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Revenue Growth and Unusual Transactions as Accounting Red Flags: Evidence from Fraud Risk Detection (F-Score) Among Listed Financial Firms in Nigeria

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ABSTRACT

This study examines the effect of two accounting red flags (revenue growth and unusual transactions) on fraud risk detection, proxied by the F-Score, among listed financial firms in Nigeria, with a sectoral analysis of banking and non-banking institutions. The study adopted quantitative, causal, ex-post facto, panel research design anchored on an objective ontology, positivist epistemology, and value-neutral axiology. Secondary data were extracted from audited annual reports of a purposively sampled panel of 17 banking and 25 non-banking listed financial firms in Nigeria (42 firms) over 2014-2024. Descriptive statistics, correlation analysis, a full battery of diagnostic tests, and robust panel regression were employed. Unusual transactions exerted a positive and statistically significant effect on fraud risk detection in all three models: banking ($\beta = 0.810$, $p = 0.000$), non-banking ($\beta = 0.502$, $p = 0.004$), and overall ($\beta = 0.779$, $p = 0.000$), making it the single most consistent accounting red flag identified in the study. Revenue growth was positive and statistically significant in the non-banking ($\beta = 0.988$, $p = 0.000$) and overall ($\beta = 1.002$, $p = 0.000$) models but was negative and statistically insignificant in the banking model ($\beta = -0.993$, $p = 0.518$). The paper contributes sector-disaggregated, Fraud-Hexagon-grounded evidence on transaction-level and revenue-based red flags in an under-researched African financial market, offering regulators and forensic practitioners empirically ranked, actionable indicators for fraud surveillance in Nigeria's banking and non-banking financial firms.

KEYWORDS: Revenue growth, unusual transactions, fraud risk detection, F-Score, Fraud Hexagon Theory, listed financial firms, Nigeria.



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1. Introduction

As corporate fraud grows in scale and complexity around the world, fraud risk detection is now a key issue in financial reporting. According to the Association of Certified Fraud Examiners (ACFE, 2022), organizations lose about 5% of their annual revenue to fraud, or roughly \$4.7 trillion globally a year, and over 86% of reported fraud cases are characterized as financial statement manipulation, asset misappropriation and/or corruption. The analytical models used for fraud detection, like the F-Score model, are used to detect fraudulent tendencies by analyzing the presence of accounting red flags, such as when the revenue growth is abnormal or the transactions are unusual. The investors lost billions of dollars due to major corporate failures like the U.S. based Enron, the German based Wirecard and the South African based Steinhoff International, which were all marked with such warning signs that they took the world's financial markets by surprise, making them appear opaquer (Transparency International, 2023).

However, financial fraud is exacerbated by structural and institutional inadequacies in Africa. According to PwC's Africa Economic Crime and Fraud Survey 2022, 60% of companies in Africa suffered at least one fraud incident in two years, with average fraud losses of USD 1.5 million (up to a peak of USD 10 million). The financial services sector was hit hardest, with 75% reporting at least one incident in two years, and the average fraud loss at a staggering USD 1.5 million, up to a maximum of USD 10 million. In more than 45% (KPMG, 2021) of fraud reports, the fraud had involved unusual transactions, such as procurement contracts that were inflated, a real or fictitious supplier contract, or related party transactions without authorization, making fraud risk detection mechanisms a growing governance imperative for African markets.

The rate of fraud has been high and alarming, especially in listed financial institutions, where the volume of transactions and compliance is high in Nigeria. In 2022, the Nigeria Deposit Insurance Corporation (NDIC, 2023) reported a fraud amount of N69.33 billion, representing more than double the amount reported during 2020, while banks were the most affected subsector with more than 70% of the reported cases, with insider involvement being the most common type of fraud. The Central Bank of Nigeria (CBN, 2023) similarly noted that electronic and unusual transactions alone resulted in losses in excess of ₦14.5 billion, pointing to transaction monitoring issues as a key systemic vulnerability that needs to be addressed, while regulatory compliance expenses increased by 22% from 2020 to 2022, a period during which shareholder-return pressures were growing (FRCN, 2023). The Fraud Risk Detection frameworks in Nigeria however, are mostly reactive and not preventive, which calls for robust frameworks with systematic monitoring like the F-Score incorporating accounting red flags.

