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FRAUD DETECTION MODELS: A Comparison between Financial Ratios Technique and Subset Logistic Regression

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ABSTRACT

The rise in corporate frauds in the wake of globalization has reflected on the confidence investors especially in recent years. This has necessitated the drive towards developing comprehensive and effective fraud detection models for the purpose of checking the excesses of managers within the books. This paper presents a comparative analysis of two separate fraud detection models; the t-test model for testing significant differences in computed financial ratios and the subset logistic regression which is a machine learning fraud detecting technique. To achieve this, emphasis is laid on all deposit money banks (DMBs) listed on the Nigerian Stock Exchange (NSE) as at December, 2019. Secondary data included fifteen financial ratios computed from the annual reports of the listed DMBs for a period of ten (10) years from 2010 to 2019. The results showed that the computation and analysis of complex financial ratios as well as the application of machine learning models like the subset logistic regression is effective for the purpose of fraud detection in financial statements. However, these models require very robust data input as they rely on fraud detection within financial data in trends and patterns over time. It is therefore recommended that in developing countries like Nigeria, the apex bank regulator alongside other regulators should encourage the use of fully standardized forensic auditing and investigation techniques to ensure that all reported financial items reflect the true economic reality of the banks.

Keywords:

INTRODUCTION

The emergence of forensic accounting has raised a lot of debates among scholars in the past few decades. Forensic accounting (also known as ***"investigative accounting"***) is the application of financial skills and investigative mentality to unresolved issues, conducted within the context of the rules of evidence. As a discipline, it encompasses fraud knowledge, financial expertise, and a sound knowledge and understanding of business reality and the working of the legal system (Ozili, 2015). Forensic accounting is the

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tripartite practice of utilizing accounting, auditing and investigative skills to assist in legal matter (Olola, 2016). It is a specialized field of accounting that describes engagements that result from litigation. Forensic accounting can, therefore be seen as an aspect of accounting that is suitable for legal review and offering the highest level of assurance. Centre for Forensic Studies (2010) report in Nigeria states that forensic accounting could be used to reverse the leakages that cause corporate failures. This can be attributed to the fact that proactive forensic accounting practice look for errors, engage in operational vagaries and deviant transactions before they crystallize into major financial frauds (Ezejiofor, Nwakoby and Okoye, 2016).

Bassey (2018) argued that the rise in financial scandals at the beginning of the 21st century was associated with increased financial fraud incidence and awareness, thereby questioning the role of auditor in fraud prevention and detection. Furthermore, the catastrophic consequences of these frauds have shown how vulnerable and unprotected the business world is in regards to this matter, since most end-damages have left the investors, employees, customers and regulatory authorities in total shock and disarray. These frauds or scandals also result in corporate collapses and deterioration of market confidence (Ngai, Yong, Wong, Chen and Sun, 2011), which is rapidly silenced by powerful high-status executives and managers, and in the end, no major prosecutions are carried out, as judgments are geared towards de-emphasizing the severity of the frauds to common managerial failures. Several accounting scandals reflect this reality, the Enron infamous case being one of the most controversial. Exposed in October 2001, this scam concluded with the bankruptcy of the company, followed by 4,500 employees who lost their jobs and pension funds, and an estimated loss of 74 billion dollars assumed by investors and stakeholders (Ezejiofor, Nwakoby and Okoye, 2016).

Financial statement frauds and other forms of corporate scandals is a worldwide problem and efforts have been made by professional accountants and legal practitioners over the years to combat these corporate ills (Ogundana, Okere, Ogunleye and Oladapo, 2018). The arguments surrounding major unanswered questions that follow the aftermaths of high corporate collapses have revealed the weaknesses in the traditional statutory audit, and has, in turn necessitated the creation of a pathway to restoring the confidence of the investors and unsuspecting public in the business world, hence, the emergence of forensic accounting. Such questions as- *What went wrong? How did things go wrong? Who are responsible? How do we detect and/or prevent these frauds?* were yet to be properly addressed until the emergence of forensic accounting in recent years.

It is important to emphasize that perpetrators of financial statement frauds (irrespective of the nature and scale of such frauds) can be motivated by personal benefits (such as maximization of compensation packages for directors), or by explicit or implied contractual obligations such as debt covenants, and the need to meet market projections and expected economic growth as can been seen in the recent Cadbury financial statement scandal in Nigeria (see, Solanke, 2007; Okaro and Okafor, 2013). Irrespective of the perpetuators' motivation, the ultimate goal is to hide the underlying performance of the entity by manipulating accounting figures and adversely selecting accounting methods that can enable the smooth implementation of their intentions. The nature of these frauds and how they are implemented usually makes it difficult for the traditional statutory auditors to effectively prevent them. In addition, Jofre (2017) argues that, given their hidden dynamic characteristics, ***"book cooking"*** accounting practices are particularly hard to detect, thus the importance of more sophisticated tools to be used to assist the early identification of risk signs and to further expose complex fraudulent schemes cannot be over-emphasized.

