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FINANCIAL STATEMENTS FRAUD OF BANKS AND OTHER FINANCIAL INSTITUTIONS IN NIGERIA

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ABSTRACT

Purpose: There is evidence that managers engage in opportunistic practice to manipulate reported performance to attract unsuspecting investors. This paper seeks to detect the likelihood of manipulations on the financial reports of financial service firms (banks and other financial institutions) as well as to identify the financial indicators that are the likely predictors of the probability of manipulations in Nigeria.

Theoretical framework: The M-score models, from Beneish (1999), are employed as theoretical basis for the paper. The model use financial ratios computed using accounting data to confirm the probability that firms' reported earnings are manipulated.

Design/Methodology/Approach: The study uses data from the Nigerian Exchange Group, from 2010 to 2019 to compute M8/M5-scores and classify firms into likely manipulators and unlikely manipulators. In addition, a probit regression model was applied to establish financial ratios that significantly predict the likelihood of FSF amongst the financial firms.

Findings: The results based on M8 (M5)-score indicate that 26.67% (23.33%) of firms likely manipulate financial books and exhibit the possibility of FSF. In addition, only sales in receivable, sales growth, depreciation expenses, leverage and accruals to assets ratios are found to be (positive) significant predictors of the probability of manipulations.

Research, Practical & Social implications: The implication of the outcome is that subjecting financial statements to empirical and statistical scrutiny should not be ignored because it would detect and reduce associated risks to manipulations. Therefore, more regulatory interventions and empirical auditing of reports are needed to ensure their readability and reliability to the investors.

Originality/Value: The study offers a novel and first evidence, based on Beneish M-score, to scrutinise reports of financial firms in Nigeria. The evidence ensures quality reporting of the financial statements in order to credibility as well as protect the integrity of the capital markets.

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DEMONSTRAÇÕES FINANCEIRAS FRAUDE DE BANCOS E OUTRAS INSTITUIÇÕES FINANCEIRAS NA NIGÉRIA

RESUMO

Finalidade: Há evidências de que os gerentes se envolvem em práticas oportunistas para manipular o desempenho relatado para atrair investidores desavisados. Este artigo procura detectar a probabilidade de manipulações nos relatórios financeiros de empresas de serviços financeiros (bancos e outras instituições financeiras), bem como identificar os indicadores financeiros que são os prováveis preditores da probabilidade de manipulações na Nigéria.
Estrutura teórica: Os modelos M-score, de Beneish (1999), são empregados como base teórica para o trabalho. O modelo usa taxas financeiras calculadas usando dados contábeis para confirmar a probabilidade de que os lucros relatados das empresas sejam manipulados.
Design/Metodologia/Abordagem: O estudo utiliza dados do Nigerian Exchange Group, de 2010 a 2019, para calcular as pontuações M8/M5 e classificar as empresas em prováveis manipuladores e manipuladores improváveis. Além disso, foi aplicado um modelo de regressão probit para estabelecer rácios financeiros que predizem significativamente a probabilidade de FSF entre as empresas financeiras.
Constatações: Os resultados baseados na pontuação M8 (M5) indicam que 26,67% (23,33%) das empresas provavelmente manipulam livros financeiros e exibem a possibilidade de FSF. Além disso, apenas as vendas a receber, o crescimento das vendas, as despesas de depreciação, a alavancagem e os rácios de juros acumulados para ativos são considerados como preditores (positivos) significativos da probabilidade de manipulações.
Investigação, Implicações práticas e Sociais: O resultado implica que a sujeição das demonstrações financeiras a um controlo empírico e estatístico não deve ser ignorada, uma vez que detectaria e reduziria os riscos associados a manipulações. Por conseguinte, são necessárias mais intervenções regulamentares e uma auditoria empírica dos relatórios para garantir a sua legibilidade e fiabilidade aos investidores.
Originalidade/Valor: O estudo oferece uma nova e primeira evidência, baseada na pontuação M de Beneish, para examinar relatórios de empresas financeiras na Nigéria. Os elementos de prova asseguram a qualidade do relato das demonstrações financeiras, a fim de assegurar a credibilidade e proteger a integridade dos mercados de capitais.

Palavras-chave: Relatórios financeiros, Detecção de Fraudes, Mercado de Capitais, M-score Beneish, Modelo Probit.

ESTADOS FINANCIEROS FRAUDE DE BANCOS Y OTRAS INSTITUCIONES FINANCIERAS EN NIGERIA

RESUMEN

Finalidad: Existen pruebas de que los gestores practican prácticas oportunistas para manipular los resultados notificados con el fin de atraer a inversores desprevenidos. Este trabajo busca detectar la probabilidad de manipulaciones en los informes financieros de las empresas de servicios financieros (bancos y otras instituciones financieras), así como identificar los indicadores financieros que son los probables predictores de la probabilidad de manipulaciones en Nigeria.
Marco teórico: Los modelos de puntuación M, de Beneish (1999), se emplean como base teórica para el artículo. El modelo utiliza ratios financieras calculadas con datos contables para confirmar la probabilidad de que las ganancias reportadas por las empresas sean manipuladas.
Diseño/Metodología/Enfoque: El estudio utiliza datos del Nigerian Exchange Group, de 2010 a 2019 para calcular las puntuaciones M8/M5 y clasificar a las empresas en posibles manipuladores y manipuladores improbables. Además, se aplicó un modelo de regresión probit para establecer ratios financieros que predicen significativamente la probabilidad de FSF entre las firmas financieras.
Hallazgos: Los resultados basados en la puntuación M8 (M5) indican que el 26,67% (23,33%) de las empresas probablemente manipulan libros financieros y exhiben la posibilidad de FSF. Además, solo las ventas a cobrar, el crecimiento de las ventas, los gastos de depreciación, el apalancamiento y las ratios de devengo por activos son predictores significativos (positivos) de la probabilidad de manipulaciones.
Investigación, Implicaciones prácticas y sociales: La consecuencia del resultado es que no se debe ignorar el hecho de someter los estados financieros a un escrutinio empírico y estadístico, ya que detectaría y reduciría los riesgos asociados a las manipulaciones. Por lo tanto, se necesitan más intervenciones normativas y una auditoría empírica de los informes para garantizar su legibilidad y fiabilidad a los inversores.
Originalidad/Valor: El estudio ofrece una novedosa y primera evidencia, basada en el puntaje M de Beneish, para examinar los informes de las empresas financieras en Nigeria. La evidencia garantiza la calidad de los informes de los estados financieros con el fin de garantizar la credibilidad y proteger la integridad de los mercados de capitales.

