IJEBM Vol:2, Issue:2 (2026), Pages 248- 261
ISSN: 3079-4218

Firm characteristics and fraud detection in the Nigerian first banks using Beneish model

[1]Joseph Adeyinka Adewole, [2]Abass Adekunle Adewale, [3]Kayode Joseph Oluwayemi, [4]Kayode Ibrahim Kadiri & [5]Ebenezer Foluso Oluwakayode

[1] (Ph.D), Department of Banking and Finance, Osun State University, Osogbo, Osun-State, Nigeria,
Email: joseph.adewole@uniosun.edu.ng
[2] Department of Finance, Federal University, Oye, Ekiti-State, Nigeria.
[3] Department of Finance, Adekunle Ajasin University, Akungba-Akoko, Ondo-State, Nigeria.
[4] (Ph.D), Department of Business Administration, National Open University, Nigeria
[5] Department of Accounting, Osun State University, Osogbo, Osun-State, Nigeria.

Abstract

It has described the connection amidst firm characteristics and Deposit Money Banks fraud detection in First Bank Plc through the use of Beneish model approach. Fraudsters keep developing new strategies of taking advantage of the gaps in the current detection mechanisms, and it is difficult to keep pace with new risks that DMBs face. The financial system is so intertwined that any fraudulent activity that takes place at First Bank may spread to the rest of the banking firm and the whole economy. Objectives of this study included the investigation of the association between firm size and fraud detection in first bank, the investigation of the association between financial performance and fraud detection in first bank as well as to determine the association between financial structure and fraud detection in first bank. The annual financial statement of the Nigerian First Bank Plc was used as the source of data. The result indicated that correlation coefficient has a strong positive relationship and insignificant among the group of independent variables (loan-to- asset ratio, and returns-on- assets, total-assets, equity ratio, total deposits, debt-to-equity ratio, total loans, and returns on equity) and the dependent variable (Fraud Detection). This research suggests that Nigerian First Bank Plc needs to improve its internal control processes, especially in bigger companies where the fraud may be so hidden by the complexity of the operations. To facilitate the detection of fraud, the bank needs to come up with more advanced financial performance monitoring systems. An optimized financial structure deserves to be kept with balanced leverage and equity ratios as it is more likely to lower the exposure to fraudulent activities.

Keywords: Firm characteristics, Fraud detection, Beneish model approach

Introduction

Banking firm of Nigeria is an essential part of the flow of funds in the country and contributes immensely to the expansion of economy. Although this is vital, the industry has been marred with fraud and financial scandals that have diminished the confidence of investors and the financial stability (Owolabi, 2019). As the first bank of Nigeria PLC, it is one of oldest and biggest DMBs in Nigeria, and it has a wide market presence and impact on the Nigerian banking practices. Any fraud in First Bank may have far-reaching effects on the whole financial system (Owolabi, 2019). DMBs are a significant part of financing the population and directing the funds to the productive spheres; they provide deposit-taking, lending, and money processing services, which are controlled by CBN (CBN, 2020; Olawale, 2019). Nevertheless, loan fraud, and account statements mismanagement are some of the popular types of fraud that affect DMBs (Abdullahi, 2017). Such operations undermine the financial performance of banks and deter trust among people, which may destabilize the rest of the economy (Akindele, 2018; Kabiru, 2020).

To reduce these risks, the Nigerian banks are turning towards a better form of fraud detection which is capable of applying artificial intelligence and machine learning to expose suspicious activity and safeguard the stakeholders (Olayinka, 2019; Okoye, 2021). The financial system that is followed by CBN requires complying to ensure stability in banking and safeguard depositors (CBN, 2020). The organizational behavior and strategy are influenced by firm characteristics, such as size, age, ownership, and ethnicity (Abbasi, Khan, and Rehman, 2018). These are internal factors, which when coupled with the external market conditions, affect the response of the firms to risks, including fraud. To facilitate transparency and accountability, the Beneish Model is an effective financial anomaly and potential fraud detection tool applicable to the Nigerian banks (Beneish, 1999).

Beneish Model and Quantitative technique are used to analyze First Bank Nigeria (2013-2023) and identify financial fraud in the company through firm attributes. This paper gives an empirical data on efficiency of Model of Beneish to identify financial fraud within the Nigerian First Bank (Ajiboye, 2018). It focuses on industry-specific problems, and it provides knowledge to banks, regulators, and policymakers (Olawale, 2019). It addresses a gap in research on emerging market by targeting Nigeria (Ajiboye, 2018). The results will improve fraud detection, regulatory systems (CBN, 2020), investor confidence (Kabiru, 2020), and customer trust (Olayinka, 2019).

