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An Analysis of Financial Statement Manipulation among Listed Manufacturing and Trading Firms in Ghana

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ABSTRACT
We analyze the likelihood of financial statement manipulation among 19 listed manufacturing and trading firms on the Ghana Stock Exchange for the period 2008 to 2017. We use the Beneish model to group the firms into those likely to engage in financial statement manipulation and those not likely to be involved in financial statement manipulation. Generally, the results show that majority of the firms are likely to be involved in financial statement manipulation. Also, we find that profitability, liquidity, financial leverage, change of audit firm, and the overall economic condition (Z-score) are firm-level factors that predict the likelihood of financial statement manipulation among listed manufacturing and trading firms in Ghana. Given the high number of manufacturing and trading firms likely to engage in financial statement manipulation, there is the need for the managers of the Ghana Stock Exchange to subject future financial reports of these firms to rigorous scrutiny to safeguard the interest of their stakeholders.

KEYWORDS
Financial statement manipulation; financial statement fraud; beneish Model; financial Ratios; manufacturing and Trading Firms; ghana Stock Exchange

1. Introduction

Three objectives drive this study. First, the study seeks to detect the likelihood of financial statement manipulation[1] among listed firms in Ghana using the Beneish (1999) model. Second, it examines whether financial ratios characteristics differ among firms that are likely to engage in financial statement manipulation and those not likely to manipulate their financial statements. Third, it determines the financial ratios[2] that predict the likelihood of financial statement fraud.

The fundamental purpose of corporate financial reporting is to provide the actual state of affairs of an entity to its stakeholders. The rationale is that users of financial reports found their economic decisions on information contained in such reports (Kanapickienė & Grundienė, 2015). It is for this reason that financial statement fraud is considered a serious legal and ethical issue in accounting practice. In this study, financial statement fraud is defined as any act of omission or misstatement deliberately done or committed

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[1]We use financial statement fraud, financial statement manipulation and corporate financial fraud interchangeably in this paper.
[2]One of the predictors in the probit model is not a financial ratio. It is a control variable.

by a firm in its financial reporting that distorts the entity's real state of affairs. This definition, to a considerable extent, dovetails into that of Apostolou, Hassell, and Webber (2000), who define corporate financial fraud as the "intentional misrepresentation of amounts or disclosures in the financial statements" (p.181).

Financial statement fraud is organizational misconduct that violates GAAP[3] (Ramírez-orellana, Martínez-romero, & Mari, 2017). Falsified financial statements may cause huge losses for investors and creditors in capital markets (Chen, Liou, Chen, & Wu, 2019). According to Chen, Wu, Chen, Li, and Chen (2017), the majority of financial reports exaggerate firms' operational activities to raise capital from investors and suppliers of credit. Evidence suggests that fraudulent behavior has become a global issue, draining up 5% of the typical organization's annual revenue (ACFE, 2016).

Interest in financial statement fraud has heightened since the occurrence of high-profile scandals at Enron, Tyco, and WorldCom, as well as other scandals in the last two decades. The devastating impact of corporate financial fraud is never in doubt. According to the 2018 Report to the nations within the Asia-Pacific region published by the Association of Certified Fraud Examiners (ACFE), financial statement fraud is the 5th most common occupational fraud scheme. It accounts for only 13% of occupational fraud cases but costs the highest median loss of US$700,000 compared to other components such as asset misappropriation (ACFE, 2018). It underscores the significance of financial statement fraud and highlights the need to identify a fraud model that accurately and consistently predicts and detects financial statement fraud (Ramírez-orellana et al., 2017). Throckmorton, Mayew, Venkatachalam, and Collins (2015) argue that continuous reviews, reforms and fines issued against curbing financial statement fraud will only be meaningful if such frauds are detected promptly.

In Ghana, the delisting of UT Bank Ltd, Golden Web Ltd, and Transaction Solutions Ltd and the suspension of African Champion Industry Ltd, Clydestone (Ghana) Limited, Pioneer Kitchenware Limited, and Cocoa Processing Company (GSE Press release, 2017) coupled with the takeover of UT Bank and Capital Bank[4] by GCB Bank and KPMG (Bank of Ghana Press Release, 2017 & 2018) after the financial reports of most of these entities had exhibited faster growth and expansion in their operations, raises serious concerns about the credibility and reliability of such reports and, by extension, those of other entities in Ghana. It supports the need to analyze the likelihood of financial statement fraud of firms in Ghana. Despite this, research on financial statement fraud remains scarce in Ghana. Most of the studies on financial statement fraud focus on developed economies. Besides, over the years, studies on financial statement fraud have been pursued from two main perspectives (Chen et al., 2017). First, the identification of probable fraud characteristics to facilitate fraud detection (Xu, Zhang, & Chen, 2017; Yang, Jiao, & Buckland, 2017). Second, the development and use of financial statement fraud detection models to predict fraud in financial reports (Chen et al., 2017; Kanapickienė & Grundienė, 2015; Kim, Baik, & Cho, 2016; Mu & Carroll, 2016; Perols & Lougee, 2011; Ramírez-orellana et al., 2017; Throckmorton et al., 2015; West & Bhattacharya, 2016). As far as we know, there is limited evidence on the combination of these two perspectives, especially in developing economies such as Ghana. This study