Although several data-informed quantitative models have been developed to automate and reduce the manual auditing processes related to false reporting identification (Bose, Piramuthu, and Shaw, 2011), but these are not sufficient to uncover complex fraudulent structures and to identify warning signs of accounting and financial statement frauds. However, since the emergence of forensic accounting and its subsequent adoption in detecting and preventing financial frauds, a lot of progress has been recorded in this regards (see Jofre, 2017; Okafor and Agbiogwu, 2016; Oyedokun, 2016; Ozili, 2015; Onodi, Okafor & Onyali, 2015; Zachariah, Masoyi, Ernest and Gabriel, 2014; and Akhidime and Uagbala-Ekatah, 2014).

Oyedokun (2016) argues that forensic accounting is a ***"Scientific Accounting"*** method of uncovering, resolving, analyzing and presenting fraud and related matters in a manner that is acceptable in the court of law. The study further conceptualized forensic accounting as the integration of accounting, auditing and investigative skills that provides evidence of frauds and how such frauds can be combatted. Forensic Accounting thus provides an accounting analysis that is suitable to the court which will form the basis for discussion, debate and ultimately dispute resolution. Forensic Accounting encompasses both Litigation Support and Investigative Accounting. Forensic Accountants, utilize accounting, auditing, investigative and legal skills when conducting investigation. They equally have ability to respond immediately and communicate financial information clearly and concisely in a courtroom setting while serving as expert witness (Oyedokun, 2016).

LITERATURE REVIEW

Corporate Fraud and the need for Fraud Detection:

The Association of Certified Fraud Examiners (ACFE) is one of the largest anti-fraud organizations responsible for providing anti-fraud training and education worldwide. In the ACFE's 2015 Fraud Examiners Manual, accounting fraud is defined as "the deliberate misrepresentation of the financial condition of an enterprise accomplished through the intentional misstatement or omission of amounts or disclosures in the financial statements to deceive financial statement users". Several synonyms of accounting fraud exist in the literature, including the so-called financial statement fraud, corporate fraud and management fraud.

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Theoretical Framework

Fraud Triangle Theory

The fraud triangle theory emphasizes the tendency to commit fraud from the perspective of ***"WHY…?"*** why do people commit fraud and ***"HOW…?"*** how are these frauds perpetrated. In 1950, Donald Cressey, a criminologist, commenced the study of fraud with an argument that there must be a reason behind the actions and decisions of people. Hence, questions such as ***"Why do people commit fraud?"*** propelled Cressey to focus his research on the drivers of trust violation, and so, he developed three drivers or factors in this regards. These three factors- ***pressure, opportunity, and rationalization*** must be present for an offense to take place. Cressey further states the following:

> ***"Trust violators, when they conceive of themselves as having a financial problem that is non-shareable and have knowledge or awareness that this problem can be secretly resolved by a violation of the position of financial trust. Also they are able to apply to their own conduct in that situation verbalizations which enable them to adjust their conceptions of themselves as trusted persons with their conceptions of themselves as users of the entrusted funds or property"*** **(Crassey 1953, p. 742).**

Therefore, the fraud triangle theory simply emphasizes three elements or drivers of fraud as summarized by Cressey; the top element represents the ***pressure*** or ***motive***- i.e. why these frauds were perpetrated, while the two elements at the bottom are ***perceived opportunity***- *i.e. how are these frauds perpetrated,* and ***rationalization***- i.e. what are the justifications for these frauds. For the purpose of the study, the fraud triangle theory is used to support the assumptions that corporate fraud prevention through the provision of forensic litigation supports goes beyond establishing that a fraud has committed. The whole process of forensic audits and investigations, fraud data collection, fraud data mining and fraud evidence presentation is geared towards providing acceptable evidence reports on such key areas that are necessary for drawing valid conclusions in legal proceedings, including establishing ***pressure*** or ***motive***- i.e. why these frauds were perpetrated, while the two elements at the bottom are ***perceived opportunity***- *i.e. how are these frauds perpetrated,* and ***rationalization***- i.e. what are the justifications for these frauds. Therefore, if enough evidence is presented by the forensic auditors to support the litigation claims in a court proceeding relating to corporate fraud, their reports can be used as ***"Expert Witness"*** to support further prosecutions.

Empirical Review:

This study is set to apply two separate fraud detection models to the same sample in order to compare the outcome of each model. The first model- i.e. the t-test model captures the outcome of the financial ratios as a fraud detection technique through ratios analysis and interpretation, while the second model- i.e. the subset logistic regression captures the outcome of the financial ratios as a fraud detection technique using machine learning methods. Prior studies on these models are hereby highlighted in paragraphs below.

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Financial Ratio Analysis for Fraud Detection

The financial analysis technique is based on the assumption that relatively stable relationships are expected to exist among economic events- in the absence of conditions to the contrary. These known contrary conditions that cause unstable relationships to exist might include unusual or non-recurring transactions or events, usually relating to accounting, environmental, or technological changes. However, listed firms experiencing these events are required (by existing laws and standards) to make disclosures. Studies providing evidence on the effectiveness of financial analysis techniques in detecting underlying financial statement frauds; these studies are hereby summarized herein.