Palabras clave: Informes Financieros, Detección de Fraudes, Mercado de Capitales, Beneish M-Score, Modelo Probit.

INTRODUCTION

Financial statement is a periodic report of a company's financial health that provides insight to stakeholders on the corporation's operations, cash flow, and overall performance. The financial statement should present company's true financial outlooks that guide shareholders and prospective investors for informed decisions. However, some managers engage in opportunistic practice to manipulate the contents in order to attract investor's funds. Financial statements fraud (FSF) involves misrepresentation of the financial states of firm through intentional distortions, omissions or misstatement of disclosures to mislead stakeholders and impact contractual outcomes in the financial markets.

FSF has been identified as a worldwide issue, particularly since the case of Xerox in 2000 which was alleged to have inflated its profits over USD1.4 billion within four year. Other exposed frauds of global corporations in the 2000's decade include Enron, Lehman Brothers, WorldCom and some notable global Banks as Bank of Montreal, Nebraska Bank, Northern Rock Bank. The largest corporate scandal implicates WorldCom and embroils an estimated loss over USD180 billion in 2002. FSF is on the top-three categories of economic fraud, alongside asset misappropriation and corruption. The Association of Certified Fraud Examiner ACFE (2022) reports that the FSF constitutes up to 8%, 10% and 11% of global common fraud scheme in the financial services in 2018, 2020 and 2022, respectively. Economic frauds in Nigeria relative to Sub-Sahara African countries accounts for about 20.60% (55/267), 16.28% (49/301) and 14.22% (61/429) cases in 2018, 2020 and 2022, respectively. The banking crises of 2002 and 2008 led to a holistic investigation by the regulators. Some banks exploited loopholes in regulations to execute insider abuse. There have been cases of bank frauds, including credit cases, overstatement of profits, and proxy fund transfers, perpetuated by management. The regulator lists 45 failed banks for various reasons, some involving FSF, between 1994 and 2006 (Central Bank of Nigeria, (CBN), 2011; 2018; Nigeria Deposit Insurance Corporation, 2022).

Recent reports indicate that the combined profit earnings of banks have increased overtime. Top 10 earners post combined profit after tax of N620.7 billion. The year 2021 shows a 19% increase, with N741.7b reported. As at March 31 2022, the top 11 banks reflect a cumulative profit after tax of N261.991 billion. Despite imminent plan to downsize by banks over increase operating costs, high inflation, low investment, and general wobbling economy, the banks' financial reports still offer impressive performance. This seeming contradiction raises suspicion on the reliability of financial reports and indicators of banks, ipso-facto, those of other financial institutions.

There is evidence that FSF can be detected and even reduced (Beneish, 1999; Nguyen & Nguyễn, 2016; Koowattanatianchai, 2018; Nguyen *et al*, 2018; Comporek, 2020; Kukreja et al., 2020; Maniatis, 2022; Andayani & Wuryantoro, 2023; Desi et al., 2023; Gbadebo et al., 2023). Efforts at fraud detection and prevention should be supported by corporate culture and ethical values that minimize fraud (Andayani & Wuryantoro, 2023). Gbadebo et al. (2023) identify that early FSF detection and good governance can reduce consistent fraud. Detecting possible fraud on financial reports is important for some reasons. First, subjecting financial statements to statistical scrutiny would detect and reduce associated risks to manipulations (Desi et al., 2023). Second, it would offer an early warning system to avert possible financial system crises. Low transparency of financial markets, complexity of financial tools and lack of proper warning signals are identified as the major causes of economics crisis (Holda, 2021). Third, it identifies the various quantifiable information of the financial institutions based on their reports examined. The financial characteristics concerning the firm's earnings information would prove useful to different stakeholders including regulators, business owners and managers, auditors, creditors and shareholders.

The study aims to verify whether banks and other financial institutions (BOFI) in Nigeria that have been reported to engage in manipulations exhibit financial features that make them different from those not dispose to financial manipulations. To do this, the study establishes the relationship between earnings indicators of firm and the likelihood to commit report manipulations by the financial institutions. We resolve three literature gaps related to the FSF of banks and other financial institutions [thereafter, BOFI] firms. First, we propose that the financial reports should be subjected to statistical analysis to detect manipulations.

We employ the Beneish-M model to detect likelihood of manipulations. We use the Beneish method to dichotomise the BOFI firms into categories of those with the likelihood to manipulate and those not inclined to manipulate. Second, we use simple univariate approach to establish, based on the distribution obtained for the M-score, evidence of significant difference between financial ratios for the likely manipulators and the unlikely manipulators. Third, we use the probit model to establish most likely financial indicators that significantly predict the likelihood of manipulations. In achieve these aims, the paper is guided by two hypotheses (a) that firms engaging in financial manipulations significantly show financial characteristics that are different from firms that are unlikely financial manipulators in Nigeria, and, (b) that financial indicators significantly predict the likelihood of manipulation for financial institutions. The paper is structured as: Section 2, 3, 4 and 5 present the literature, methods, results, and conclusions, respectively.