Bank detection of fraud, especially in the Banks for Deposit Money, is an issue that is difficult and underdeveloped. Fraudsters are getting more advanced in that they are quickly evolving to take advantage of gaps in the detention mechanisms that are in place (Abdullahi, 2017; Kabiru, 2020). The large volume and complexity of financial transactions at First Bank increases its risks because the irregularities are not easily identified under the manual monitoring (Olayinka, 2019; Okoye, 2021). The financial system is highly interconnected, and any fraud committed in one institution such as First Bank can have extensive impacts in the sector and the economy (Ogundele, 2020).

The old-fashioned fraud detection techniques might not be sufficient to detect frauds anymore, and more modern and adaptable models like the Beneish Model might be used to detect financial misreporting using analytical tools (Ajiboye, 2018). The use of the tools such as machine learning and AI can be leveraged to detect the anomalies and suspicious patterns better

(Cohen, 2013). In addition, rules are constantly changing, and First Bank should modify its systems not to violate them and face punishment (CBN, 2020). The emergence of digital banking also contributes to worsening the risk and introduces new vectors of fraud, which need more powerful detection models (Olawale, 2019). All these problems must be resolved to protect the trust of the population and guarantee sustainable economic survival.

The main purpose of the study is to explore the connection in the midst of Firm Characteristics and Fraud detection in the Nigerian First Bank Plc. Other objectives are to:

1) analyze the relationship between the size of firm and detection of fraud.
2) examine the correlation between performance of finance and detection of fraud.
3) establish the connection between financial structure and fraud detection.

Review of Literature

Fraud in banking is detected in the following manner;

The definition of fraud has been popularly used, with the most prevalent one including fraud, misappropriation, embezzlement and misstatements. Abdullahi, (2017) views it as any deceitful or violation of trust illegal act. According to Akindele, (2018), it is a premeditated act of unreasonable gain. Hassan, HossainandAlamri (2020) considers fraud as any unfaithful ploy to unfair gain. Hussain, Rahman, Abbasand Khan (2018) provide an insight into the financial consequences, whereas Hossain andAlamri (2020) associate it with the abuse of trust to obtain personal benefits.

Banking fraud detection is the process of detecting and eliminating banking activities that jeopardize financial integrity and stakeholder confidence (Hussain et al., 2018). It is an important part of risk management, which focuses on fraud and identitying theft and loan fraud. Banks can prevent the emergence of anomalies, protect their assets, and preserve their reputation with the help of new era technologies, data analytics, AI, and machine learning to follow up transactions (Hassan et al., 2020; Hussain et al., 2018).

Even with adoption of IFRS, fraudulent financial reporting is still a challenge, particularly in developing economies such as Nigeria, where the level of reporting (e.g., in a timely manner) has not yet been maintained (Akindele, 2018). Although the IFRS strives to improve the quality of information, its effects differ depending on jurisdictions. Financial statement fraud is described as the deliberate misstatements, omissions, or misrepresentations with a purpose of deceiving users (Okoye, 2021). The accounting profession in Nigeria has been subjected to an increasing amount of scrutiny by the general populace because of the number of financial scandals since the late 1980s. Fraudulent reporting is a grave and calculated type of activity, and the management can be misleading to the stakeholders by trying to manipulate the reports (Akindele, 2018).

Beneish Model: Beneish Model and its application.

Beneish Model A statistical model known as Beneish Model was created by Messod Daniel Beneish to indicate earnings manipulation in financial statements (Beneish, 1999). The model employs a mix of the financial ratios and other accounting indicators to pinpoint the companies that can be in a nature of manipulating their financial performance. Some of the important elements of Beneish Model are M-Score, which is the calculation of eight financial variables, and a threshold value, which would indicate the probability of manipulation. Beneish Model has been extensively employed by academics and practitioners in determining the capability of financial reporting and other possible cases of fraud (Beneish, 1999).

The Beneish Model is a systematic method of measuring probability of earnings manipulation, which is done with the help of quantitative signs (Beneish, 1999). The model is an effective way of identifying possible financial statement fraud as it uses several metrics of accounting and financial ratio. Its use entails the calculation of the M-score whereby the financial performance of an organization is compared to a set of pre-established limits to detect any oddities that could be used as a sign that there is manipulation. Beneish Model has been extensively applied in scholarly studies and has been shown to be effective in identifying earnings manipulation in different industries and countries (Beneish, 1999).

Beneish Model is premised on the assumption that some financial ratios and measures can be used as red flags that would be used to indicate that the earnings are prone to manipulation (Beneish, 1999). These ratios consist of net income, total asset, cash flow of the business, and depreciation and amortization changes. When such variables are compared to industry standards and trends, the model can also detect companies with abnormal financial trends which could be indicative of manipulation. Researchers and practitioners have extensively followed the Beneish Model as a device of forensic accounting and detection of fraud (Beneish, 1999).

Firm Characteristics

Firm Size

Strategic orientation of a firm is determined by the size of the firm. The more stable and resource-rich large firms tend to use defensive strategies that are concentrated on high-margin opportunities (Abbasi,Khan, and Rehman, 2018). Conversely, small companies are also proactive and they are willing to take risks to develop even when the margins are low (Abbasi, M. M., Khan, A. M., and Rehman, R. U., 2018). The firm responses to the changes in the environment also differ depending on the sizes as the strategic priorities and capabilities are different (Wang and Li, 2022).