Ongoro (2018) provides evidence on the topic *"The Use of Financial Ratios in Detecting Fraudulent Financial Reporting: The Case of Companies Listed on the Nairobi Securities Exchange*". The study investigated the use of financial ratios in detecting fraudulent financial reporting (FFR) among companies listed on the Nairobi Securities Exchange by determining whether selected financial ratios of fraudulent firms differed from those of non-fraudulent firms. Stepwise logistic regression was used and the result revealed that profitability ratios, asset composition ratios, earnings quality ratios, management quality ratios and liquidity ratios were found to be significant in detecting FFR. Similarly, Agbaje and Oloruntoba (2018) also carried out a study on *"An Assessment of Impact of Financial Statement Fraud on Profit Performance of Manufacturing Firm in Nigeria: A Study of Food and Beverage Firms in Nigeria"* focusing on the use of financial ratios to assess financial statement fraud and how these ratios affect profitability in the long run. The findings of the analysis revealed that there is a significant relationship between financial statement fraud and profitability in Nigerian manufacturing industry. The authors further emphasized the importance of financial ratios in achieving their objectives.

The study Ragab (2017) contains evidence on *"Financial Ratios and Fraudulent Financial Statements Detection: Evidence from Egypt"*. This study aimed to identify which financial ratios are significant to detect fraudulent reporting. Using a sample of 66 companies in Egypt, this study tests twenty five financial ratios based on studies that examined financial ratios indicative capabilities. Only three ratios were included in Logistic regression model. The model correctly classified fraud and non- fraud financial statements approximately 66.4%. The study concludes that financial ratios have the ability the occurrence of Fraudulent Financial Statements.

Oriko (2016) also carried out a study on *"The Power of Financial Ratios in Detecting Fraudulent Financial Reporting at the Nairobi Securities Exchange"*. The study aimed at proving that the financial ratios currently computed by listed companies at the Nairobi Securities Exchange may not assist users of the financial reports towards detection of fraudulent financial reports; other ratios can bring to light possible fraud. The results at different levels of this study indicate that the best financial ratios able to bring to light fraudulent financial statements are; Financial Investment/Total Assets Ratio; TO/TA = Total Operating Expenses/Average Total Assets; WC/TA = Working Capital/Total Assets;

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CF/NP = Cash Flow/Net Profit; NP/TA = Net Profit/Total Assets; and, DIV = Dividend Return Ratio. In another study, Somayyeh (2015) focused on comparing financial ratios between fraudulent and non-fraudulent firms and a sample of 134 companies listed on the Tehran Stock Exchange was used. Data consist of financial ratios computed from the financial statements of the selected firms over a period of 6 years. The results revealed that there is a significant difference between the mean of computed financial ratios between the various groups of firms as identified above.

Kanapickiene and Grundiene (2015) conducted a study on the topic *"The Model of Fraud Detection in Financial Statements by Means of Financial Ratios".* The authors identified and analyzed of financial ratios as one of those simple methods to identify frauds. The authors' theoretical survey revealed that, in scientific literature, financial ratios are analyzed in order to designate which ratios of the financial statements are the most sensitive in relation with the motifs of executive managers and employees of companies to commit frauds. This finding places the use of financial ratios as the first, simple but effective means of detecting early signs of financial frauds.

In another study by Dalniala, Kamaluddin, Sanusia and Khairuddina (2014) which aimed to investigate whether there are any significant differences between the means of financial ratios of fraudulent and non-fraudulent firms and to identify which financial ratio is significant to detect fraudulent reporting. The sample comprised of 65 fraudulent firms and 65 samples of non-fraudulent firms of Malaysian Public Listed Firms. The study found that there are significant mean differences between the fraud and non-fraud firms in ratios such as total debt to total equity, account receivables to sales. Although a similar study by Radziah, Politeknik and Negeri (2013) provided earlier evidence by examining financial ratios as a tool to discriminate fraudulent financial statements (FFS). The results show that all the financial ratios have significant relationships with FFS except for Gross Profit-to-Assets ratio, percentage of Inventory-to-Total Assets, Gross Margin Index and Z-Scores.

Following the literatures discussed in relation to fraud detection using the financial ratios analysis, this study hereby propose the null hypothesis that:

***HO_1:** Financial ratios analyses are not effective for fraud detection in financial statements*

Machine Learning and Fraud Detection and Prevention

Machine learning models are also used by forensic auditors as techniques to discover and analyze patterns in large data sets involving methods at the intersection of machine learning, statistics, and database systems. The extant literature has provided evidence on the effectiveness of machine learning techniques for detecting financial anomalies (or frauds) in financial statements. Some of the recent related studies are summarized herein;

Minastireanu and Mesnita (2019) carried out a study on *"An Analysis of the Most Used Machine Learning Algorithms for Online Fraud Detection"*. The study reviewed the existing literature on fraud detection with the aim of identifying algorithms used and analyzes each of these algorithms based on certain criteria. Findings revealed highlights, in a new way, emphasizing that the most suitable techniques for detecting fraud by combining three selection criteria: accuracy, coverage and costs.