THEORETICAL FRAMEWORK

The Beneish model, from Beneish (1999), serves as the theoretical foundation for the study. The approach replicates a statistical model that employs financial ratios computed with periodic accounting data of 'specific' firm to confirm probability that the firms' reported earnings are manipulated. The model uses information on financial statements to construct an M-score based on either 5 or 8 financial ratios. The model is a reliable hand-on tool which adapts effectively to conditions of the financial market for forensic applications, and has become handy to researchers, auditors and regulators in detecting accounting violations (Nguyen & Nguyễn, 2016). Such forensic investigation demonstrate that accounting exerted significant effects on qualitative characteristics and enhanced financial reporting systems Desi et al., 2023). Nguyen and Nguyễn (2016) underscore that Beneish model facilitates the improvement in accounting report quality. The M-score dichotomise firms that likely misreport financials (i.e., the manipulators) and those that do likely present their true financials (i.e., the non-manipulators). The Beneish M-score is computed from either eight-equation (1) or five-equation (2) of financial ratios.

$$\mathrm{M8} = -4.840 + 0.920 * \mathrm{DSRI} + 0.528 * \mathrm{GMI} + 0.404 * \mathrm{AQI} + 0.892 * \mathrm{SGI} + 0.115 * \mathrm{DEPI} - 0.172 * \mathrm{SGAI} - 0.327 * \mathrm{LEVGI} + 4.679 * \mathrm{TATA} \quad (1)$$

$$\mathrm{M5} = -6.065 + 0.823 * \mathrm{DSRI} + 0.906 * \mathrm{GMI} + 0.593 * \mathrm{AQI} + 0.717 * \mathrm{SGI} + 0.107 * \mathrm{DEPI} \quad (2)$$

Each financial ratio components are obtained from periodic (mostly, annual) reported firms' financials as summarised in Table 1. The models (1) and (2) provide financial ratios that contain either information on the "actual distortions" of financial statements due to earnings manipulations (i.e., AQI, DEPI, DSRI, TATA) or cause the "predisposition" to engage in earnings manipulation (i.e., GMI, LEVI, SGAI, SGI). Firms with M-Score greater than a benchmark of -2.22, for 8-variable model (-2.76, for 5-variable model) are considered to probably engage in FSF (Maniatis, 2022;).

Beneish approach is useful to detect fraud for single firms (Kukreja et al., 2020; Koowattanatianchai, 2018) or for multiple combined individual firms (Nguyen et al., 2016) as well as to detect fraud between two parallel periods (Maniatis, 2022; Nguyen *et al*, 2018) and multiple periods (Comporek, 2020; Kukreja et al., 2020).

Table 1: Variables of the Beneish model

Index	Indicator	Description	Computation
DSRI	Day's Sales in Receivable Index	$DSRI$ compares firm's trade receivables to sales ratios between current (t) and previous $(t-1)$ years. $DSRI > 1$ indicates earning overstatement because an increase trade receivable owned in the current period. A monumental rise of $DSRI$ provides an indication for investigation to establish whether the credit term is modified or reports manipulated.	$= \left(\frac{\text{Receivables}_t}{\text{Sales}_t}\right) / \left[\frac{\text{Receivables}}{\text{Sales}_{t-1}}\right.$
GMI	Gross Margin Index	GMI is the ratio of gross margin of previous $(t-1)$ to current (t) year. The Gross margin, i.e., gross profit over the total income, measures the firm's profitability, while GMI is the firms' profitability prospects. A fall in gross profit is an undesirable indication firms's future prospects. A $GMI > 1$ shows decrease in firm's gross profit, hence signals a decline in firm's profit prospects and indicates earning overstatement.	$= \frac{\left[\frac{\text{Gross Mmrgin}_{t-1}}{\text{Sales}_{t-1}}\right]}{\left(\frac{\text{Gross Mmrgin}_t}{\text{Sales}_t}\right)}$
AQI	Asset Quality Index	AQI compares asset quality of current (t) to previous $(t-1)$ year. It measures the quality of a firm's non-current assets offer future benefits. A $AQI > 1$ means a decline in the asset quality. With an increase in non-current assets and deferred expenses, this condition signals earning overstatement (Beneish, 1999).	$= \frac{\left(1 - \frac{\text{CA}_t + \text{PP\&E}_t}{\text{Total assets}_t}\right)}{\left[1 - \frac{\text{CA}_{t-1} + \text{PP\&E}_{t-1}}{\text{Total assets}_{t-1}}\right]}$
SGI	Sales Growth Index	SGI is the ratio of current (t) and previous $(t-1)$ years' sales. It indicates if there is improvement the current period's sales relative to the previous. A $SGI < 1$ indicates a decrease in film's sales, while A $SGI > 1$ shows increase in firm's sales, and implies earning overstatement (Mihalcea, 2020).	$= \frac{\text{Sales}_t}{\text{Sales}_{t-1}}$
DEPI	Depreciation Index	DEPI compares the depreciation to fixed assets amount before depreciation of previous $(t-1)$ to current (t) year. A $DEPI < 1$ means an increase in the fixed assets' depreciation, but if $DEPI > 1$ decrease in firms' assets' rate of depreciation. This indicate that the level at which assets depreciated has low likelihood that the firm upwardly revised assets useful life-span. This an earning overstatement.	$= \frac{\left[\frac{\text{Depreciation}_{t-1}}{\text{Depreciation}_{t-1} + PP\&E_{t-}}\right.}{\left(\frac{\text{Depreciation}_t}{\text{Depreciation}_t + PP\&E_t}\right)}$
SGAI *	Sales, General and Administrative Expenses Index	SGAI compares selling, general, and administrative expenses to sales of current (t) and previous $(t-1)$ years. Conversely, if $SGAI > 1$ indicates an increase in the firm operation's expenses or sales' decrease. Conversely, a $SGAI < 1$ indicates decline in the	$= \frac{\left(\frac{\text{Sales., Gen. \& Adm. Exp.}_t}{Sales_t}\right)}{\left[\frac{\text{Sales., Gen. \& Adm. Exp.}_{t-1}}{Sales_{t-1}}\right.}$