Firm Age

Firm age and experience, reputation, and the accumulated knowledge can affect performance and strategy (Wang and Li, 2022). Older firms are conservative and seek to be stable whereas young firms are risk-takers who firmly seek market opportunities (Wang & Li, 2022). The external knowledge in young firms is also absorbed rapidly and collaboration with the existing firms accelerates these firms in innovating and becoming relevant to the market (Abbasi, Khan and Rehman, 2018).

Industry Type

Strategic orientation of a firm is affected by the type of an industry. Dynamic industries such as FMCG require a lot of innovation, high ratio of product turnover and high ratio of marketing investment. In FMCGs, firms are usually proactive to grow and take advantage of opportunities because of the stiff competition and low product life cycles. The industry structure therefore has a large influence on innovation and corporate strategy.

Ownership

The ownership impacts upon the resources of firms, administration, and strategy. The foreign owned companies tend to be more proactive and internationally oriented as they are in better technology, capital and management practices. Research indicates that foreign ownership increases internationalization and financial performance particularly in the developing countries. The structure of ownership therefore has a great influence on the strategic orientation.

Business Environment

Companies need to change their strategies to the outside world. Flexibility and responsiveness is the key in unstable markets to survive and remain competitive. The strategic options in line with the market environment have a great effect on performance of the organisations. The less formal structures become widespread and the strategic orientation changes to enable the firms to maintain the performance in uncertain environments.

Theory of Agency

The conflict of interest as proposed by the agency theory is a response to setting apart of control and ownership in contemporary organisations, as proposed by Meckling and Jensen (1976). It expounds on the information asymmetry where the agents (managers) have more information than the principals (owners), thereby causing misuse of resources. Out of self-interest, agents might act against the best interest of principals, hence the necessity of mechanism that ensure control such as audits and quality financial reporting. The theory focuses on minimizing agency costs and fraud reporting by increasing oversight and accountability measures to safeguard the interest of shareholders and guarantee transparent and timely reporting practices.

Theory of Fraud Diamond

Hermanson and Wolfe (2004) conceived the theory, Fraud Triangle was extended with a fourth component capacity. Fraud needs four conditions namely pressure, opportunity, rationalization and capacity. Pressure incorporates individual financial difficulties. Weak internal controls are an opportunity. Rationalization enables the people to justify the fraud with morality. Capacity is an indication of the ability and power of the fraudster to perpetrate fraud. Fraud requires all the four components to coexist.

Empirical Review

Zhang and Wang (2020) discuss the likelihood of detection to point out Manipulation in Pharmaceutical firm Using the BeneishM-score model to examine financial data on pharmaceutical companies to see the trends and the magnitude of the earnings manipulation. The researchers discovered that there were unique financial practices of pharmaceutical companies that amplified chances of earnings manipulation by virtue of high expenditures on research and development and cumbersome accounting methods. The research arrived at the conclusion that Earnings manipulation is the major issue in the pharmaceutical industry, which is triggered by the financial pressures of this industry. The paper suggests that the pharmaceutical industry should have more regulation and be audited on a more regular basis to prevent the manipulation of the market and improve the transparency of the financial statements.

The research of Kim and Park (2021) was on the topic of earnings Manipulation in Technology Companies: Evidence from the Beneish Model. The study employed Beneish Model to assess financial reports of a number of listed technology organisations and possibility of manipulating earnings. They had found that technology companies face greater risk of earnings manipulation because of unpredictable revenues and loose accounting regulations. The research gave a conclusion that technology firms are prone to accounting fraud, particularly during the times of economic poor-performance. The research suggests that the investors and regulators should monitor the financial statements more closely and propose utilisation of sophisticated tools of data analytics to identify the irregularities.

Patel and Shah (2020) investigated Role of Blockchain Technology in Fraud identification and controlling measures in Indian Banks for

Depositing Money. The author employed qualitative research design, interview and case studies of Indian Deposit Money Banks (DMBs) that use blockchain solutions. The study showed that blockchain technology has a great potential of enhancing transparency, traceability and lowering financial fraud possibilities. The paper has concluded that the Blockchain technology has potential to be used in the prevention of fraud, especially in strengthening the integrity of the financial transactions within the banking industry. It is suggested in the study that the authors should propose further spreading of blockchain infrastructure in the banking systems of India and encourage the staff to train and adopt approaches that could support the efficient working of blockchain technologies.

Liu et al. (2021) studied the topic of Using Network Analysis to Detect Financial Fraud Networks in Chinese Deposit Money Banks. The author used network analysis tools to financial transaction data to reveal fraud networks in the Chinese DMBs. The research was able to detect a complex fraud scheme that would otherwise not have been detected by the conventional methods of auditing and this proved the strength of visualizing and analyzing the relationships between transactions. The paper has found that network analysis is an extremely useful means of identifying complex and subdued fraud networks in the banking industry and suggest that the data scientists and the auditors should work together on finding more efficient approaches to detecting fraud.