[3]Generally accepted accounting principles.
[4]The acquisition of UT Bank and Capital Bank was due to their financial distress.

seeks to bridge this gap by applying both aspects to gain a broader insight into financial statement fraud with data from 19 listed manufacturing and trading firms in Ghana.

The first stage of the study follows previous literature (Beneish, 1999; Herawati, 2015; Ramírez-orellana et al., 2017) by measuring financial statement fraud using the Beneish (1999) model. The second stage of the analysis examines 21 financial ratios concerning firm likely to engage in financial statement fraud and their counterparts to establish their characteristics. The third stage uses probit regression technique to determine the financial ratios that predict the likelihood of financial statement manipulation.

The findings show that the majority of the listed manufacturing and trading firms in Ghana are likely to manipulate their financial statements. Also, the mean of profitability, liquidity, financial leverage, and overall financial condition ratios differ among firms that are likely to commit financial statement fraud and those not inclined to undertake financial statement manipulation.

The study contributes to the existing literature in the following ways. To the extent that previous research (e.g., Herawati, 2015; Kanapickienė & Grundienė, 2015; Ramírez-orellana et al., 2017) on financial statement fraud has paid little or no attention to developing economies, the findings provide some insight on the subject in developing economies. Second, the results of this study offer guidance to auditors and other stakeholders in identifying key areas within financial statements that are prone to manipulation. Third, the findings represent the means of quantitatively detecting early signs of financial statement manipulation in Ghana.

The remaining parts of the paper are structured as follows. The second section covers the methods used in the article. The third section outlines the empirical results. The fourth section provides the conclusion of the study.

2. Methods

2.1 Research Design, Sampling and Data Collection

We select a total of 19 manufacturing and trading firms out of 43 listed firms in Ghana. The variables in the Beneish model support the use of manufacturing and trading firms. The 24 non-manufacturing and trading firms are excluded from the sample because they do not have inventories and account receivables data required by the Beneish (1999) model. We use secondary data obtained from the Ghana Stock Exchange website, the firms' websites, and www.africanfinancials.com for our analysis.

In stage one, we group the 19 listed firms into firms likely to manipulate their financial statements and those not likely to manipulate their financial statements. It is accomplished through the application of the Beneish (1999) model to detect the likelihood of manipulation in their financial statements. Any listed firm with M-score less than −2.22 indicates no possibility of manipulation, while firms with M-score higher than −2.22 suggests the likelihood of manipulation. At this stage, we apply both the 5-variable model and the 8-variable model. The five-variable model identifies five firms not likely to engage in financial statement manipulation and 14 firms likely to manipulate their financial statements, whereas the eight-variable model recognizes six and thirteen firms, respectively.

In the second stage of the study, we identify the financial ratio characteristics of firms not likely to manipulate their financial statements and firms likely to engage in financial statement manipulation using T-test technique. We assess a total of twenty-one financial ratios, ranging from profitability, liquidity, financial leverage, asset composition, capital turnover, and overall financial condition. The study adopts Dalnial, Kamaluddin, Mohd, and Syafiza (2014) groupings of financial ratios and makes modifications based on prior studies (Kanapickienė & Grundienė, 2015). We check multicollinearity in this study using correlation matrix and variance inflation factor.

The third stage of the study focuses on establishing the financial ratios that significantly predict the likelihood of financial statement manipulation. We use likely and not-likely fraud firms[5] identified by the Beneish (1999) model to create binary data in which a likely fraud firm is coded "1," and a not-likely fraud firm is coded "0". We use the binary data to conduct a probability to commit financial statement fraud analysis using the probit regression technique.