		firm operation's expenses or sales' increase, and evidence of earning overstatement.	
LEVGI*	Leverage Index	LVGI compares leverage between current (t) and previous $(t-1)$ years. A $[LEVGI > 1$ $[LEVGI < 1]$ indicates increase [decrease] debt composition of assets of the firm. The $LEVGI > 1$ condition shows the potential for an earning overstatement (Mihalcea, 2020).	$= \dfrac{\left(LTD_t + \dfrac{CL_t}{\text{Total assets}_t}\right)}{\left[LTD_{t-1} + \dfrac{CL_{t-1}}{\text{Total assets}_{t-1}}\right]}$
TATA*	Total accruals to Total Assets**	$TATA$ ratio indicates the proportion of total accruals to total assets in year (t). Accrual earnings determines the extent of by which earnings is magnified through managers' discretionary decisions. Beneish (1999) notes that high TATA ratio shows potential condition of firm for earning overstatement via rise in the firms' accrual transactions.	$= \dfrac{\Delta CA_t - \Delta Cash_t - \Delta CL - \Delta Current\ maturities\ of\ LT - \Delta ITP_t - \text{Depreciation exen}}{(\text{Total assets}_t)}$

*These Indexes/Ratios are not significant in the original Beneish model (i.e., the M8), hence excluded in the M5 model.

**TATA is the only rate in the Beneish model, which is a ratio, while others are Indexes.

Note: CA_t is Current Assets; CL_t is Current Liabilities; LTD_t is Long Term Debts; ITP_t is Income TAx Payable; 〖PP&E〗_t is Plants,Properties,and Equiplments. Mihalcea (2020) dichotomises these variables as those that measure the causes of earnings manipulation {GMI, LVGI, SGAI, SGI} and those set observe to identify the effect of earnings manipulation {AQI, DEPI, DSRI, TATA}.

Source: Authors (2023)

METHODOLOGY

Models

The empirical procedure involved details in three stages, each corresponding to the study objective. To resolve the first gap, in Beneish approach to FSF, available studies adopt two procedures to dichotomise sample into manipulators and non-manipulators: (1) Some studies identify manipulators as firms issued regulatory sanctions/media release on manipulations, but the non-manipulator is the control sample without sanctions (Hołda, 2021); (2) Some studies use the computed M-score for two-year sample or 'average' M-score for multiple-year sample to compare with the benchmark (Mihalcea, 2020). We follow the second procedure and use formula in Table 1 to calculate the financial ratios. We estimate M8 and M5 of each year, for all firms. We dichotomise BOFI firms as likely financial statement manipulators (FSM/Manipulators) and the unlikely financial statement manipulators (NFSM/Non-manipulators).

To resolve the second gap, we show whether there was a significant difference between financial ratios for the likely manipulators and unlikely manipulators. We offer statistical information (basic statistics and correlation matrix) for the financial ratios and the distributions of both M8 and M5 scores for the FSM and NFSM group. We estimate the Satterthwaite-Welch t-test, Wilcoxon/Mann-Whitney test on the mean and Bartlett tests on the differences in mean, median and variance of financial ratios, respectively, based on M8.

To resolve the third gap, we employ the probit regression model to establish financial ratios that significantly predict the likelihood of FSF of BOFI firms (Koowattanatianchai, 2018). The dependent variable denotes the conditional probability to commit FSF. We discuss some diagnostic tests to establish the validity of the estimated model for policy purpose. We perform multicollinearity using the variance inflation factor (VIF), before the estimation, to confirm that the stacked financial ratios of predictors are not perfectly collinear. We select the non-collinear ratios suitable for the multivariate probit regression. We estimate the model with Maximum Likelihood Estimation (MLE) and obtain both Z-score coefficients and marginal (probability) effects of the financial ratios. We present the distribution characteristics of the estimated probabilities of manipulation for the full sample, FSM and NFSM as well as test for possible differences in mean, median and variance of estimated probabilities of manipulation.

The probit regression (eq.4) transforms dichotomy outcome, Y_t $(eq.3)$, to continuous data with a cumulative normal distribution, $\Phi(Z)$ or $(eq.5)$, that ranges between 0 and 1 (for all values of Z). We consider the linear model (3), in which Y_t is a binary variable, make transformation to estimate the Z-score (6).

$$(Y_t = 1|X_{it}; i = 1,2,..,k) = \beta_0 + \sum_{i=1}^{k} \beta_i X_{i,t} + e_t \tag{3}$$

$$P(Y_t = 1|X_{it}; i = 1,2,..,k) = \Phi\left(\beta_0 + \sum_{i=1}^{k} \beta_i X_{i,t} + e_t\right) \tag{4}$$

$$(Z) = \int_{-\infty}^{Z} \frac{1}{\sqrt{2\pi}} \exp\left(\frac{Z^2}{2}\right) dz \tag{5}$$

$$Z = \beta_0 + \sum_{i=1}^{k} \beta_i X_{i,t} \tag{6}$$

Where:

$(X_i,\ i = 1,2,..,k)$ are the predictors and since Φ is a non-linear in Z, OLS estimates would be biased, so the probit model uses the MLE. While β_i (conditional probabilities of FSF) reflects the change in Z-score due to change in X_i, the marginal (probability) effect shows the impacts of X_i on the probability of manipulation. The total marginal effects equal the combined effect of all X_i: $\left(\beta_i * \sum_{i=0}^{k} \beta_i X_t\right)$. We use probit model to establish the financial ratios that predict the likelihood of manipulation, $P(FSF)$. Beneish (1999) specifies probit model to estimate the probability that FSF equals 1.