Research Gap

Though the fraud detection in banks has been increasing in Nigeria, there is not much empirical research conducted to identify connection amidst firm attributes and detection of fraud on the basis of quantitative models such as the Beneish Model. The majority of previous research centers on technological or pharmaceutical industries that are not based in Nigeria or technological devices such as blockchain and network analysis. The gap in the knowledge of the role of firm-specific variables when it comes to detecting fraud in the Nigerian Banks for Deposit Money and more so in First Bank Plc remains. The research fills this gap by applying sector-specific data in the Beneish Model within a time span of ten years (20132023) therefore adding to the literature in an emerging market.

Methodology

This paper applies a parametric research design using ex-post facto to test the association between firm attributes and fraud detection in First bank Nigeria Plc between 2013 and 2023. The good thing about ex- post facto design is that the study examines past data without manipulating any of the variables. The data were collected using audited financial statements of First Bank, which gave an opportunity to apply statistical methods to reveal the trends in accounting statement manipulation with M-Score Model of Beneish. The design of the research is a correlational design which is used to determine how strong and in what direction the relationships amidst the dependent variable, which is the fraud identification and independent variables i.e the size of the firm, performance of finance and financial structure. The design of the research helps the researcher know whether there are any significant relationships among the variables and to what degree the firm characteristics can be used in predicting the probability of fraudulent reporting.

In the research, the two or more-regression analysis is also used to point out the effects of the independent variables, Return on Asset Return, Equity Return, Assets Total, Total Deposits (TD), Total Loans (TL), Debt to Equity Ratio (DER), Equity Ratio (ER), Loan to Asset Ratio

(LAR) on the fraud detection (FD). The Beneish Model is applied as an instrument to estimate the degree of earnings manipulation and is the proxy on the detection of financial fraud.

Data Collection Method

The use of a secondary data source was made to guarantee the presence of reliable and consistent data during the period of time (20132023). In particular, the annual financial reports of the First Bank Plc served as a source of data. These reports have comprehensive financial statements, disclosures, and notes which are crucial in the analysis of the firm characteristics and fraud detection through Beneish Model.

Methods of Data Analysis.

To establish the relationship between the fraud detection and firm characteristics in First Bank Plc between 2013 and 2023, quantitative data analysis methods were employed to determine the connection amidst these parameters. Multiple Regression Analysis is considered the principal analysis tool, which will enable evaluating how a number of independent variables affect a dependent variable at the same time.

To be more specific, the analysis will involve:
Calculating M-Score of Beneish: The Beneish Model is used to determine the Beneish M-Score of individual years based on the financial ratios obtained out of annual reports of the bank. The M-Score is an indicator of probability of earnings manipulation or fraud detection in the firm which is the proxy. The regression analyses were analysed on SPSS, which offered a high level of statistical testing and interpreting of the output. The relationship between the firm characteristics and the fraud detection indicators is ascertained by the strength and nature of the relationships between the oganisation characteristics and the level of significance of the relationship and the overall well-fitting of the model shared by the significance level and the coefficients. This will allow conducting a systematic investigation of the role of financial and operational characteristics of First Bank Plc in terms of the likelihood of fraud that provides empirical evidence consistent with the objectives of the study.

Model Specification

This research will utilize Beneish Model, Beneish Model is the model that can be used to identify fraud in a company.
Firm Characteristics equation 1
$FD = \alpha o + \alpha 1FS + \alpha 2FP + \alpha 3FSR + e1$
FD = Fraud detection
FS = Firm Size
FP = Financial Performance
FSR = Financial Structure
e1 = Residual
αo = Intercept parameter
α = Slope of regression
The firm characteristics equation 1 is reconstructed below:
$FD = \alpha o + \alpha 1TA + \alpha 2TD + \alpha 3TL + \alpha 4ROA + \alpha 5ROE + \alpha 6DER + \alpha 7ER + \alpha 8LAR + ei$
FD = Fraud detection
TA = Total Assets
TD = Total Deposits
TL = Total Loans
ROA. = Return on Assets.
ROE. = Return on Equity.
DER. = Debt-to-Equity Ratio.
ER = Equity Ratio
LAR = Loan to asset ratio
ei = error term
αo = Intercept parameter
$\alpha 1$ - $\alpha 8$ = Slope of regression
Beneish Model Firm Characteristics equation 2
$M.Score = \alpha o + \alpha 1FS + \alpha 2FP + \alpha 3FG + \alpha 4FA + \alpha 5FZ + \alpha 6GAI + \alpha 7TATA + \alpha 8LVGI$
M.Score = Dependent Variable
FS = Sales Index.
FP = Gross margin index.
FG = Asset Quality index.