In another study, Mohanty, Thakur and Manju (2019) while investigating *"Enron Corpus Fraud Detection"* aimed to identify the person of interest based on the email data from the Enron corpus which is made public for research. Fraud detection is done using artificial neural network (ANN) and Adam optimizer and ReLU activation functions which is a machine learning approach. The study devised a method that can be implemented on accounting data of an organization, company or firm to identify the individuals susceptible of committing fraudulent activities by manipulating the financial statements to mislead the investors and shareholders. This ultimately aimed to reduce the losses suffered by the investors and shareholders by detection of various fraudulent entities in the given organization

Jan (2018) also investigated *"An Effective Financial Statements Fraud Detection Model for the Sustainable Development of Financial Markets: Evidence from Taiwan".* The study takes 160 companies (including 40 fraudulent companies) to evaluate multiple data mining techniques including ANN and SVM. Also four types of decision trees (classification and regression tree (CART), chi-square automatic interaction detector (CHAID), C5.0, and quick unbiased efficient statistical tree (QUEST)) were used in this study. The results of this study show that the ANN+CART model yields the best classification results, with an accuracy of 90.83% in the detection of financial statements fraud.

Decunha (2018) carried out a study on *"Fraud Detection - A Machine Learning Approach"*. The study describes a machine learning approach to fraud detection within the Enron Corpus data set. Two predictive models are trained to the task of identifying persons of interest within the data set. Finally, it is concluded that machine learning is not only a viable approach to fraud detection, but it is quite well adjusted to the task. Both classifiers achieve an acceptable level of accuracy, precision and recall for the given task of differentiating fraud cases from non-fraud cases. It is concluded that any company with a dedicated fraud detection team trained in machine learning should be able to detect fraud at an extremely high degree of accuracy.

Gerlach and Jofre (2018) carried out a study on *"Fighting Accounting Fraud through Forensic Data Analytics"*. Accordingly, the study aimed to improve the detection of accounting fraud via the implementation of several machine learning methods to better differentiate between fraud and non-fraud companies, and to further assist the task of examination within the riskier firms by evaluating relevant financial indicators. From the sample used in the study, the results suggest that there is a great potential in detecting falsified financial statements through statistical modeling and analysis of publicly available accounting information.

Sharma and Panigrahi (2012) investigated the topic *"A Review of Financial Accounting Fraud Detection based on Data Mining Techniques"*. The authors argue that data mining techniques are providing great aid in financial accounting fraud detection, since dealing with the large data volumes and complexities of financial data are big challenges for forensic accounting. This paper presents a comprehensive review of the literature on the

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application of data mining techniques for the detection of financial accounting fraud and proposes a framework for data mining techniques based accounting fraud detection. The findings of this review show that data mining techniques like logistic models, neural networks, Bayesian belief network, and decision trees have been applied most extensively to provide primary solutions to the problems inherent in the detection and classification of fraudulent data.

Following the literatures discussed in relation to fraud detection using the financial ratios analysis, this study hereby propose the null hypothesis that:

HO_2: *Machine learning models are not effective for fraud detection in financial statements*

RESEARCH METHODOLGY

In light of the objectives of this study, the survey ex-post facto research design is applied throughout the study. This was facilitated by the need to collect past financial data from pubic available annual report of selected firms that will be used to calculate the required ratios. To achieve this, emphasis is laid on all deposit money banks (DMBs) listed on the Nigerian Stock Exchange (NSE) as at December, 2019. Secondary data were obtained from the annual reports of the listed DMBs for a period of ten (10) years from 2010 to 2019. These data are raw financial items used to compute fifteen (15) general and bank-specific financial ratios required for further analysis in this study.

Model Specification:

This study adopts two models following the respective tests required for each fraud detection technique and the hypothesis formulated in the earlier section. These models are;

1. T-test Model (Financial Ratios Analysis and Interpretation Technique)

The t-test model focuses on testing the significant difference (if any) between two supposedly different population means. The computed financial ratios will provide the basis for separating the selected banks into two different groups or populations, that is, *Non-Fraudulent Banks* and *Fraudulent Banks*. The t-test model is given as follows;

$$\boldsymbol{t} = \frac{\widehat{\boldsymbol{x}}_{\mathbf{1}} - \widehat{\boldsymbol{x}}_{\mathbf{2}}}{\sqrt{\left(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}\right)}}$$

Where $\widehat{\boldsymbol{x}}_{\mathbf{1}}\, and\, \widehat{\boldsymbol{x}}_{\mathbf{2}}$represents the sample mean, $\boldsymbol{s}_{\mathbf{1}}^{\mathbf{2}}$ and $\boldsymbol{s}_{\mathbf{2}}^{\mathbf{2}}$ is the sample variance and $\mathbf{n_1}$ and $\mathbf{n_2}$ is the sample size. Also, sub-1 makes reference to Non-Fraudulent banks and sub-2 to Fraudulent banks. The t-test model will be used to test the effectiveness of the financial ratios analysis and interpretation techniques in detecting frauds in financial statements. Therefore, the following hypotheses are specified:

$H0_1$: $\mu_1 = \mu_2$ *(Accept null hypothesis)*
$H0_2$: $\mu_1 \neq \mu_2$ *(Reject null hypothesis)*

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Where the $\boldsymbol{\mu_1}$ and $\boldsymbol{\mu_2}$ are not equal as specified by ***(H0₂: μ₁≠ μ₂)***, this means that the mean of Non-Fraudulent banks is significantly different from the mean of Fraudulent banks for the respective financial ratios, and the implication of this is to reject the null hypothesis.