Some studies include price index, capital formation and/or Gross Domestic Product (Anning & Adusei, 2020; Koowattanatianchai, 2018), while some include others financial characteristics such as capital to sales ratio, liquidity, overall financial conditions and/or networking capital to sales (Septiani *et al., 2*020; Repousis, 2016; Kara et al. 2015) specific to countries, industry and periods under investigation. The probit model to estimate the influence of financial ratios on the probability of FSF based on 8- and 5- variable models are respectively, equations (7) and (8).

$$P(FSF) = \alpha_0 + \alpha_1 DSRI_{i,t} + \alpha_2 GMI_{i,t} + \alpha_3 AQI_{i,t} + \alpha_4 SGI_{i,t} + \alpha_5 DEPI_{i,t} + \alpha_6 SGAI_{i,t} + \alpha_7 LVGI_{i,t} + \alpha_8 TATA_{i,t} + \varepsilon_{i.t} \quad (7)$$

$$P(FSF) = \beta_0 + \beta_1 DSRI_{i,t} + \beta_2 GMI_{i,t} + \beta_3 AQI_{i,t} + \beta_4 SGI_{i,t} + \beta_5 DEPI_{i,t} + \epsilon_{i.t} \quad (8)$$

We create dichotomous variable, $P(FSF)$, coded 1 for likely manipulators, and otherwise 0. Equation 7 (8) is based on 8 (5) variables model. $P(FSF)$, same as $P(FSF = 1|X)$, denotes the conditional probability that FSF equals one given the predictors X. X is the vector of the 8 (5) financial ratios obtained according to Table 1. The $\varepsilon_{i.t}$ [$\epsilon_{i.t}$] is residuals for the 8 [5] variables model. Each variable is expected to have positive effect on the probability of FSF. We expect all $\alpha_i's$ and $\beta_i's$ to positively impact both Z-score and the likelihood of FSF.

Data

We use annual records from the NGX and consolidated financial statements. Financial services comprise 52 amongst 161 listed firms on the record obtained. We consider firms which have completed data over the study periods (2010–2019). The period is meticulously selected taken into account that: (a) the periods show record increase in cases of FSF in Nigeria as reported by the ACFE; (b) we avoid the influence of financial crisis and the possible bias of manipulations due to the global crisis (Cimini, 2015), hence managed the study to the post-crisis periods; and (c) the year 2010 follows a number of investigations of financial institutions which led to sanctions by the regulatory body.

To assemble the final sample, we set two criteria: First, the firm reports vital financials or close proxies needed to compute variables of the Beneish M-score. Second, the firm has been listed at least a year before 2010. Under this consideration, we eliminate 10 firms majority of which began listing in 2013. We exclude 3 Insurance firms for incomplete data, for some variables. We exclude all (precisely, 9) financial services firms categorised under Bureaux-de-Change (BDCs), Development Finance Institutions (DFI's), Non-Interest Banks (NIBs) and

Payment Service Banks (PSBs) for reasons that include – the fact that the operations of some depends excessively on the central banks supply, so the main financials are difficult to manipulate. Some of the firms (e.g., Non-Interest Banks) have other motives for their establishment beyond interest profit making and hence their operations is based on principals controlled by faith and business, thus may not necessarily engage in fraudulent practice (Abubakar et al., 2020). Finally, we select a total of 30 financial firms which comprise 13 Commercial Banks, 11 Insurance firms, 3 Micro-finance Banks/Savings and Loan firms, and 3 Primary Mortgage Banks.

RESULTS AND DISCUSSION

Results

Table 2 presents the results of dichotomising the firms into likely FSM and NFSM. Firm with an average M-score less than -2.22 (-2.76) indicates no likelihood of manipulation. The evidence based on the M8 score indicates that about 26.67% firms (8 out of 30) supposedly manipulate their books, whereas the evidence based on M5 score discloses that only 23.33% (7 out of 30 firms) may exhibit the possibility of FSF. The results reveal the existence of manipulations of financial statement amongst the banks and other financial firms in the country. The correlation test in Table 3 shows that the correlations between pairs of the financial ratios are low, except for a few mention. We follow a wider coverage to present the evidence of the distribution of the variables for the likely manipulators and non-manipulators. Table 4 presents the result for the basic statistical characteristics for the full sample, manipulators and non-manipulators, as well as the test of statistical difference in the mean and standard deviation of each variable for manipulators and non-manipulators used to verify H1.