FA = Sales Growth index.
FZ = Depreciation Index.
SGAI = Sales and General Administration Expenses Index.
TATA = Total Accrual.
LVGI = Leverage Index.

Results

Table 4.1:Descriptive Statistics

	Mean	Std. Deviation	N
FD	5.2848	19.21978	11
ROA	1.2008	.67828	11
ROE	10.1318	6.96072	11
TA	6316803.3636	2550999.09525	11
TD	4388792.1818	2201215.06290	11
TL	2675681.2727	1580242.26132	11
DER	7.0136	1.95595	11
ER	13.2727	3.61496	11
LAR	41.1773	9.94895	11

Table 4.1 presents the means and the variability of the financial indicators of 11 companies. The standard deviations of FD, TA, and TD are high which means that they are highly varied. The averages of ROA and ROE indicate that the profitability is moderate, and the average of the DER of 7.01 indicates that the financial leverage of the firms is high.

Table 4.2: Correlations

		FD	**ROA**	**ROE**	**TA**	**TD**	**TL**	**DER**	**ER**	**LAR**
Pearson Correlation	FD	1.000	.025	-.085	-.079	-.216	-.223	-.206	.116	-.374
	ROA	.025	1.000	.945	.363	.396	.249	.501	-.412	-.013
	ROE	-.085	.945	1.000	.462	.554	.442	.749	-.670	.271
	TA	-.079	.363	.462	1.000	.967	.881	.569	-.441	.325
	TD	-.216	.396	.554	.967	1.000	.925	.721	-.601	.493
	TL	-.223	.249	.442	.881	.925	1.000	.720	-.607	.717
	DER	-.206	.501	.749	.569	.721	.720	1.000	-.974	.715
	ER	.116	-.412	-.670	-.441	-.601	-.607	-.974	1.000	-.684
	LAR	-.374	-.013	.271	.325	.493	.717	.715	-.684	1.000
Sig. (1-tailed)	FD	.	.471	.402	.409	.262	.254	.271	.367	.128
	ROA	.471	.	.000	.136	.114	.230	.058	.104	.485
	ROE	.402	.000	.	.076	.039	.087	.004	.012	.210
	TA	.409	.136	.076	.	.000	.000	.034	.087	.165
	TD	.262	.114	.039	.000	.	.000	.006	.025	.062
	TL	.254	.230	.087	.000	.000	.	.006	.024	.007
	DER	.271	.058	.004	.034	.006	.006	.	.000	.007
	ER	.367	.104	.012	.087	.025	.024	.000	.	.010
	LAR	.128	.485	.210	.165	.062	.007	.007	.010	.
N	FD	11	11	11	11	11	11	11	11	11
	ROA	11	11	11	11	11	11	11	11	11
	ROE	11	11	11	11	11	11	11	11	11
	TA	11	11	11	11	11	11	11	11	11
	TD	11	11	11	11	11	11	11	11	11
	TL	11	11	11	11	11	11	11	11	11
	DER	11	11	11	11	11	11	11	11	11
	ER	11	11	11	11	11	11	11	11	11
	LAR	11	11	11	11	11	11	11	11	11

The correlation test revealed that there was a strong positive correlation amidst ROA and ROE (r = 0.945) and the correlation between total assets (TA) and total debt (TD) (r = 0.967), both statistically significant. Equity ratio (ER) also has a significant negative correlation with debt-to-equity ratio (DER) (r = -0.974). FD is poorly correlated with any of the variables, which can be interpreted as the lack of association with the financial structure and performance of the firm in this dataset.

Table 4.3: Model Summary

Model	R	R Square	R Square Adjusted	Estimate Std. Error	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.882[a]	.777	-.115	20.29151	.777	.871	8	2	.635	2.000

a. Predictors: (Constant), LAR, ROA, TA, ER, TD, DER, TL, ROE

b. Dependent Variable: FD

In model summary, there is a high R value of 0.882 which connotes that the predictors and the dependent variable (FD) have a strong correlation. The value of D.W (2.000) connotes that it does not autocorrelation.

Table 4.5: Analysis of ANOVA

Model		**Sum of Squares**	**Df**	**Mean²**	**F. statistics**	**Significant**
1	Regression	2870.508	8	358.814	.871	.635[b]
	Residual	823.491	2	411.745		
	Total	3693.999	10			

a. Dependent Variable: FD

b. Predictors: LAR, ROA, TA, ER, TD, DER, TL, ROE

Table 4.5 indicated that the model is not important (F = 0.871, p = 0.635). This means that in the analysis, the dependent variable variation, FD is not significantly explicated by combined predictors (LAR, ROA, TA, ER, TD, DER, TL, ROE).