2. Subset Logistic Regression Model (Machine Learning Technique)

Logistic regression is a technique for analyzing problems in which there are one or more independent variables that determine a dependent variable (outcome). In most cases, the dependent variable is a dichotomous variable (in which there are only two possible outcomes).

$$\sigma(x) = \frac{1}{1 + \exp(-x)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (\mathrm{I})$$

The goal of logistic regression is to find the best fitting model to describe the relationship between the dichotomous characteristic of interest (dependent variable) and a set of independent (predictor or explanatory) variables. Logistic regression generates the coefficients (and its standard errors and significance levels) of a formula to predict a logit transformation of the probability of a presence of the characteristic of interest:

$$\mathbf{Logit}\ (\mathbf{P}) = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + L + b_iX_i \ldots\ldots\ldots (\mathrm{II})$$

Where P is the probability of the presence of the characteristic of interest and bi is the regression coefficient for X_i, while X1….Xi represent the computed financial ratios. Mathematically, logistic regression uses a maximum likelihood estimation procedure rather than the least squares estimation procedure that is used in linear regression. The logit transformation is defined as the logged odds:

$$\mathbf{Odds} = \frac{\mathbf{P}}{\mathbf{1-P}} = \frac{\textbf{Probability presence of the characteristics}}{\textbf{Probability absence of the characteristics}} \ldots\ldots (\mathrm{III})$$

$$\mathbf{Logit}\ (\mathbf{P}) = \mathbf{Ln}\ \left[\frac{\mathbf{P}}{\mathbf{P-1}}\right] = b_0 + b_iX_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (\mathrm{IV})$$

Where P is the probability that the event **Y** occurs, **P=(Y=1)**; **P/(1-P)** is the “odds ratio”; and **Ln [P/(1-P)]** is the log odds ratio or **“logit”**. The equation may also be inverted to give an expression for the probability **P** as;

$$\mathbf{P(X)} = \frac{1}{1 + \exp[-(b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + L + b_iX_i)]} \ldots\ldots\ldots\ldots\ldots (\mathrm{V})$$

Where:

P(X): Probability of outcome X
X: Actual outcome of being Fraud of Non-Fraud
X_1-X_i: Predictor variables (i.e. computed financial ratios)
Odds ratio (OR) = exp(b)

For the purpose of this study, the logistic regression will used to test the effectiveness of machine learning techniques in detecting and preventing frauds in financial statements. To finally decide if an observation is classified as fraudulent or non-fraudulent, and then a threshold of 0.05 will

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be considered. Consequently, the predefined decision rules implemented in this case are the following:

If X≥ 0.5, then FRAUD
If X≤0.5, then NO-FRAUD

RESULTS AND DISCUSSION

Data Collection and Preparation:

Table 1: Summary of Financial Ratios used as Explanatory Variables

PROFITABILITY		LEVERAGE/DEBT		EFFICIENCY		LIQUIDITY	
Ratio	Definition	Ratio	Definition				
-NITA -RETA -EBITTA -NISE	*-Net Income to Total Assets* *-Retained Earnings to Total Assets* *-Earnings Before Interest and Tax to Total Assets* *-Net Income to Shareholder Equity*	-TDTA -TDTE -LTDTA -T1CTA	*-Total Debts to Total Assets* *-Total Debts to Total Equity* *-Long Term Debt to Total Assets* *-Tier-1 Capital to Total Assets*	-CAR -NPLR -MER	*-Capital Adequacy Ratio* *-Non-Performing Loan Ratio* *-Management Efficiency Ratio*	-LCR -NSFR -CCNI -CFFONI	-Liquidity Coverage Ratio -Net Stable Funding Ratio -Cash and Cash Equivalents to Net Income -Cash Flow from Financing to Net Income

Source: Author's Classification

All fifteen (15) financial ratios listed on Table 1 were computed from the annual reports of the selected banks for the period considered. These financial ratios were transformed to averages for the study periods and will be used to rate and classify each bank as either ***"Non-fraudulent"*** *or* ***"Fraudulent"*** *as* shown on Table 2 to 5 estimate the both models. The rule of thumb for each ratio was used to rank the respective banks.