Table 2: Computation of BOFI firms M-score

BOFI	$DSRI$	GMI	AQI	SGI	$DEPI$	$SGAI$	$LVGI$	$TATA$	$M5$	$M8$
1	1.246	0.575	0.899	1.232	1.017	0.973	1.043	-0.399	-2.993	-4.187
2	1.089	1.543	0.903	1.581	0.839	1.004	1.015	0.693	-2.012*	1.586*
3	1.148	1.064	0.850	0.850	0.886	0.995	1.192	-1.249	-2.947	-8.424
4	1.105	-0.601	0.797	1.893	0.632	0.985	1.224	-0.438	-3.803	-4.676
5	1.093	0.751	1.128	1.013	0.601	1.055	1.174	-0.561	-3.026	-5.199
6	0.884	-0.952	0.901	0.995	0.818	0.977	1.106	-0.373	-4.865	-5.457
7	1.346	1.245	0.861	0.881	0.944	0.209	0.447	-0.059	-2.586*	-2.159*
8	0.685	0.230	0.887	0.914	1.120	0.514	1.077	0.184	-3.992	-2.366
9	1.088	0.588	0.798	1.009	0.849	0.977	1.229	-2.087	-3.349	-12.543
10	2.921	-0.058	0.764	1.011	1.813	1.059	1.120	-0.035	-2.342*	-1.475*
11	1.079	0.391	0.777	0.888	0.972	0.946	1.101	-1.567	-3.622	-10.280
12	0.431	1.346	0.824	1.022	0.986	0.962	1.080	0.083	-3.163	-2.504
13	0.872	1.374	0.896	0.861	0.944	1.020	0.909	-0.422	-2.853	-4.519
14	2.143	-0.862	0.884	0.938	1.217	1.000	1.058	-0.435	-3.755	-4.545

15	2.436	1.414	0.804	1.026	1.785	0.929	1.031	-0.094	-1.375*	-1.344*
16	0.658	1.256	0.866	0.999	0.941	0.973	0.931	-0.353	-3.054	-4.344
17	0.997	1.328	0.863	0.927	1.040	1.072	0.915	0.192	-2.753*	-1.512*
18	1.369	0.936	0.851	0.976	0.432	1.023	1.098	-0.353	-2.840	-4.010
19	0.543	1.010	0.851	0.963	1.238	1.016	0.949	-0.057	-3.376	-3.212
20	2.464	0.688	0.906	0.873	1.638	0.957	1.057	1.362	-2.075*	4.988*
21	2.459	-1.688	0.874	1.051	1.049	1.020	1.246	-0.114	-4.187	-3.172
22	0.631	-2.726	0.987	1.035	0.811	1.039	0.921	-0.179	-6.601	-5.600
23	1.621	-3.704	0.814	0.981	0.872	0.949	1.100	-0.462	-6.808	-6.686
24	3.130	2.680	0.966	0.994	0.807	1.043	1.064	-0.377	0.312*	-1.464*
25	0.689	0.692	0.859	0.942	1.739	0.978	1.094	-0.504	-3.500	-5.338
26	1.300	0.803	0.833	0.949	1.123	1.094	1.281	0.943	-2.973	1.899*
27	1.610	0.374	0.858	0.942	0.727	0.982	1.079	-0.501	-3.140	-4.758
28	0.682	0.710	0.934	1.340	0.413	1.023	1.091	-0.468	-3.302	-4.939
29	1.656	0.547	0.868	0.907	1.898	1.028	1.039	-0.494	-2.838	-4.478
30	1.585	-2.645	0.856	1.056	1.560	0.883	1.204	-0.382	-5.726	-5.646

Table 2 identifies firm with strong likelihood of FSF and those with less likelihood to manipulate. *Indicates manipulator (FSM): M8 [M5]>-2.22 [-2.76].
Source: Authors (2023)

Table 3: Correlation matrix for covariates

X_i	DSRI	GMI	AQI	SGI	SGAI	DEPI	LVGI	TATA
DSRI	1							
GMI	0.067	1						
AQI	-0.853**	0.541**	1					
SGI	-0.142**	0.306	0.066	1				
SGAI	0.132	0.084*	0.263	0.183	1			
DEPI	0.043	-0.014	0.017	0.004	-0.017	1		
LVGI	-0.116*	0.072	-0.022	0.104	-0.109	0.001	1	
TATA	-0.129**	0.330'	0.427*	-0.367*	0.745**	0.494	0.883	1

The * and ** indicate statistical significance at the level 1% and 5% (2-tailed).
Source: Authors (2023)

Table 4 (Panel A) presents statistical characteristics and econometric test of the financial ratios, based on the full sample, used subsequently as control variables for the probit models. The result discloses that the mean of the full sample for DRSI, SGI, DEPI and LVGI are each greater than one and SGAI which is lesser than one, all denotes possible overstatement. Table 4 (Panel B) reports the statistical characteristics as well as test of differences FSM and NFSM. FSM had a significantly higher surge in the sales in receivables, greater deterioration of gross margin and the asset quality, increase in asset depreciation, rise in sales, general and administrative expenses, and large records of accrual relative to the NFSM. This is not surprising because, as noted, sample manipulators are typically known to overstated financials by reporting fictitious, unearned revenues and improper costs.

The Satterthwaite-Welch (mean), Wilcoxon/Mann-Whitney (median) and Bartlett (variance) tests compare the distribution statistics for the FSM and NFSM. The financial conditions differ among firms inclined to FSF and those not. Although the distribution of some variables, for instance DRSI and SGI (mean test) as well as DRSI and SGI (median test) are not significant, the overall evidence supposes that the ratios are significantly different for FSM and NFSM. Notably, established correlations are low, but some few predictors of the FSF exhibit high and significant association, making us to complete the VIF multicollinearity evaluation. The test ensures that one endogenous variable required to establish the financial ratio that would significantly predict the likelihood of FSF would not accurately linearly explain the other. The results (Table 4, Panel A) indicate that no multicollinearity exists, since the highest VIF is less than 10.

