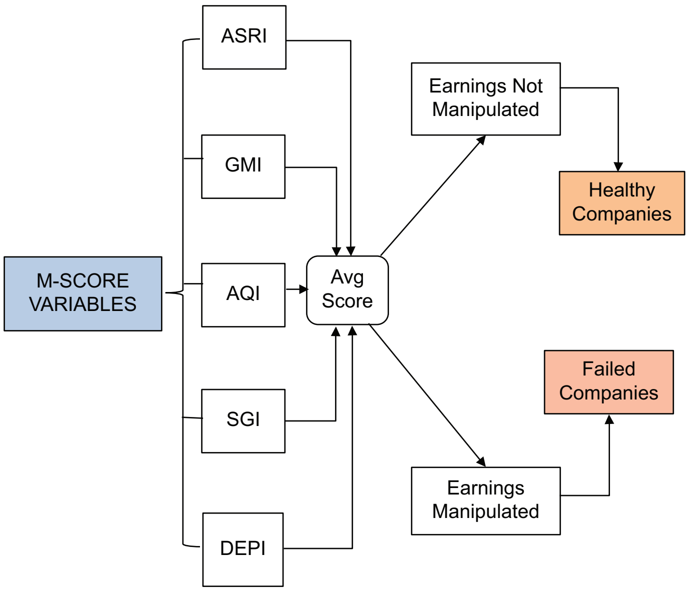
This ratio expresses a firm's total accruals as a percentage of its total assets. It is calculated by deducting a firm's cash flows from operations in the current year (t) from the income from continuing operations in the same year (t). The net result is then divided by the firm's total assets for the year under review (Beneish, 1999; Adu-Gyamfi, 2020). An average score of 0.018 is a sign of non-financial manipulation while an average score of 1.031 and above signifies that the financial data might have been intentionally altered (Repousis, 2016).

3.2.8. LVGI

LVGI refers to the proportion of total debt to total assets in the current accounting period (t) compared to the previous period (t-1). A firm's LVGI >1 denotes rising leverage (Beneish, 1999; Nwoye et al., 2012; Repousis, 2016), hence, a threat to investors' future returns. A LEVI above 1 means that the company's leverage position has increased (Beneish, 1999; Harrington, 2005). In other words, the company has financed its operations with debt as against equity, thereby increasing the risk exposure of the equity investors.

The research conceptual framework is shown in Figure 3, which depicts a connection between independent variables and how each

Figure 3: Endogenous variables of the M-score model



Source: Authors' framework (2022)

variable affects the dependent variable of the study. The research data was analysed using IBM SPSS version 20 and Microsoft Excel software. The procedure has been endorsed by many researchers including Arkkelin (2014).

The next section details the M-score model specification and estimation criteria.

3.3. Model Specification and Estimation

Table 1 depicts the outcome variable for the M-score and the measurement criteria. According to Beneish et al. (2013), where the M-score value is <−1.78, there is low probability that corporate earnings were manipulated. Conversely, a value >−1.78 depicts a high probability of corporate earnings manipulation by management. Beneish et al. (2013) also established a direct link between aggressive accounting practices and corporate failures. Figure 3 describes the independent variables that can collectively affect the going concern status of a business. Beneish et al., opined that firms that apply aggressive and unethical accounting concepts, policies and standards eventually collapse. Therefore, corporate managers are entreated to adopt pragmatic strategies in their quest to increase corporate earnings. The two scenarios are shown in Figure 3.

The paper further relied on binomial tests to assess the statistical significance of M-scores deviations of firms with a low probability of earnings manipulations from those with a high probability of earnings manipulations. In addition, the logistic regression model was used to establish the association between earning manipulation and business failures. The choice of these approaches was based on the set objectives and hypotheses of the study. The model is considered one of the most accurate tools for parametric failure prediction by academics, regulators and supervisors in the financial sector (Beneish, 1999; Beneish et al., 2013; MacCarthy, 2017).