Table 2: Summary of Banks' Average Scores and Ratings for Profitability Ratios

S/N	BANKS	NITA		RETA		EBBITA		NISE	
		Avg.	Rating	Avg.	Rating	Avg.	Rating	Avg.	Rating
1	ACCESS	0.6415	0	0.5659	0	0.0737	0	0.5961	1
2	ECO	0.8067	1	0.2637	1	0.0678	0	0.5032	1
3	FIDELITY	0.8211	1	0.3391	1	0.0267	1	0.0133	0
4	GTB	0.5017	0	0.4731	0	0.0481	1	0.0241	0
5	STERLING	0.6166	0	0.5958	0	0.0639	0	0.3166	0
6	UBA	0.3369	0	0.3169	1	0.0737	0	0.0369	0
7	UNION	0.7946	1	0.6736	0	0.0413	1	0.6160	1
8	UNITY	0.2790	0	0.2469	0	0.0749	0	0.0704	0
9	WEMA	0.4381	0	0.2079	1	0.0447	1	0.1373	0
10	ZENITH	0.6551	0	0.6051	0	0.0362	1	0.3506	0

Source: *Computed from Annual Reports of the Selected Banks, 2010-2019*

In the case of Leverage, we also selected four special ratios. We expected high profitability ratios from banks with high equity base and large asset base. However, it will be fraudulent for the purpose of this study when abnormally high profitability is not accompanied by increasing equity base or asset base.

Table 3: Summary of Banks' Average Scores and Ratings for Leverage/Debts Ratios

S/N	BANKS	TDTA		TDTE		TLDTA		T1CTA	
		Avg.	Rating	Avg.	Rating	Avg.	Rating	Avg.	Rating
1	ACCESS	0.1536	0	0.2291	0	0.1494	0	0.1606	1
2	ECO	0.5400	1	0.6856	1	0.2764	1	0.2374	0
3	FIDELITY	0.5080	1	0.4180	0	0.4916	1	0.3983	0
4	GTB	0.1321	0	0.1311	0	0.1214	0	0.1778	1
5	STERLING	0.5090	1	0.6090	1	0.2779	1	0.2484	0
6	UBA	0.1490	0	0.2590	0	0.1303	0	0.1370	1
7	UNION	0.5438	1	0.6038	1	0.2409	1	0.2227	0
8	UNITY	0.1179	0	0.1137	0	0.0975	0	0.0889	1

9	WEMA	0.1415	0	0.6638	1	0.1310	0	0.1354	1
10	ZENITH	0.0445	0	0.0645	0	0.0390	0	0.2415	0

Source: *Computed from Annual Reports of the Selected Banks, 2010-2019*

Here we expected a positive ratio from all the selected banks across all the leverage ratios, and we are looking out for high leverage ratios which indicates high (and maybe uncontrollable) debts as signs of underlying poor performances and fraud tendencies.

Table 4: Summary of Banks' Average Scores and Ratings for Efficiency Ratios

S/N	BANKS	CAR		NPLR		MER	
		Avg.	Rating	Avg.	Rating	Avg.	Rating
1	ACCESS	0.4247	0	0.0445	0	0.4991	1
2	ECO	0.4803	0	0.3085	1	0.2488	0
3	FIDELITY	0.0990	1	0.3092	1	0.2866	0
4	GTB	0.1026	1	0.0428	0	0.1836	0
5	STERLING	0.3861	0	0.1321	0	0.5067	1
6	UBA	0.1122	1	0.0634	0	0.1631	0
7	UNION	0.2378	0	0.1490	0	0.8051	1
8	UNITY	0.0833	1	0.3825	1	0.5010	1
9	WEMA	0.1179	1	0.3179	1	0.5056	1
10	ZENITH	0.3351	0	0.1780	0	0.1378	0

Source: *Computed from Annual Reports of the Selected Banks, 2010-2019*

For efficiency ratios, we expect a positive ratio in the case of CAR, NPLR and MER. For the purpose of this study, we assume that fraudulent banks are likely to reveal poor and inconsistent efficiency ratios, especially when compared to industry averages.

Table 5: Summary of Banks' Average Scores and Ratings for Leverage/Debts Ratios

S/N	BANKS	LCR		NSFR		CCNI		CFFONI	
		Avg.	Rating	Avg.	Rating	Avg.	Rating	Avg.	Rating
1	ACCESS	0.7044	0	0.4803	0	3.6214	0	0.5400	0
2	ECO	0.2456	1	0.1142	1	0.0940	1	0.1298	1
3	FIDELITY	0.3385	1	0.3861	0	1.7428	0	0.5090	0
4	GTB	0.5013	0	0.2378	0	0.8445	1	0.2095	0
5	STERLING	0.2942	1	0.4247	0	2.1912	0	0.1536	1
6	UBA	0.5063	0	0.0990	1	1.5597	0	0.2080	0
7	UNION	0.2986	1	0.3351	0	0.6073	1	0.0445	1
8	UNITY	0.3360	1	0.1002	1	1.1772	0	0.2878	0
9	WEMA	0.3013	1	0.1056	1	3.7972	0	0.1470	1
10	ZENITH	0.7492	0	0.2276	0	1.0476	0	0.4131	0

Source: *Computed from Annual Reports of the Selected Banks, 2010-2019*

We expected a positive relationship in the case of LCR, NSFR, CCNI and CFFONI. For the purpose of this study, we assume that fraudulent banks are prone to liquidity problems especially in the areas of meeting their core banking operations.