2.2 Beneish Model (M-Score)

The literature identifies various approaches for detecting fraud in corporate financial statements. Researchers (Kim et al., 2016; Kirkos, Spathis, & Manolopoulos, 2007; Ravisankar, Ravi, Rao, & Bose, 2011; West & Bhattacharya, 2016; Zhou & Kapoor, 2011) have employed various techniques to analyze the likelihood of financial statement fraud. These include data mining techniques such as decision trees, neural networks, Bayesian belief networks, multilayer feed-forward neural network, support vector machine, genetic programming, group method of data handling, and probabilistic neural network. Apart from data mining techniques, some studies use financial ratios to examine corporate financial fraud (Dalnial et al., 2014; Herawati, 2015; Kanapickienė & Grundienė, 2015; Perols & Lougee, 2011; Ramírez-orellana et al., 2017; Repousis, 2016). Kanapickienė and Grundienė (2015) identify financial ratios as the most sensitive tool for financial statement fraud detection. The above approaches for detecting financial statement manipulation have limitations such as operational complexity, large data requirements, language dynamics, data availability, and cost-effectiveness.

This study opts for the Beneish (1999) model and financial ratio analysis. In particular, the choice of the Beneish (1999) model is informed by its worldwide utilization by numerous studies (Anh & Linh, 2016; Herawati, 2015; Maccarthy, 2017; Mahama, 2015; Omar, Koya, Sanusi, & Shafie, 2014; Ramírez-orellana et al., 2017; Repousis, 2016) due to its simplicity, cost-effectiveness and ability to determine the probability of fraud in financial reports of reporting entities. Herawati, 2015 and Ramírez-orellana et al. (2017) identify the Beneish model as one of the most effective tools for financial statement fraud detection.

The Beneish M-score model was developed by Beneish (1999) in his quest to detect earnings manipulations. It is a forensic financial tool frequently employed by forensic auditors, accountants, and regulators to identify areas of potential fraud in an entity's financial reports (Maccarthy, 2017). It is used to differentiate between firms that exploit

[5]Likely, and not-likely fraud firms refer to firms likely to manipulate their financial statements and those not likely to manipulate their financial statements. This should be noted throughout the rest of the paper.

financial accounts and their counterparts. It is calculated from 5 or 8 independent variables obtained from an entity's financial statements. It requires two consecutive periods of financial ratios. A higher M-Score (that is, M-score greater than −2.22) for a specific entity suggests that it is likely that it engages in financial statement manipulation. Its main weakness is that it is a likelihood model; therefore, it cannot predict the possibility of financial statement fraud with 100% accuracy. The M-score models are specified below:

M-Score (5 variables) = −6.065 +.823 DSRI + .906 GMI + .593 AQI + .717 SGI + .107 DEPI

M-Score (8 variables) = −4.84 + .920 DSRI + .528 GMI + .404 AQI + .892 SGI + .115 DEPI −.172 SGAI + 4.679 TATA – .327 LEVGI

We explain the variables contained in the models below:

DSRI (Day's Sales in Receivable Index)

It measures the ratio of receivables to sales rate in the current period compared to the preceding period. If DSRI is greater than 1, it means the percentage of receivables to sales in the current period is greater than of the previous period (t – 1). It is an indication that the financial report with regards to DSRI has been manipulated, or it is a signal that the entity has varied its credit policy and currently offering more credit than it did previously. If this effect does not depict a fairly uniform trend, it indicates that more revenues are either produced on credit terms rather than in cash or that the business has difficulty collecting cash from its trade debtors. A growing DSRI index could be an entity's precise lawful action to ensure that it extends more credit to its customers, which results in revenue overstatement. Hence, a rapid increase in DSRI index gives a hint to forensic examiners to prove that financial reports are manipulated, or credit terms are modified (Maccarthy, 2017). An unusual increase in day's sales in receivables can arise as a result of revenue inflation. Thus, an increase in receivables that is not proportionate to sales may be a sign of revenue hiking. There is a higher likelihood that overstating revenues/profits would be associated with a large growth in DSRI (Beneish, 1999).

GMI (Gross Margin Index)

It is a measure of the ratio of gross margin in the previous period (t – 1) to the gross margin in the current period (t). When GMI of a firm is greater than 1, it means that its gross margin has declined, and it represents an undesirable signal about its financial performance (Beneish, 1999). Alfian and Triani (2019) and Lev and Thiagarajan (1993) argue that declining gross profit is an unwanted signal for the future of the entity. According to Warshavsky (2012), when evaluating an entity's financial health, the quality of its earnings remains an integral part. Hence, entities are lured into earnings manipulations when they are falling. Given this, there should be a positive relationship between GMI and the likelihood of financial statement fraud (Beneish, 1999).