Table 1: Description of outcome variables for M-score

M-score	Outcome
M<−1.78	Low probability of earnings manipulation
M>−1.78	High probability of earnings manipulation

Source: Beneish et al. (2013)

4. DISCUSSION OF RESEARCH RESULTS AND FINDINGS

This section deals with the research results and analyses. It consists of three sub-sections:
- The Analysis of the M-score outcome;
- Binomial test for proportions of the M-score classification; and
- Logistic models fitting.

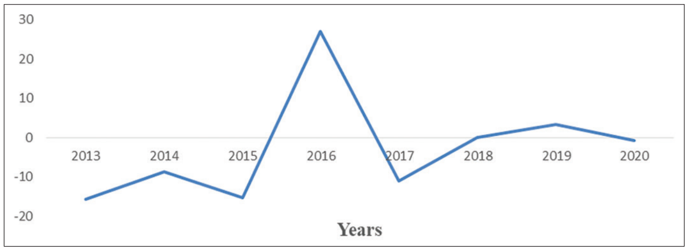
4.1. Analysis of M-scores Outcome

To answer the research question of whether or not the financial statements of microfinance companies are being manipulated, descriptive statistics were employed to determine the M-score values for each year between 2013 and 2020. Table 2 shows the number of microfinance entities that were evaluated in each of the years. It also displays the minimum, maximum, mean and standard deviation of M-score values for each of the years. It is observed from Table 2 that only 114 microfinance companies qualified under Yamane's (1973) criterion for being included in the final sample in 2013 and 2014, and 254 institutions from 2015 to 2018. The overall minimum M-score was recorded in 2015 (−2439.19), and the maximum value of 1836.49 was registered in 2016.

The M-score averages showed an increasing trend from 2013 to 2016, where it obtained its maximum before declining sharply to 1.65 in 2017. It is also observed that the M-score produced a similar trend but smaller and negative values over the period. Figure 4 shows a graphical overview of the M-score's yearly averages over the 8 years from 2013 to 2020. A negative M-score was recorded in each of the first 3 years. This was followed by a sharp increase in 2016 to 27.03 and then a sudden drop to record a negative M-score of 10.89.

The minimum and maximum average M-score values of −15.53 and 27.03 were recorded in 2013 and 2016 respectively. The year 2013, 2014, 2015 and 2017 recorded average negative M-score values of 15.53, 8.60, 15.21, and 10.89 respectively. These values were all below the minimum benchmark value of −1.78 for non-manipulated firms as suggested by Beneish (1999) and Beneish et al. (2013). Impliedly, the collapse of microfinance companies in these years are unlikely to be attributable to prior earnings manipulations by corporate managers. Conversely, the year 2016, 2018, 2019, and 2020 respectively recorded M-score values of positive 27.03, 0.06, 3.52 and negative 0.57 respectively. Since the Beneish benchmark of M-score of −1.78 was exceeded in each case, the probability of earning being manipulated prior to the firms' collapse is between 73 and 76% (Adu-Gyamfi, 2020; Chadha, 2016; Omar et al., 2014).

Figure 4: Trend analysis of the averages for M-score variable from 2013 to 2020



Source: Authors' computation (2013-2020)

The results signal a high probability of earnings manipulations by the management of microfinance companies beginning the year 2016 (with 2017 as the only exception). Though a positive correlation seems to exist between the mass closure of microfinance companies by the BOG (Bank of Ghana, 2018) and the established trend, further scientific investigations are required to determine the likely reasons for this phenomenon. A binomial test is performed in the next section to assess whether earnings in 2013, 2014, 2015, and 2017 (low probability of earnings manipulation) differ from that of 2016, 2018, 2019, and 2020 (high probability of earnings manipulation).