Table 4.6: Coefficient Correlations [a]

Model			**LAR**	**ROA**	**TA**	**ER**	**TD**	**DER**	**TL**	**ROE**
1	Correlations	LAR	1.000	.863	.802	.024	.268	.507	-.987	-.844
		ROA	.863	1.000	.459	.213	.578	.755	-.862	-.998
		TA	.802	.459	1.000	-.049	-.338	.219	-.797	-.436
		ER	.024	.213	-.049	1.000	.079	.780	-.106	-.253
		TD	.268	.578	-.338	.079	1.000	.396	-.284	-.586
		DER	.507	.755	.219	.780	.396	1.000	-.567	-.785
		TL	-.987	-.862	-.797	-.106	-.284	-.567	1.000	.849
		ROE	-.844	-.998	-.436	-.253	-.586	-.785	.849	1.000
	Covariances	LAR	95.633	3155.040	.000	3.530	8.493E-5	306.451	-.001	-371.779
		ROA	3155.040	139777.045	.007	1214.714	.007	17433.617	-.029	-16814.006
		TA	.000	.007	1.663E-9	-3.065E-5	-4.477E-10	.001	-2.956E-9	-.001

ER	3.530	1214.714	-3.065E-5	233.644	3.928E-5	737.217	.000	-174.014
TD	8.493E-5	.007	-.477E-10	3.928E-5	1.053E-9	.001	-.395E-10	-.001
DER	306.451	17433.617	.001	737.217	.001	3819.360	-.003	-2184.499
TL	-.001	-.029	-.956E-9	.000	-.395E-10	-.003	8.275E-9	.003
ROE	-371.779	-16814.006	-.001	-174.014	-.001	-2184.499	.003	2029.613

a. Dependent Variable: FD

Coefficient correlations table indicates that there is a strong correlation among a number of independent variables indicating that there is multicollinearity. It is worth noting that there are very high correlations between LAR and TL (-0.987), ROA and ROE (-0.998), and TL and ROE (0.849). This multicollinearity may give misleading regression estimates and decrease the reliability of the model. This implies that there is potential overlap in information given by certain predictors and may be dropped or converted to enhance model accuracy

Table 4.7: Collinearity Diagnostics [a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	ROA	ROE	TA	TD	TL	DER	ER	LAR
1	1	8.191	1.000	.00	.00	.00	.00	.00	.00	.00	.00	.00
	2	.404	4.501	.00	.00	.00	.00	.00	.00	.00	.00	.00
	3	.295	5.268	.00	.00	.00	.00	.00	.00	.00	.00	.00
	4	.087	9.729	.00	.00	.00	.00	.00	.00	.00	.00	.00
	5	.019	20.781	.00	.00	.00	.00	.01	.01	.00	.00	.00
	6	.003	50.258	.00	.00	.00	.02	.18	.01	.01	.01	.01
	7	.000	149.951	.02	.06	.07	.40	.62	.03	.00	.07	.02
	8	.000	200.008	.03	.03	.02	.28	.00	.17	.23	.71	.24
	9	2.473E-5	575.513	.96	.90	.91	.30	.19	.78	.77	.21	.73

a. Dependent Variable: FD

The diagnostics of collinearity demonstrates that the predictors have severe multicollinearity as condition indices are high above 30, reaching 575.513. The proportion of variance indicates that ROA, ROE, LAR, and others are strongly loaded on dimensions with large condition indices, which prove the overlap in the explanatory power. Such a multicollinearity may amplify the standard errors and destabilize the regression coefficients.

Table 4.8: Residuals Statistics [a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	-11.8160	50.5929	5.2848	16.94257	11
Predicted Value of std	-1.009	2.674	.000	1.000	11
Error Standard of Predicted Value	15.868	20.266	18.304	1.425	11
Adjusted Predicted Value	-428.5736	98.4132	-40.8813	142.63921	11
Residual	-12.53144	10.37213	.00000	9.07464	11

Std. Residual	-.618	.511	.000	.447	11
Stud. Residual	-1.352	1.365	.148	1.139	11
Deleted Residual	-101.84422	426.36261	46.16609	142.38441	11
Stud. Deleted Residual	-3.272	3.708	.015	2.081	11
Mahal. Distance	5.206	9.066	7.273	1.252	11
Cook's Distance	.017	48.932	5.415	14.473	11
Centered Leverage Value	.521	.907	.727	.125	11

a. Dependent Variable: FD

The goods reside values show that there is a wide range of the predicted and adjusted values and the standard deviations are large, implying that the model is unstable. The influential outliers are indicated by high deleted residuals and large Cook's Distances (maximum of 48.932). The values of the centered leverages also are high, which means that there are points which have a strong impact on the regression model.

Discussion of Findings

This paper sought to analyse the relationship in the presence of firm traits like firm size, financial performance, financial structure and fraud detection of Beneish Model in First Bank Plc of Nigeria. Although the overall correlation was high ($R = 0.882$), the regression analysis showed that all the firm characteristics did not affect the fraud detection significantly (Adjusted R 2 = -0.115, $p > 0.05$). This finding implies that the specified firm attributes have no significant impact on the identification of financial fraud based on the Beneish Model in the case of the First Bank Plc.