Revenue growth of Nigerian listed financial firms has been seen to be inconsistent over the years and has raised an alarm on the possibility of fraud detection. According to NDIC (2023), some banks experienced an increase in their earnings by more than 20% in the banking sector, which was accompanied by reported frauds valued at ₦59.33 billion in 2022, but there was no significant growth in their loan books or deposits, pointing to the potential for misclassification of income. For non-banking companies, premium income rose by 17% in 2021, while uncollected income increased by 23%, indicating that premium income may have been over-recognized. The patterns indicate that abnormal revenue growth, not backed by operations, is a measurable red flag. Another is unusual transaction, which accounted for ₦45 billion of his losses in the banking sector in 2022, representing over 75% of his reported cases, according to the CBN Fraud and Forgeries Report (2023); PwC Nigeria (2022) noted that 41% of the non-banking firms had unusual procurement or related-party transactions which did not have any economic justifications, some of which involved misvalued assets in excess of ₦10 billion that later led to regulatory sanctions. These evidences provide an indication that unusual transactions are systemic and are directly connected with large-scale fraud risks in the banking and non-banking segments of Nigeria's financial system.

Frauds result in loss of shareholder value, capital markets instability, and loss of regulatory credibility, which led researchers and regulators all over the world to develop fractionalism risk detection models like F-Score. Despite these developments, fraud continues to be an issue in fragile and weakly-governed emerging economies. When the volumes of frauds reported in Nigeria were scrutinized, it was seen that many of these cases were preceded by accounting red flags such as sharp increases in reported revenues, and irregular, unexplained transactions, that would cloud a firm's real financial position and thus erode the integrity of the financial system.

While the implications of this are serious, there is a lack of empirical evidence to the effect of the impact of revenue growth and unusual transactions, specifically on fraud detection in the two major sectors of the Nigerian financial sector namely banking firms and non-banking firms. Previous empirical studies have focussed usually on indicators related to revenue or indicators related to transaction, either as performance measures (Chen & Wang, 2024; Munyua & Kamau, 2022) or as abstract behavioural construct within the fraud hexagon framework (Riyanti & Trisanti, 2021; Salim et al., 2024), but have not combined them into a comprehensive quantitative verifiable fraud-risk-detection framework specifically applicable to financial institutions. The majority of this evidence comes from Asian contexts (mostly Indonesia), in which it has been applied to a wide range of sectors, including non-financial sectors such as manufacturing, infrastructure, and so on, as well as state-owned enterprises (SOEs) and in regulatory and governance settings that are very different from those of the financial services sector in Nigeria (Al-Rizky et al., 2024; Puspaningrum et al., 2024; Wicaksono & Suryandari, 2021). Existing findings are therefore limited to listed financial firms in Nigeria due to conceptual gaps (revenue growth and transaction irregularities perceived as performance or

behavioural constructs and not as measurable red flags for fraud detection), methodological gaps (short windows of observations; perception-based instruments; composite fraud-detection models like the F-Score are not available), and population gaps (evidence gathered from non-financial or differently regulated firms). This current research fills these gaps by carrying out a sectoral analysis of listed Nigerian financial firms and using the F-Score model to generate sectoral measure of accounting red flags for detecting fraud in the context of revenue growth and exceptional transactions with the aim of providing localised, policy relevant evidence to aid in the detection of fraud risk. This study aims to:

- i. Evaluate the effect of revenue growth (RG) on fraud risk detection (F-Score) in Nigerian listed financial firms.
- ii. Examine the influence of unusual transactions (UT) on fraud risk detection in Nigerian listed financial firms.

The hypotheses of this study are stated in null form as follows:

H₀₁: Revenue growth (RG) has no significant effect on fraud risk detection (F-Score) in Nigerian listed financial firms.

H₀₂: Unusual transactions (UT) have no significant effect on fraud risk detection in Nigerian listed financial firms.

2. Literature Review

2.1 Conceptual Review

2.1.1 Fraud Risk Detection

Fraud risk detection is the identification and evaluation of conditions that could lead to material misstatement of financial statements as a result of fraud, in a systematic manner. It is not just about identifying mistakes but also about intentionally and knowingly providing false and misleading financial information to gain an advantage for self or organisation. ISA 240 (2023) of the International Auditing and Assurance Standards Board (IAASB) defines fraud as “an intentional act by one or more individuals, members of management, those charged with governance, employees or third parties, involving the use of deception to obtain an unjust or illegal advantage.” ISA 240 also outlines the fraud risk indicators in a three-part structure in line with the current thinking around the fraud triangle and its newer extensions, the fraud diamond and the fraud hexagon, which are incentive/pressure, opportunity, and rationalization.