AQI (Asset Quality Index)

It is a measure of the ratio of asset quality in the current period compared to the previous period (t – 1). Alfian and Triani (2019) assert that amplifying asset realization risk tends to breed escalation of asset capitalization and cost deferrals by entities. An index greater than 1 shows that the firm has increased its cost deferral or raised its tangible assets and bred earnings manipulation. Pustylnick (2009) also argues that such a higher index (more than 1) is a sign of expenses capitalization and deferral of others to future periods. Harrington (2005) asserts that a rise in AQI is a sign of capitalization of extra expenses to sidestep posting them to the income statement to cause a reduction in profit. Hence, a positive relationship exists between AQI and the likelihood of manipulating financial results (Beneish, 1999).

SGI (Sales Growth Index)

It is a measure of the ratio of sales in the current period to the previous period (t – 1). Where SGI is greater than 1, it indicates positive growth. Growth in sales itself does not necessarily mean manipulations. However, there is a tendency that growth will impose pressure on management in keeping an entity's position and in meeting earnings target. Harrington (2005) argues that entities having a high growth level tends to be significantly inspired to perpetrate fraud when there is a reversal in such trends. When a firm experiences magnificent losses in its inventory, it may serve as an inducement to manipulate its earnings.

DEPI (Depreciation Index)

It is a measure of the ratio of the depreciation rate in the previous period (t – 1) compared to the depreciation rate in the current period. An index greater than 1 shows a diminishing depreciation rate. It could be a result of a possible adjustment of the valuable life of property, plant, and equipment upwards, assets been revalued, and the use of a new method for revenue increase (Beneish, 1999). Alfian and Triani (2019) argue that a slow rate of non-current assets depreciation amplifies the possibility of a variation in the estimation of assets' useful lives or new depreciation method adaptation aimed at enhancing earnings. Thus, there is a link between DEPI and financial statement fraud.

SGAI (Selling, General and Administrative Expenses Index)

It measures the ratio of selling, general, and administrative expenses (SGAEs) to sales in the current period compared to the SGAEs rate in the previous period (t – 1). SGAI emanates from the findings of Lev and Thiagarajan (1993). Likewise, an upsurge in SGAI is a sign of an inefficient administrative and marketing management and hence, may lead to an entity manipulating its earnings.

LEVGI (Leverage Index)

It is a measure of leverage in the current period compared to the LEVGI in the previous period (t – 1). An index greater than 1 is an indication of rising debt levels. Thus, the firm is borrowing more to finance its operations. The fundamental purpose of LEVGI's inclusion in the Beneish model is to detect manipulation of earning triggered by an inducement in debt contracts. It explicitly ascertains the extent of errors in the entity's debt estimations, with the assumption that debts occur randomly. A high level of leverage could motivate a firm to manipulate its earnings. This explains the link between LEVGI and financial statement fraud.

TATA (Total accruals to total assets)

It is a measure of the ratio of total accruals to total assets. It ascertains the degree to which managers modify earnings by making discretionary accounting decisions. Jones (1991) states that total accruals have been employed by many studies to assess the extent to which management devise accounting policies to enhance profit. TATA is employed by

Beneish (1999) to ascertain the extent to which cash is used as the basis of reporting profit and indicates that higher positive accruals may be associated with the higher likelihood of financial report manipulation (Beneish, 1999).

2.3 Probit Model specification and justification

We develop probit regression models for the study. Models 1 and 2 seek to identify which ratios are statistically significant to financial statement fraud detection. Model 1 adopts the five-variable model, while Model 2 also adopts the eight-variable approach. We specify such models because of the binary nature of the dependent variable. We group into two: those likely to commit financial statement manipulation and those not likely to manipulate their financial statements with each member of the former attracting the code of 1 and each member of the latter attracting the code of 0. The probit regression models are as follows:

Model 1

P (FSF) = $\beta_0 + \beta_1 Z - score + \beta_2$Cash/CL + $\beta_3 SAL/TA$+$\beta_4 SAL/FA$ + $\beta_5 NP/TA$ + $\beta_6 CHAGOFAUDF$ + e … … … … … … … … … … … … … … … Model 1 (5 – variables).

Model 2

P (FSF) = $\beta_0 + \beta_1 Z - score + \beta_2$Cash/CL + $\beta_3 SAL/TA$+$\beta_4 SAL/FA$ + $\beta_5 NP/TA$ + $\beta_6 CHAGOFAUDF$ + e … … … … … … … … … … … … … … … Model 2 (8 – variables).

Where:

Z-score = Altman's (2000) Z – Score

Cash/CL = Cash/Current Liability

SAL/TA = Sales/Total Assets

SAL/FA = Sales/fixed assets

NP/TA = Net Profit/Total Assets

CHANGOFAUDF = Change of audit firm. It is a dummy variable that attracts the value of 1 if the firm has changed its audit firm in the year under review and 0 otherwise.