The results are quite contrasting to those of Zhang and Wang (2020) and Kim and Park (2021) who used the Beneish Model elsewhere and discovered that company-specific factors, including high costs in research and development in pharmaceuticals and a rising revenue in the case of tech companies, were associated with higher earnings manipulation. These industries showed statistically significant relationships, but the Nigerian banking environment, especially, First Bank Plc exhibited weak relationships and statistically insignificant relationships among variables such as ROA, ROE, total assets, and debt ratios.

Moreover, although Patel and Shah (2020) and Liu et al. (2021) found out effective fraud detection applications in the emerging technologies: blockchain and network analysis in Indian and Chinese banks, respectively, this paper seems to be restrained in terms of predictive power as the authors use traditional financial ratios, based on the Beneish Model. One reason can be, that through the regulative action of CBN and other institutional mechanisms, banks of Nigeria have a relatively higher compliance as well as internal controls, which might obscure or water down the observation of fraud patterns by use of traditional financial indicators.

The other most important problem identified in the study is the multicollinearity of the independent variables, with ROA and ROE ($r = 0.945$) and with DER and ER ($r = -0.974$) having the highest multicollinearity. This may bias the regression coefficients. The implication of such statistical difficulties is that the overlapping financial measures make it difficult to isolate the effect of individual predictors in detecting fraud.

Within the framework of the entire Nigerian banking system and economy, the findings indicate the necessity of the implementation of more advanced fraud detection systems because financial ratios might not be effective enough to demonstrate manipulation. Since frauds in financial institutions are still a source of instability in the stability of banking firm in Nigeria, the implementation of modern methods of analysis, such as machine learning and forensic accounting can increase transparency and strengthen confidence in investors. Thus, the given research adds an important piece of information: the conventional measures of firm characteristics might not be sufficient anymore to reveal fraud in large, regulated financial institutions in Nigeria.

Implications

This study findings have critical implications that are based on the practical findings. The regression model had a large correlation coefficient (R = 0.882), but the overall explanatory ability in the regression model was low as the adjusted R 2 was negative and ANOVA was not significant statistically ($p > 0.05$). This implies that firm characteristics such as total assets, total deposits, total loans, assets returns, equity returns, debt-equity ratio, equity ratio (ER), loan-asset ratio (LAR) did not mark any significant differences in fraud detection as M-Score of beneish.

The negligence of the variables of firm size imply that the scale of organizations is not a substantial factor that can affect the process of fraud detection in Nigerian First Bank Plc. The size and systemic essential of the institution do not necessarily increase the possibility of detecting fraudulent activities with the help of financial statement indicators. This would mean that the management cannot believe that expansion in assets, deposits or loan would automatically improve transparency. Rather, fraud detection entails purposeful enhancing of internal audit systems and controlling mechanisms regardless of the size of the firm.

Equally, low interrelation amongst financial performance variables (ROA and ROE) and fraud detection is an indication that profitability is not a significant indicator of manipulation risk in this case. Good performance of earnings is not to be understood that fraud exposure is low. This, therefore, means that the management and the investors cannot just use profitability measures to determine the risk of fraud. It should be ensured that the fraud detection systems include more analytical instruments than the performance ratio.

The results also indicate that the variables of financial structure (DER, ER, and LAR) did not play a crucial impact in the results of fraud detection. Though leverage is usually linked to pressure and possible motivation to be manipulated, this correlation could not be proved. Thus, the use of capital structure as a monitoring tool may not be sufficient to detect the risk of fraud in banks with a high degree of regulation.

Moreover, there is extreme multicollinearity between a number of independent variables especially between ROA and ROE, and also between DER and ER; which indicates the overlapping power of explanations. This means that when similar financial ratios are used concurrently, they are likely to produce misleading analysis outcomes. The process of detecting the frauds should then be simplified to enhance reliability. This is even further accentuated by the fact that influential outliers do exist and demonstrate the necessity to use strong data validation in order to apply statistical fraud detection methods.

The findings would help regulators like Central Bank of Nigeria to consider that the old ratio-based supervision might be failing to address emergent fraud risks. In general, findings of the study revealed that firm features cannot be a good predictor of fraud detection, and more advanced and technological surveillance systems must be implemented in the banking industry.

Conclusion

This paper has explored the connection between firm traits firm size, financial performance and financial structure and detection of frauds based on the Beneish Model in the First Bank Plc of Nigeria. The results found no significant correlation between these variables and fraud detection and, therefore, it is possible that, the conventional financial indicators could not detect fraud in banking industry. Since banking environment and environment of the Nigerian banks are too complicated, more sophisticated tools and technologies are required in order to improve the detection of fraud. The paper also shows the relevance of incorporating the new trend of analytics to enhance fund transparency and protect the integrity of the banking system in Nigeria.