RESULTS AND DISCUSSION

T-test Result:

The first objective of this study is to test the effectiveness of financial ratios analysis and interpretation for fraud detection in financial statements. All relevant information of the testing approach is presented, including the sample mean, sample standard deviation and the sample size of each group, as well as the corresponding t-statistics, degrees of freedom and p-values for all selected financial ratios. The result is hereby presented below;

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Table 6: T-tests for the Difference in the Mean of Non-Fraud and Fraud Firms for the 15 Financial Ratios

	Mean*		Standard Deviation*		Sample Size		t-stat**	Degrees of Freedom	p-value (two-tailed)
	Non-Fraud	Fraud	Non-Fraud	Fraud	Non-Fraud	Fraud			
NITA	0.4956	0.8075	0.4472	0.3873	70	30	0.1172	1.5	0.0064
RETA	0.5267	0.2819	0.4124	0.7229	60	40	-2.6184	8.8	0.0099
EBITTA	0.0708	0.0394	0.2514	0.2206	50	50	-0.7767	7.5	0.0615
NISE	0.1356	0.5718	0.4581	0.2068	70	30	-1.3648	4.0	0.0023
TDTA	0.1231	0.5252	0.6623	0.3381	60	40	-9.4689	2.3	0.0000
TDTE	0.2026	0.6406	0.1750	0.4467	60	40	-5.9906	3.6	0.0180
LTDTA	0.1114	0.3217	0.3953	0.3587	60	40	-2.3173	2.7	0.0206
T1CTA	0.2697	0.2699	0.3116	0.2894	50	50	-4.2537	1.4	0.0000
CAR	0.3728	0.1030	0.2358	0.8209	50	50	8.4075	3.1	0.0000
NPLR	0.1016	0.3295	0.2324	0.7837	60	40	1.8523	2.0	0.0341
MER	0.2040	0.5635	0.9141	0.5945	50	50	0.9936	4.0	0.0259
LCR	0.6153	0.3024	0.2736	0.3945	40	60	5.1082	2.7	0.0000
NSFR	0.3486	0.1048	0.1435	0.1565	60	40	-5.1946	3.8	0.0000
CCNI	2.1624	0.5153	0.2212	0.2286	70	30	-3.2283	2.9	0.0013
CFFONI	0.3612	0.1187	0.1332	0.5998	60	40	9.5354	2.3	0.0000

Notes:
The ratios are reported in four decimal places,
Two-sample t test with unequal variance

A complete analysis of financial ratios has been performed. First, the use of ratios as explanatory variables of accounting fraud is justified along with the definition of 15 financial ratios constructed on the basis of specific items of financial statements, and this provided the basis for classifying the selected bank as either Fraudulent or Non-Fraudulent for each financial ratio used. Then, the Two Sample T-test was applied to assess the significant differences between the respective means of Fraudulent and Non-Fraud banks for each financial ratio. The results obtained from hypothesis testing reveals a significant difference between the financial ratios computed for fraudulent and for non-fraudulent banks; except that further review of the results reveals that, with respect to the two sample t-test, the EBITTA ratio showed that the difference between the sample means of both fraudulent banks and non-fraudulent banks is not significant at 5%, while the T1CTA ratio showed that there is no significant difference between the mean of both groups. However, On the basis of the above results obtained, we hereby reject the hypothesis that financial ratio analysis and interpretation techniques are not effective in detecting and preventing frauds in financial statements.

Subset Logistic Regression Result:

The second objective of this study is to test the effectiveness of machine learning methods such as the subset logistic regression model for fraud detection in financial statements. As discussed earlier, the subset logistic regression is a simple binary outcome model which is considered to be the foundational scheme for detecting accounting fraud since the aim is to classify future observations into only two possible values: *Fraud* or *Non-Fraud*. This study produced a subset logistic regression result from an independently conducted analysis that combines all thirteen (13) computed financial ratios from the ten (10) selected deposit money banks employed in this study. These results are hereby presented below.

Table 7: Subset Logistic Regression Result for all Deposit Money Banks (DMBs)

TABLE 7: CSLR classification accuracy - All DMBs

Sample Size (n): 100

K	Accuracy	Specificity	Sensitivity	Precision	G-Mean	F-Measure	AUC
NITA	0.781	0.898	0.836	0.833	0.782	0.651	0.657
RETA	0.874	0.764	0.789	0.843	0.521	0.643	0.667
EBITTA	0.939	0.855	0.756	0.884	0.725	0.630	0.660
NISE	0.879	0.655	0.756	0.984	0.625	0.630	0.860
TDTA	0.779	0.673	0.747	0.920	0.628	0.627	0.660
TDTE	0.862	0.866	0.741	0.913	0.635	0.627	0.663
LTDTA	0.799	0.988	0.733	0.841	0.733	0.623	0.660
T1CTA	0.549	0.655	0.756	0.884	0.525	0.530	0.540
CAR	0.941	0.794	0.731	0.843	0.837	0.623	0.762
NPLR	0.928	0.992	0.726	0.821	0.734	0.620	0.759
MER	0.896	0.596	0.709	0.812	0.723	0.608	0.848
LCR	0.903	0.768	0.720	0.827	0.829	0.615	0.854
NSFR	0.871	0.598	0.716	0.825	0.627	0.613	0.752
CCNI	0.801	0.796	0.707	0.846	0.829	0.610	0.752
CCFONI	0.871	0.690	0.701	0.915	0.730	0.607	0.851