3. Results and Discussions

3.1 Detection of the Likelihood of Financial Statement Fraud

The results presented in Table 3.1 comprise both five variables (M-Score 1) and eight variables (M-Score 2) of the Beneish Model. The results from the 5–variable model (M-Score 1) show that five listed firms out of the total 19 listed firms representing 26.3% of the sample are not likely to engage in financial statement fraud. In contrast, 14 of the firms representing 73.7%, are likely to engage in financial statement fraud. In contrast, using the 8-variable model (M-Score 2), the results show that six firms out of the 19 firms representing 31.6% are not prone to financial statement fraud while 13 firms representing 68.4% are prone to financial statement fraud. The 8-variable approach (M-Score 2) increases the number of firms likely to engage in financial statement manipulation by 1. The results from the two models suggest that the majority of listed manufacturing and trading firms in Ghana may be engaged in financial statement manipulation. Any of the established reasons for financial statement fraud in the empirical literature, including access to capital, could help explain this outcome.

3.2 Comparison of financial ratios of firms likely to manipulate their financial statements and those not likely to manipulate their financial statements

Table 3.2 reports the T-Test statistics results on the mean differences of financial ratios between firms likely to engage in financial statement fraud and those not likely to do so based on the 5-variable Beneish and the 8-variable Beneish models. An examination of the 5-variable model results brings to light two interesting observations. First, among the ten financial ratios adopted for firm profitability, only sales to fixed assets (SAL/FA) is significant at a 5% significance level. This finding affirms the work of Kanapickienė and Grundienė (2015), which shows that firms likely to manipulate their financial reports and those not likely to do so can be differentiated using SAL/FA. Further checks disclose that SA/FA ratio is smaller in firms likely to manipulate their financial statements compared to those not likely to do so.

Second, the results show that non-financial statement manipulation firms have a higher total debt to total asset (TD/TA) mean than those likely to engage in financial statement manipulation. It contradicts Dalnial et al. (2014), who find that non-fraud firms have lower financial leverage ratios than fraud firms. It may be due to financial-statement-manipulation firms understating the values of their liabilities. Christie (1990) concludes that the inability of firms' accounting policies to prevent debt covenants violations may provide an incentive for managers to under-estimate liabilities or assets. None of the liquidity ratios, asset composition ratios, capital turnover ratios, and overall financial condition ratio mean has a significant statistical difference. Hence, only two out of the 21 financial ratios have substantial differences (sales to fixed assets ratio and total debt to total assets ratios).

The 8-variable model identifies six financial ratios as having significant statistical differences. These ratios are earnings before interest and tax to sales (EBIT/SAL), gross profit to sales (GP/SAL), cost of sales to sales (COS/SAL), working capital to total assets (WC/TA), current assets to current liabilities (CA/CL) and z-score. Further analysis of the results indicates that out of these six ratios, three of them are profitability ratios (EBIT/SAL, GP/SAL, and COS/SAL). Non-financial statement fraud firms experience a higher EBIT/SAL and GP/SAL compared to those with the tendency to manipulate their financial statements. The cost of sales to sales ratio (COS/SAL) of firms likely to commit financial statement fraud is higher than that not likely to commit financial statement fraud. These results intersect with those of Kanapickienė and Grundienė (2015) who find that gross profit to sales (GP/SAL), cost of sales to sales (COS/SAL) and earnings before interest and tax to sales (EBIT/SAL) are key profitability ratios used to distinguish between financial statement fraud firms and non-financial statement fraud firms.

Two liquidity ratios (working capital to total assets – WC/TA and current assets to current liabilities -CA/CL) are statistically significant. Both ratios are lower in firms likely to commit financial statement fraud compared to not likely to do so. This finding challenges Kanapickienė and Grundienė (2015), who identify no significant differences between working capital to total assets ratio of fraud and non-fraud firms. It indicates that low liquidity can contribute to the probability of financial statement fraud. The Z-score mean is significantly different among firms with no tendency to commit financial manipulation and those with the tendency to do. The mean of non-fraud firms' z-score is relatively higher than those likely to engage in financial statement fraud. It suggests that firms in distress have a higher likelihood to engage in financial statement fraud than healthy firms. This finding is in line with Dalnial et al. (2014).

In sum, profitability ratios (SAL/FA EBIT/SAL, GP/SAL and COS/SAL); liquidity ratios (WC/TA & CA/CL) financial leverage (TD/TA); and overall financial condition (Z-score) are the financial ratios whose means differ significantly among manufacturing and trading firms in Ghana likely to engage in corporate financial manipulation and those not likely to do so. There are limited studies on financial statement fraud in developing economies. Therefore, these findings provide some hint about firm-level factors that could be used to distinguish between firms that likely to engage in corporate financial fraud and those not likely to manipulate their financial statements.