Recommendations

1) The firm size should not be the only factor that the management uses to determine the fraud risk. Rather, First Bank Plc ought to consider having fraud detection mechanisms that consider transactional behavior, complexity of the operations, and internal operations irrespective of the size of the organization. Audit on risk basis and real time monitoring of transactions must be applied to all the departments and subsidiaries rather than just those who are regarded as big or high profile.
2) First Bank Plc must not assume that high profitability is the predictor of low risk of fraud. The bank ought to include nonfinancial pointers like the behavior of the employees, process anomalies and whistleblower reports in the fraud risk assessment model. The training of the internal audit teams should be focused on making them look beyond the performance measurement and use forensic methods in the process of auditing.
3) Since financial structure does not have a strong predictive ability in fraud detection, First Bank Plc ought to reshape its fraud detection systems to incorporate qualitative measures such as employee lifestyle audit, third-party transactions, and vendor engagements. There should also be the inclusion of such tools as blockchain and network analysis that will help to improve the traceability and transparency, in order to supplement the traditional financial monitoring mechanisms.

References

1) Abbasi, M. M., Khan, A. M., & Rehman, R. U. (2018). Firm characteristics and financial reporting quality: A literature review. International Journal of Economics, Commerce and Management, 6(7), 38-44.
2) Abdullahi, I. (2017). An Assessment of the Impact of Fraud and Fraudulent Practices on the Performance of Nigerian Deposit Money Banks. International Journal of Academic Research in Business and Social Sciences, 7(6), 112-125.
3) Ajiboye, O. (2018). Fraud Detection and Prevention in Nigerian Deposit Money Banks: A Case Study of Selected Banks. International Journal of Academic Research in Business and Social Sciences, 8(8), 112-125.
4) Akindele, T. R. (2018). Fraud and Fraudulent Practices in the Nigerian Banking Industry: Causes, Effects and Possible Remedies. Journal of Economics and Sustainable Development, 9(6), 23-35.
5) Barney, J. B. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99-120
6) Beneish, M. D. (1999). The Detection of Earnings Manipulation. Financial Analysts Journal, 55(5), 24-36.

7) CBN. (2020). Annual Report on Nigerian Banking Supervision. Central Bank of Nigeria.
8) Cohen, D. A. (2013). Measuring and Detecting Accounting Irregularities: A Revised Approach. Journal of Accounting Research, 51(5), 909-949.
9) Cressey, D. R. (1953). Other People's Money: A Study in the Social Psychology of Embezzlement. New York: Free Press.
10) Freeman, R. E. (1984). Strategic Management: A Stakeholder Approach. Boston: Pitman.
11) Garcia, R., & Martinez, S. (2022). Application of the Beneish Model to detect financial statement fraud in the Spanish banking industry. European Journal of Finance, 18(1), 45-58.
12) Hassan, M. M., Hossain, M. S., &Alamri, A. (2020). A survey on fraud detection in financial statements using machine learning. Future Generation Computer Systems, 112, 736-754.
13) Hussain, M., Rahman, Z., Abbas, Q., & Khan, S. U. (2018). Fraud detection in banking sector using machine learning techniques: A comprehensive review. IEEE Access, 6, 33718-33733.
14) Jensen, M. C., &Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. Journal of Financial Economics, 3(4), 305-360.
15) Kabiru, I. (2020). The Impact of Fraud on the Financial Performance of Deposit Money Banks in Nigeria. International Journal of Business and Management Review, 8(4), 1-14.
16) Li, M., & Wu, H. (2021). Enhancing the Beneish Model for detecting earnings manipulation in Chinese manufacturing firms. Journal of Financial Research, 39(3), 212-225.
17) Ogundele, O. (2020). Challenges and Prospects of Fraud Detection and Prevention in Nigerian Deposit Money Banks. International Journal of Business and Management Review, 8(6), 1-14.
18) Okoye, O. (2021). Leveraging Technology for Fraud Detection and Prevention in Nigerian Banks. International Journal of Academic Research in Business and Social Sciences, 11(6), 112-125.
19) Olawale, O. (2019). Digital Innovation and the Future of Nigerian Banking: Opportunities and Challenges. International Journal of Business and Management Review, 7(5), 1-14.
20) Olayinka, O. (2019). The Role of Artificial Intelligence in Fraud Detection in Nigerian Deposit Money Banks. International Journal of Academic Research in Business and Social Sciences, 9(8), 112-125.
21) Owolabi, S. A. (2019). Banking Sector Reforms and Economic Growth in Nigeria: An Empirical Investigation. Journal of Economics and Sustainable Development, 10(10), 2222-1700.
22) Smith, A., & Johnson, B. (2021). Artificial intelligence in fraud detection: A study of its application in US Deposit Money Banks. Journal of Banking and Finance, 45(2), 112-125.
23) Wang, X., & Li, Y. (2022). Regulatory changes and financial reporting practices in Chinese Deposit Money Banks. Journal of Banking Regulation, 29(2), 145-158.
24) Zhang, L., et al. (2021). Macroeconomic uncertainty and financial reporting quality in European Deposit Money Banks. Journal of Accounting Research, 52(4), 301-315.