4.2. Binomial Test for Proportions of the M-score Classification

To enhance the reliability of the earnings manipulation predictions, the data were further classified into two groups: Group 1 (low probability of earnings manipulation – unmanipulated earnings) and Group 2 (high probability of earnings manipulation – manipulated earnings). This test helped investigate whether the proportion for "un-manipulated" earnings is the same as that of "manipulated" earnings at a 5% significance level. A binomial test for proportions was employed to investigate the assertion, and the result is summarised in Table 3.

It is observed from Table 3 that there is no significant difference between the proportions of Group 1 and Group 2 in 2014, 2016, and 2020 at a 5% significance level, even though there exist some differences in the proportions for these 3 years. However, it can be noted that there is a significant difference between the proportions of Group 1 and Group 2 in 2013, 2015, 2017, 2018, and 2019 since their $P < 0.05$. It further revealed that the proportions of microfinance companies with a low probability of earnings manipulation (Group 1) annually were higher than the proportion of high probability of earnings manipulation in 2013, 2015, 2017, 2018, and 2019, and that was also observed in the entire period of study. The study shows that some microfinance companies have a high probability of earnings manipulation over the 8 years of study.

Each of the predator variables in the M-score model might have been caused by other factors. Also, given that M-score model has not been an absolute predictor of corporate earnings manipulations (Adu-Gyamfi, 2020; Aghghaleh et al., 2016; Chadha, 2016; Nyakarimi, 202; Omar et al., 2014), a detailed scrutiny is essential for the effect of each explanatory variable entering the Benenish M-score model.

Table 2: Descriptive statistics for M-score variables from 2013 to 2020

Year	Variable	n	Minimum	Maximum	Mean	Std. Deviation
2013	M Score	114	−505.03	90.13	−15.53	69.78
2014	M Score	114	−201.51	76.66	−8.60	29.07
2015	M Score	254	−2439.19	8.48	−15.21	153.25
2016	M Score	254	−167.54	1836.49	27.03	179.17
2017	M Score	254	−406.54	71.14	−10.89	41.99
2018	M Score	254	−58.97	129.15	0.06	14.96
2019	M Score	254	−548.72	1482.98	3.52	101.91
2020	M Score	254	−164.13	201.74	−0.57	21.01
Total	M Score	1752	−2439.19	1836.49	−1.00	102.13

Source: Authors' computation

Table 3: Binomial test for proportions of the M-score classification

Years	Category	n	Observed prop.	Test prop.	P-value (2-tailed)
2013	Group 1	69	0.61	0.50	0.031
	Group 2	45	0.39		
	Total	114	1.00		
2014	Group 1	48	0.42	0.50	0.111
	Group 2	66	0.58		
	Total	114	1.00		
2015	Group 1	190	0.75	0.50	0.000
	Group 2	64	0.25		
	Total	254	1.00		
2016	Group 1	111	0.44	0.50	0.052
	Group 2	143	0.56		
	Total	254	1.00		
2017	Group 1	161	0.63	0.50	0.000
	Group 2	93	0.37		
	Total	254	1.00		
2018	Group 1	164	0.65	0.50	0.000
	Group 2	90	0.35		
	Total	254	1.00		
2019	Group 1	106	0.42	0.50	0.010
	Group 2	148	0.58		
	Total	254	1.00		
2020	Group 1	111	0.44	0.50	0.052
	Group 2	143	0.56		
	Total	254	1.00		
All the years	Group 1	1020	0.58	0.5	0.000
	Group 2	732	0.42		
	Total	1752	1.00		

Group 1: M-score≤−1.78 and Group 2: M-score>−1.78. Source: Authors' computation (2013–2020)

4.3. Logistic Models Fitting

This subsection presents the logistic regression model to the fitted data. The response variable for the logistic regression model was the M-score which takes values 0 and 1, where 0 denotes the low probability of earnings manipulation and 1 denotes the high probability of earnings manipulation. The predictor variables for the logistic regression model were DSRI, GMI, SGI, DEPI, SGAI, TATA and LVGI. The AQI was excluded from the predictor variables due to incomplete data.

Table 4 presents the estimates and the odd ratio of the logistic regression model with an M-score of the response variable.