Table 5 presents the MLE for the probit models. Panel A reports the coefficients α_i (β_i), which reflects the change in the Z-score due to change in the financial ratio regressor, X_i. The result shows the marginal effects which predict the impact of a change of each financial ratio on the probability of FSF. We compute the marginal effects at the mean (MEM) value of all predictors. Based on the eight predictors of the likelihood of FSF, the result indicates that six of the variables (DSRI, AQI, SGI, DEPI, LVGI and TATA) are positive and consistent with predicted expectation on their possible effects on the likelihood of FSF. An increase in these financial ratios would increase the chance of the firms to indulge in manipulations. The coefficient of GMI (-0.728) is inconsistent in its sign expectations but significant. SGAI (-0.584) is inconsistent with prediction and insignificance. This shows that decrease in financial variables may result in possible increase in FSF.

Table 4: Univariate test of equality mean and variability

X_i	μ	m	σ	μ_{Se}	$\tilde{\mu}_3$	$\tilde{\mu}_4$	Normality P_r(JB)	Multicollinearity (VIF) Uncentered	Multicollinearity (VIF) Centered
Panel A: Basic statistics and econometric tests									
DSRI	1.365	1.126	0.719	0.131	0.964	3.037	0.098	2.709	3.112
GMI	0.277	0.690	1.413	0.258	-1.270	4.203	0.007	5.259	5.990
AQI	0.872	0.862	0.070	0.013	1.630	7.305	0.000	3.297	2.833
SGI	1.035	0.987	0.220	0.040	2.646	9.909	0.000	4.576	1.154
DEPI	1.057	0.958	0.399	0.073	0.698	2.716	0.282	1.642	1.358
SGAI	0.956	0.990	0.172	0.031	-3.382	14.15	0.000	4.455	2.319
LVGI	1.063	1.079	0.153	0.028	-2.119	9.952	0.000	2.051	1.485
TATA	-0.283	-0.375	0.649	0.119	-0.182	4.989	0.078	0.449	1.735

Panel B: Basic statistics and tests of differences in statistics between FSM and NFSM

	FSM [Manipulators, N=72]			NFSM [Non-manipulators, N=198]			Null (H_0): No significant difference (two-tailed)		
							Mean	Median	Variance
X_i	μ	m	σ	μ	m	σ	SWT(t)	W/M-W	Bart.
DSRI	1.960	1.891	0.868	1.149	1.090	0.527	0.261	0.431	0.319
GMI	1.205	1.287	0.791	0.061	0.561	1.449	0.001*	0.002*	0.017**
AQI	0.903	0.862	0.063	0.855	0.863	0.073	0.031**	0.210	0.108
SGI	1.030	0.971	0.230	1.037	0.988	0.221	0.588	0.049**	0.269
DEPI	1.249	1.081	0.427	0.987	0.943	0.375	0.002*	0.028**	0.018**
SGAI	0.995	1.024	0.293	0.969	0.984	0.108	0.005*	0.016**	0.063
LVGI	0.991	1.044	0.243	1.088	1.093	0.099	0.000*	0.001*	0.269
TATA	0.328	0.078	0.604	-0.506	-0.428	0.515	0.004*	0.045**	0.053

Table 2 reports the distribution statistics [N,μ,m,σ,μ ̃_3,μ ̃_4,P_r (JB)] for each Beneish financial index, X_i (2010 – 2019). N ≡ Number of firms, μ ≡ Mean, m≡ Median, σ≡ Standard deviation, μ ̃_3 ≡ Skewness, and μ ̃_4 ≡ Kurtosis.

The P_r(JB) is the probability of the Jarque–Bera (JB) statistics to confirm normality for X_i, and VIF is the Variance Inflation Factor for Multicollinearity check. The VIF = (〖1/(1-R〗 _j^2), and R_j^2 is the coefficient of determination of the (unreported) multiple regression of one control variable j on other covariates. VIF ≥ 10 indicates the existence of multicollinearity.

SWT(t) is Satterthwaite-Welch t-test, W/M-W is Wilcoxon/Mann-Whitney, and Bart is Bartlett. Each test verify the hypothesis that the corresponding statistics indicated is equal for both the likely manipulators and Non-manipulators. * and ** indicate significance at the level 1% and 5% (2-tailed). Reported p-values offer the least likelihood to incorrectly refute the null.

Source: Authors (2023)

The coefficient of DSRI (1.427), SGI (1.589), DEPI (0.393), LVGI (0.833), and TATA (5.860) are all significant predictors of the probability of manipulation. The unusual increase in receivables by the financial firms may be due to upward manipulations of income. For the 5-variable model, the estimates show that only gross margin is inconsistent with predicted signs; and except for the asset quality, all variables are significant. This position which agrees with the second null that financial indicators significantly predict the likelihood of manipulation in Nigeria holds. The Pseudo R^2 of 97.49% and 96.56%, respectively, for equations (3) and (4), presupposes that the models had a high degree of explanatory validity. The likelihood ratio (LR) test indicates that the models have high significant power based on the χ^2 statistics (*p*-values) of 367.41 (0.000) for the 8-predictor model and 358.97 (0.000), for the 5-predictor model.