Source: Stata Output, 2020

Overall Accuracy: it measures the ability to differentiate both fraudulent and genuine observations correctly. For all ratio considered, the model is able to accurately differentiate both fraudulent and genuine ratios included with high accuracy metrics above 70% for all observations except for T1CTA ratio with an accuracy metric barely above 50%.

Specificity: it evaluates the ability to determine non-fraudulent cases correctly. For all ratio considered, the model is able to correctly classify non-fraudulent ratios with specificity metrics of 60% or more for all ratios considered.

Sensitivity: it assesses the capacity to classify fraudulent cases correctly. The sensitivity metric for all ratios considered is not below 70%. This simply indicates that all ratios considered have the capacity to classify fraudulent cases using subset logistic regression model.

Precision: it measures the predictive power of the model. The result summarized on Table 4 shows that the model generally has a high predictive power as the relationship between the true positive cases and the predicted positive cases are accurately predicted at precision levels higher than 80%.

Area under the Curve (AUC): The AUC is the probability that the binary classifier will rank a randomly chosen positive instance higher than a randomly chosen negative one. As such, AUC is always a positive number range between 0 and 1, so the closer to the unit, the better is the model as it means it is correctly separating instances into the non-fraud and fraud groups. From the results obtained, all selected ratios showed AUC metrics higher than 65% except for the T1CTA ratio with AUC metric of 54%.

In summary, the overall result summarized on Table 7 simply confirms the effectiveness of machine learning models such as the subset logistic regression model for identification and classification of fraudulent and non-fraudulent cases with regards to pre-calculated financial ratios. The subset logistic regression like other machine learning models helps to identify and classify both fraudulent and non-fraudulent patterns in a set of financial data. When the resulting metrics are low for a given financial ratio, the implication is that such ratio considered unfit for fraud prediction.

Financial Ratios Analysis and Interpretation vs. Subset Logistic Regression

The determination of suspicious patterns or questionable trends in a set of financial data highly sophisticated financial ratios is the simplest form of fraud detection that has been used over the years. It relies on the relationship between financial data in trends and across section over time. In this study, efforts were made to classify the selected banks based on their performance as revealed by the ratios computed. However, in the case of subset logistic regression, further classification is done by the model in order to test the predictive and detective power of each financial ratio. Unlike the T-test model that focuses on the difference between two data sets with respect to certain variables- i.e. ratios, the subset logistic regression model focuses on the data set as a whole, but measures the significance of the selected variables for fraud detection using certain predefined metrics as discussed above.

CONCLUSION AND RECOMMENDATIONS

Conclusion

Following the results obtained and discussed in the previous paragraph, it is pertinent to state in conclusion that the computation and analysis of complex financial ratios as well as the application of machine learning models such as the subset logistic regression is effective for the purpose of fraud detection in financial statements. However, these models require very robust data input as they rely on fraud detection within financial data in trends and patterns over time.

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Recommendations

i. It is recommended that management and owners of banks should embrace forensic audits as part of the drive towards ensuring transparency and credibility of financial reports.
ii. This study also recommends especially for developing countries like Nigeria, that the apex bank regulator alongside other regulators should review their techniques for examining the financial statements of banks from time to time. This will involve the use of fully standardized forensic auditing and investigation techniques to ensure that all reported financial items reflect the true economic reality of the bank.
iii. Finally, the Nigerian government should provide the enabling environment for forensic accounting profession to thrive in the country by strengthening the legal, educational and political framework of the field in the country. Forensic accounting and audits should become a critical part of the field of accounting in Nigeria, as this will complement the efforts of statutory auditors.
iv. It is important for potential investors and other members of the general public to employ the services of forensic auditors to comprehensively investigate the publicly available financial figures of firms they are interested in, or look out for forensic audit evidences in an on-going court proceeding relating to specific firms that want to invest in, as this will provide them with deeper insights about the firm's well-being.
v. This study also recommends advanced training in the application of forensic auditing and investigation techniques for professional accountants and auditors in Nigeria. The auditors must be well capacitated materially and technically to improve their effectiveness in this regards.
vi. Finally, the Nigerian government should provide the enabling environment for forensic accounting profession to thrive in the country by strengthening the legal, educational and political framework of the field in the country. Forensic accounting and audits should become a critical part of the field of accounting in Nigeria, as this will complement the efforts of statutory auditors.

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