Table 4: Logistic regression model for M-score as the response variable

Variables	Coefficients (B)	Standard error	Wald Stats.	df	P-value	Odds ratio (Exp [B])
DSRI	1.006	0.090	126.117	1	0.000	2.736
GMI	0.766	0.091	70.478	1	0.000	2.151
SGI	0.733	0.070	108.182	1	0.000	2.081
DEPI	0.744	0.253	8.624	1	0.003	2.105
SGAI	−2.084	0.V346	36.326	1	0.000	0.124
TATA	1.093	0.071	237.032	1	0.000	2.983
LVGI	−0.092	0.029	10.008	1	0.002	0.912
Constant	−2.414	0.187	165.979	1	0.000	0.089

Source: Authors' computation (2022). DSRI: Daily sales and receivable index, GMI: Gross margin index, SGI: Sales growth index, DEPI: Depreciation index, SGAI: Expenses index, TATA: Total accrual to total assets index, LVGI: Leverage index

Table 5: Confusion matrix for classification of the predicted values

M-score	Group 1	Group 2
Group 1	956	42
Group 2	100	530

Source: Authors' computation (2022)

Table 6: Performance measures of logistic regression

Statistics	Percentage
Accuracy	91.3
Sensitivity	90.5
Specificity	7.3

Source: Authors' computation (2022)

It is observed that all seven predictor variables significantly predicted the response variable, M-score. The Wald test shows that the seven predictor variables recorded $P < 0.01$. The odds ratio recorded for DSRI and TATA predictor variables is approximately 3, which means that for DSRI and TATA, the high probability of earnings manipulation is approximately 3 times more than the low probability of earnings manipulation over the period of the study. Furthermore, GMI, SGI and DEPI each recorded an odds ratio of approximately 2, which implies that the high probability of earnings manipulation is approximately 2 times more than the low probability of earnings manipulation.

The LVGI recorded an odds ratio of a little less than one, which means that the high probability of manipulation of earnings is approximately equal to the low probability of earnings manipulation. However, SGAI recorded an odds ratio of 0.124, implying that the high probability of earnings manipulation is 0.124 times less than the low probability of earnings manipulation (Table 5).

The Confusion matrix for classifying the predicted values is displayed in Table 5. It is observed that 956 low probabilities of earnings manipulation were correctly classified, whiles 42 low probabilities of earnings manipulation were wrongly classified as a high probability of earnings manipulation. The logistic regression model recorded a predictive accuracy of 91.3% (Table 6). Meanwhile, the percentage for correctly predicting the low probability of earnings manipulation (sensitivity) is 90.5% compared to the specificity value of 7.3% (correctly predicting high probability of earnings manipulation when using the logistic regression model).

5. CONCLUSION AND RECOMMENDATIONS

The paper investigated whether the earnings of microfinance companies are manipulated and whether there exists a link between earnings management and the demise of MFIs. The research further tested the optimality of the M-score in predicting corporate failures. Apart from expanding the literature on the topic, the paper concluded that:

Though unethical, earnings management is still practiced by corporate managers of MFIs in Ghana. The paper established a link between earnings manipulations and business failures. These observations will help institutional regulators such Bank of Ghana and professional accountancy bodies to introduce measures that can build public confidence in microfinance and other financial service sectors. Key among the institutions to benefit from these findings are the Institute of Chartered Accountants (Ghana) and the Institute of Internal Auditors (Ghana).

The study also found that the M-score model could be employed as an effective tool to uncover the symptoms of corporate earnings management promptly. This will help the investing public to avert many negative repercussions associated with the practice.

However, the findings of this research are confined to the microfinance sector of Ghana over an 8-year interval. Reasons behind earning manipulations could not be deduced from the research conclusions. A qualitative inquiry must be considered in future studies to explain the reasons for this phenomenon. Collecting and analysing data from more than one sector and across the geographical boundaries of the country may offer more accurate results.

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