3.3 Prediction of Financial Statement Fraud

3.3.1 Descriptive Statistics and Correlation Analysis

Table 3.3 presents the summary statistics of the independent and the control variables adopted for the probit regression models. The independent variables are Z-score, cash to current liabilities (CASH/CL), sales to total assets (SAL/TA), sales to fixed assets (SAL/FA), and net profit to total assets (NP/TA). We use a change of audit firm (CHANGEOFAUDF) as a control variable. As indicated above, it is a dummy variable, which attracts the value of 1 if a manufacturing or trading firm changed its audit firm the year under review and 0 otherwise. The postulation is that when a firm changes its audit firm, it is more likely that the new audit firm may uncover financial irregularities not likely to be detected by the old audit firm. Studies have argued that keeping one audit firm for an extended period could lead to laxity in the audit work due to familiarity with the financial processes of the organization, which may compromise the detection of financial record manipulation. The engagement of a new audit firm comes with a fresh perspective and skepticism the previous audit firm may lack (Silvers, 2003).

The results show that the Z-score, which measures the overall financial condition of the firm, records a mean of 2.06. It is satisfactory. CASH/CL, which is a measure of liquidity, has a mean value of 0.28. It suggests that for every GH¢ 1 current liability, listed manufacturing and trading firms in Ghana have 28 pesewas to pay. It depicts lower liquidity. SAL/TA, which is a measure of how efficiently management utilizes the assets of the entity to achieve higher returns in sales, exhibits a mean of 1.51. It is an indication that for each GH¢1 investment in assets, a gain of GH¢1.51 in the form of sales is realized. It smacks of the high efficiency of listed manufacturing and trading firms. Support for this claim is found in the 5.64 mean of SAL/FA. It implies that for every GH¢1 investment in fixed assets, GH¢5.64 sales are made. NP/TA, which is a measure of profitability, has a mean of –0.03. It is an indication that the majority of firms may be efficient at using their fixed assets to generate sales. However, their inability to control their expenses creates losses for them. CHANGEOFAUDF, which is used as a control variable, has a mean of 0.40.

The results of correlation and variance inflation analyses are reported in Tables 3.4 and 3.5, respectively. The results in Table 3.4 indicate that the correlations between pairs of the variables in models 1 and 2 are low. The above, coupled with the results in Table 3.5, suggests that multicollinearity is not an issue in this study.

3.3.2 Prediction of Financial Statement Manipulation using Financial Ratios

Table 3.6 presents the probit regression results when we use the five-variable Beneish model. Two profitability ratios (SAL/TA and SAL/FA) emerge as significant predictors of the likelihood of financial statement manipulation. Whereas an increase in the SAL/TA ratio of listed manufacturing and trading firm is more likely to motivate it to engage in financial statement fraud, an increase in the SAL/FA ratio is less likely to inspire financial statement manipulation. The positive association between the propensity to engage in financial statement manipulation and SAL/TA aligns with Gaganis (2009), who finds that SAL/TA is significant in discriminating between financial statement fraud and non-financial statement fraud. The results demonstrate that Z-score, Cash/CL, NP/TA, and CHANGEOFAUDF are not significant predictors of the probability of financial statement manipulation.

Table 3.7 presents the results when we use the 8-variable Beneish model. The results show that SAL/TA, SAL/FA, and NP/TA are statistically significant predictors of the probability of financial statement manipulation at a 5% significance level. At a 10% significance level, z-score, cash/CL, and CHANGEOFAUDF are statistically significant in the detection of the likelihood of financial statement manipulation. Cash/CL, SAL/TA, and change of audit of a firm have positive coefficients. It suggests that holding other factors constant, an increase in any of these variables increases the likelihood of manufacturing and trading firms in Ghana committing financial statement manipulation. On the other hand, NP/TA and SAL/FA have negative coefficients. The implication is that a decrease in any of these ratios can lead to an increase in the likelihood of financial statement fraud, *ceteris paribus*. The negative coefficient of z-score suggests that when firms' overall economic conditions deteriorate, there is the likelihood that it will engage in financial statement manipulation. This finding accords with Dalnial et al. (2014), whose study reveals that a firm with lower z-score is more likely to engage in financial statement fraud.