The total marginal probability effects (Untabulated), at the mean of X_i is computed as $\left(\beta_i * \sum_{i=0}^{k} \beta_i X_{i,t}/N\right)$. The combined marginal probability effects based on 8 (5) variable predictors equals 0.1778 (0.066). This means that the probability of FSF would increase by 17.78% (6.6%) with a unit increase in all the financial ratio. The 8-variable model indicate that marginal effects of GMI (-0.129) and SGAI (0.104) had negative impacts on likelihood of FSF effects. This supposes that the probability to manipulate would decrease by 12.90% and 10.4%, *ceteris paribus*, with any incremental increase in GMI and SGAI. Other variables had positive marginal effects, indicating that a unit increase in DSRI, AQI, SGI, DEPI and LVGI will increase the probability of manipulation by 25.4%, 8.9%, 28.2%, 0-07% and 14.8%. TATA had the highest marginal effect of 104.1%. For the 5-variable model, only GMI would decrease the probability of manipulation due to associated change, whereas other index would have positive incremental impacts on the probability of fraud, and change in DSRI would be expected to exhibit the highest possible influence of 16.10% on the likelihood of fraud.

Table 5 [Panel B] presents the statistics and equality tests for estimated probabilities of manipulations. Based on the 8 (5) variable model, the estimation predicts that the probability of FSF for full sample is 69.6% (66.9%), whereas the model predicted a mean of 0.879 (0.986) for the probability of FSF for manipulators and 0.325 (0.026) for non-manipulators. The Satterthwaite-Welch mean difference test with statistic -107.91 (-111.49) and Wilcoxon/Mann-Whitney median difference with statistic 13.767 (14.081) for both 8 and 5 variable estimation, respectively, is not sufficient to accept the null that predicted probabilities for FSM and NFSM are from the same distribution. Overall, the evidence discloses that the likelihood of FSF increases with abnormal increases in receivables, improvement gross margins, deteriorating asset quality, sales growth, diversified debt composition and increasing accruals.

Discussion

The results have some similarity with pioneer evidence (Mihalcea, 2020). Sales in receivable, asset quality, sales growth, depreciation expenses, leverage and accruals to assets have positive and significant influences on fraud likelihood consistent with expectation and prior studies. Unusual increase in receivables by the financial firms, for instance, due to upward manipulations of income may increase fraud likelihood. This estimate for gross margin is inconsistent with the preposition that firms with low profitability prospects exhibit greater incentives to commit fraud (Shakouria *et al.*, 2021; Alfian & Triani, 2019). The result suggests that a fall in gross profit, and undesirable indication firms' future prospects, serve as incentives for firms to manipulate. Both asset quality and The Sales, General and Administrative Expenses measures are insignificant, suggesting that they may be associated with earnings management, and not necessarily manipulations. Asset quality estimate is consistent with Beneish's observation that a change in a firm's treatment of cost deferral may increase the probability of manipulation. Shakouria *et al.* (2021) find that asset quality, depreciation index, gross margin, sales growth, sales receivable, and TATA had positive significant effect on FSF. Shakouria *et al.* (2021) show that both leverage and SGAI had significant negative impact on FSF.

Alfian and Triani (2019) note that an increase in asset realisation risk may cause cost readjustment and escalate asset capitalisation. The sales growth is consistent with fact. Growing firms may have incentives to manipulate earnings if they face slowing growth prospects. The depreciation is consistent with the fact when firms use depreciation to extend useful lives of assets, which may suppose incentives to manipulate earnings. The leverage indicates that the incentives to observe with debt obligations may not be sufficient enough to prompt manipulation. The TATA in line with manipulators had fewer cash behind income. Anning and Adusei (2020) use the probit regression and find that liquidity, leverage, profitability, change in auditor, and overall condition (Z-score) are incentives that predict the manipulation likelihood.

Septiani et al. (2020) note that in categorising the banks as manipulators or non-manipulators, DSRI, GMI, AQI, DPI, and TATA ratios prove significant. Koowattanatianchai (2018) shows that only the accruals to assets ratio significantly and positively affect FSF manipulation index in Thailand. Repousis (2016) indicates that asset quality, days sales in receivable, sales leverage, depreciation, selling, general and administrative expenses, accruals to assets proportion and gross margin index are significant on their effect frauds' prediction. However, asset quality leverage, and sales index are not statistically significant. Kara et al. (2015) discover that the ratio of working-capital to sales, networking capital to sales and logarithm of total debts are all effective in identifying fraud.

CONCLUSION

Subjecting financial reports to forensic and statistical assessment help to detect and reduce associated risks to earnings manipulations. With recent evidence of prevalence of FSF in most global banks (Septiani *et al.*, 2020), this study aims to examine reports of banks and other financial institutions in Nigeria, in order to detect the existence of manipulations as well as to identify the indicators that well predict the likelihood of manipulations. We apply the Beneish method and compute the different financial index use to dichotomise the firms into groups of likely manipulator and unlikely manipulators. Based on the distribution and average of the M-score, evidence based on M8 indicates that 26.67% (8) firms likely manipulate their books, whereas the evidence based on M5 discloses that 23.33% (7) firms exhibit the possibility of FSF. According to the financial ratio's impact, we find that only sales in receivable, sales growth, depreciation expenses, leverage and accruals to assets are the significant predictors of the probability of manipulations. The result offers sufficient proof for quantitative information to ascertain propensity for financial manipulation engagements of firms.

However, there are a few reservations to the outcome of the study, particularly on the choice of method. Because the method of fraud detection largely influences the outcomes, some authors (Comporek, 2020; Kukreja, et al., 2020) require a mild interpretation for evidence based on the Beneish model. The result would be reflected as an average approach to support auditors' assessment and FSF instruments to detect accounting violations. Despite this, Kukreja et al. (2020) note that Beneish M-score is still more reliable but less predictable of fraud relative to Altman Z-score. In addition to auditing, regulators should mandate financial firms to engage and submit report of a research-based quality assessment of their financial reports, which should be included in their statutory auditor reports. Subjecting financial reports to such scrutiny would improve the usefulness of financial information, protect investor's funds as well as build confidence in the nation's capital market and the overall financial system.

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