4. Conclusion

The research seeks to detect financial statement manipulation among 19 listed manufacturing and trading firms in Ghana using the Beneish model and financial ratios. The study covers 2008 to 2017 fiscal years. We use a probit regression technique to predict the probability of a listed manufacturing and trading firm engaging in corporate financial fraud. The results demonstrate that the majority of listed manufacturing and trading firms are likely to engage in financial statement manipulation. The study, therefore, concludes that financial statement manipulation may be prevalent among listed manufacturing and trading firms in Ghana. Again, sales to fixed assets ratio (SAL/FA), total debt to total assets ratio (TD/TA), earnings before interest and tax to sales ratio (EBIT/SAL), gross profit to sales ratio (GP/SAL), cost of sales to sales ratio (COS/SAL), working capital to total assets (WC/TA), current assets to current liabilities (CA/CL) and Z-score are the financial ratios that differ significantly between firms likely to engage in corporate financial statement fraud and those not likely to do so. A probit regression analysis has shown that profitability, overall financial condition, liquidity ratios as well as a change of their external auditors predict the likelihood of listed manufacturing and trading firms getting involved in financial statement manipulation.

Two policy implications of the study stand out. First, given the high number of manufacturing and trading firms likely to engage in financial statement manipulation, there is the need for the managers of Ghana Stock Exchange to subject financial reports of these firms to rigorous scrutiny to protect the interest of their users. Second, the study highlights the need for auditors, investors, business analysts, regulatory bodies, government agencies, and other interested parties to demonstrate more interest in the prevention, detection, and minimization of financial statement manipulation among firms in Ghana.

The only known weakness of this study is its small sample size that has been dictated by data availability constraints. That notwithstanding, the paper carries a high potential to provide more verve to the discourse on the reliability of financial reports of listed firms in particular and non-listed firms in general. The application of the methods we have deployed in this study to listed manufacturing and trading firms in other developing economies will expand the frontiers of the limited financial statement fraud literature in developing economies. Future research should take this up.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Appendix

Table 3.1 M – Score of Listed Firms in Ghana.

S/N	DSRI	GMI	AQI	SGI	DEPI	SGAI	TATA	LVGI	M-Score 1	M-Score 2
1	1.06	0.79	1.18	1.10	1.10	1.06	−0.17	1.19	−2.88	−3.25
2	1.45	−1.92	1.87	1.61	1.09	1.54	−0.52	1.87	−1.52	−6.89
3	1.99	1.01	1.12	1.14	0.97	1.08	−0.06	0.95	−1.93	−1.66
4	0.95	0.86	0.88	1.10	1.22	1.14	−0.06	1.01	−3.06	−2.82
5	1.01	1.03	0.95	1.08	1.13	1.13	−0.02	1.06	−2.84	−2.51
6	4.13	1.81	0.80	0.95	4.37	1.27	−0.34	1.21	0.75	0.13
7	1.06	0.98	1.11	1.17	1.00	1.26	0.02	1.17	−2.68	−2.33
8	0.86	1.00	1.22	1.18	0.90	1.04	0.06	1.03	−2.79	−2.12
9	1.26	1.23	0.92	1.25	1.09	1.06	−0.01	1.13	−2.36	−2.00
10	1.04	1.22	0.99	1.24	1.12	0.99	−0.10	1.06	−2.41	−2.67
11	1.12	0.78	0.62	1.02	0.88	1.32	−0.10	0.93	−4.98	−4.05
12	1.11	1.00	0.97	1.29	1.12	1.01	−0.07	1.01	−2.56	−2.36
13	1.16	1.02	2.56	1.33	1.13	0.99	−0.10	1.00	−1.60	−1.87
14	1.11	1.07	1.56	1.10	0.95	1.09	−0.06	1.08	−2.38	−2.38
15	1.26	0.98	0.69	1.16	1.03	1.20	−0.05	1.07	−2.79	−2.52
16	1.06	1.05	0.85	1.08	0.97	1.05	−0.11	1.03	−2.85	−2.89
17	0.99	1.03	1.18	1.27	1.05	1.00	−0.07	0.99	−2.59	−2.46
18	0.99	0.99	1.00	1.18	1.03	1.04	−0.07	1.02	−2.80	−2.66
19	1.45	1.09	1.57	1.66	1.34	1.48	−0.17	1.04	−1.62	−2.03

Source: Ghana Stock Exchange Market data. M-Score > −2.2 means that there is the possibility of financial statement fraud. M-Score < −2.2 means that there is no possibility of financial statement fraud.

Table 3.2 T-test Mean Comparison of NFSF and FSF for 5 and 8 Variables of the Beneish Model.

	5 – Variables			8 – variables		
	NFSF	FSF		NFSF	FSF	
Variables	Mean	Mean	Diff.	Mean	Mean	Diff.
Profitability						
EAIT/SAL	−0.11	−0.02	−0.09	−0.01	−0.06	0.06
EBIT/SAL	0.06	0.04	0.02	0.09	0.03	0.06**
SAL/FA	10.36	4.10	6.26**	5.19	5.85	−0.66
GP/SAL	0.29	0.26	0.02	0.32	0.25	0.07
EAIT/TA	−0.18	0.02	−0.19	0.06	−0.07	0.13
OE/SAL	0.40	0.27	0.13	0.29	0.31	−0.03
SAL/RECV	31.09	20.03	11.06	11.39	27.89	−16.50
COS/SAL	0.72	0.74	−0.02	0.68	0.75	−0.07**
Liquidity						
WC/TA	−0.15	−0.01	−0.14	0.06	−0.09	0.15**
CASH/CL	0.25	0.29	−0.03	0.29	0.28	0.02
INV/CA	0.42	0.55	−0.13	0.52	0.52	0.01
CA/CL	1.225	1.452	1.40	1.82	1.21	0.61**
RECV/SAL	0.176	0.143	0.03	0.18	0.14	0.04
Financial leverage						
TD/TE	2.54	1.97	0.58	1.95	2.18	−0.23
TD/TA	0.80	0.61	0.19**	0.59	0.69	−0.10
Asset composition						
CA/TA	0.51	0.51	0.01	0.54	0.49	0.05
INV/TA	0.19	0.23	−0.05	0.24	0.21	0.03
RECV/TA	0.22	0.18	0.04	0.20	0.19	0.02
Capital turnover						
SAL/TA	1.56	1.49	0.07	1.34	1.58	−0.24
Overall financial condition						
Z-Score	1.40	2.27	−0.88	2.71	1.77	0.94**

Source: Authors' estimations. ** means Significant at 5% and * denotes significant at 10%

Table 3.3 Summarized Descriptive Statistics of Independent Variables and Control Variable.

Variables	Obs	Mean	Std. Dev	Min	Max
SAL/TA	172	1.51	1.31	0.02	7.92
Z-SCORE	171	2.06	2.95	−21.30	11.02
SAL/FA	172	5.64	16.56	0.02	211.07
CASH/CL	172	0.28	0.63	−0.19	4.77
NP/TA	172	−0.03	0.61	−7.74	0.40
CHANGEOFAUDF	172	0.40	0.49	0.00	1.00

Source: Authors' estimations

Table 3.4 Correlation Matrix for the Independent Variables in Model 3.

	SAL/TA	Z-score	SAL/FA	Cash/CL	NP/TA	CHANGOFAUDF
SAL/TA	1					
Z-score	0.04	1				
SAL/FA	0.59	−0.49	1			
Cash/CL	−0.11	0.48	−0.07	1		
NP/TA	−0.32	0.71	−0.90	0.12	1	
CHANGOFAUDF	−0.26	−0.24	0.03	−0.18	−0.09	1

Source: Authors' estimations

Table 3.5 Variance Inflation Factor for Independent Variables in Model 3.

Variables	VIF	1/VIF
NP/TA	14.25	0.07
SAL/FA	13.1	0.08
Z-score	4.5	0.22
SAL/TA	2.98	0.34
Cash/CL	1.82	0.55
CHANGOFAUDF	1.22	0.82
Mean	**6.31**	

Source: Authors' estimations

Table 3.6 Probit Regression Results of Financial Ratios for Five Variables Beneish Model.

Variables	Coef.	Std. Err.	z	P>|z|
Z-Score	0.08	0.08	0.95	0.35
Cash/CL	−0.23	0.24	−0.97	0.33
SAL/TA	0.38	0.18	2.15	0.03**
SAL/FA	−0.12	0.04	−2.98	0.00**
NP/TA	0.36	0.82	0.43	0.67
CHANGEOFAUDF	−0.12	0.24	−0.51	0.61
CONS	0.63	0.25	0.01	0.14
Pseudo R-sq.	0.08			
LR chi2(6)	14.88			
Prob > chi2	0.02			

Source: Authors' estimations. ** means Significant at 5% and * means significant at 10%

Table 3.7 Probit Regression Results of Financial Ratios for Eight Variables Beneish Model.

Variables	Coef.	Std. Err.	z	P>|z|
Z-Score	−0.14	0.08	−1.74	0.08*
Cash/CL	0.44	0.25	1.77	0.08*
SAL/TA	0.59	0.16	3.61	0.00**
SAL/FA	−0.09	0.03	−3.23	0.00**
NP/TA	−1.81	0.76	−2.37	0.02**
CHANGEOFAUDF	0.01	0.23	0.06	0.06*
CONS	0.30	0.24	0.21	0.21
Pseudo R-sq.	0.12			
LR chi2(6)	24.30			
Prob > chi2	0.01			

Source: Ghana Stock Exchange Market data. ** means Significant at 5% and * denotes significant at 10%