There have been several measurement frameworks for fraud risk detection: Beneish M-Score, Altman Z-Score and Grover G-Score. However, the Dechow F-Score has become popular for its use of accrual and performance-based measurements to predict material misstatements (Dechow et al., 2011). Relying on criteria including changes in receivables, inventories, sales, and earnings, the F-Score assesses whether a company's performance trends are typical of business as usual or sign of manipulation, resulting in a continuous probability scale instead of a single classification. This study uses the Dechow F-Score (also known as the Piotroski F-Score) as the measure of fraud risk detection because it directly relates to the fraud risk detection principle of ISA 240, which is that fraud risk is detected by anomalies in revenue recognition, accrual accounting, and unusual financial relationships, and because the quantitative formulation of this score fits the econometric design of the present study.

2.1.2 Revenue Growth (RG)

One of the clearest accounting ratios to measure a company's performance and possible accounting misrepresentation is revenue growth. From a conceptual point of view, revenue growth is the percentage change in a company's total sales or income over a given period. In normal times, a firm's revenue growth is a sign of its growth and the efficiency of its management, but when the growth is particularly high or irregular, it could indicate that the firm is engaged in some sort of accounting fraud or aggressive sales tactics. ISA 240 (IAASB, 2023) identifies unusual fluctuations in revenue trends as a major red flag in financial reporting that is typically the easiest method to intentionally misstate the financial statements.

Empirical evidence from the literature is extensive that abnormal revenue growth is connected with fraudulent financial reporting practices. Dechow et al. (2011) emphasize that firms with unprecedented high revenue growth compared to its peers are more likely to be engaging in accrual manipulation or premature recognition of sales to obtain their earnings targets, and other studies have found that very high revenues are correlated with increases in receivables, likely indicative of fictitious or early revenue recognition. In this study, the year to year growth in total revenue of the firm, i.e. the percentage change in the firm's total revenue from one year to the next is termed as revenue growth (RG). The

reasons for considering RG as a red flag are threefold. Firstly, it is one of the earliest and most apparent signs of management manipulation, secondly, it reflects the incentive-or-pressure aspect of the fraud triangle mentioned in ISA 240, and thirdly, in emerging markets like Nigeria, the firm could take advantage of the volatile market conditions to inflate revenues.

2.1.3 Unusual Transactions (UT)

An unusual transaction is one that is clearly an accounting red flag that is widely followed and may signal the presence of fraudulent financial reporting. ISA 240 (IAASB, 2023) defines unusual transactions as transactions that are "significant in size, complex in nature, or are rare in occurrence, and are not reasonably expected to be repeated, or if they are expected to be repeated in the future, do not have a clear business purpose. In academic research, unusual transactions have emerged as one of the most reliable indicators of fraudulent financial reporting—and are defined as large related-party transactions, asset swaps, or unexpected gains or losses, which are not properly disclosed, and used to manipulate the reported earnings, hide other cash-flow irregularities, or shift assets for personal gain.

In a measurement sense, unusual transactions (UT) would normally be defined as such in terms of the ratio of related-party transactions to assets, the percentage of nonrecurring income to total income or a dummy variable representing the presence of significant unusual transactions. Unusual transactions are the "opportunity" side of the fraud triangle, in that they tend to happen when internal controls are weak or when an accounting system is complex enough that the management can hide the manipulation. In the study, the test of UT is through the ratio of related party transactions to total assets, which reflects the size of non-recurring or related party transactions in relation to total assets and thus allows for identification of financial transactions that are irregular, and may indicate that financial misreporting is likely.

2.2 Empirical Review

Using a fixed-effects panel regression and an ex-post facto design, Adepoju and Ibrahim (2025), examined the relationship between revenue growth and earnings quality of Nigerian listed financial firms for the period (2013–2022), and 25 banks were sampled. Greater revenue growth corresponded to lower rates of earnings management, which would lead to more credible earnings-quality. The study, however, did not rely on a rule of thumb for the revenue growth indicator as a fraud indicator, did not use a composite fraud-detection indicator like the F-Score, and only focused on the banking sub-sector. The current study addresses these gaps with a specialized fraud-detection system applicable to banking and non-banking firms.

Al-Yahyaee et al. (2024) examined the issue of earning management, earnings quality and sustainability for distressed and non-distressed firms in the Gulf Cooperation Council (GCC) in the listed companies that are used as samples (839: 2011-2022) and method of analysis used is panel regression which includes ordinary least square (OLS), fixed effect (FE), and 2SLS. The higher the growth rate, the greater the managerial incentive to manage earnings due to increased earnings volatility and decline in earnings quality and sustainability, particularly for distressed companies, but the study did not specifically examine fraud risk detection and the findings of the study are specific to the GCC region. The present study tackles this conceptual and population gap with the development of a fraud model that is applied to financial firms in Nigeria.

In their study, Munyua and Kamau (2022) assessed the effect of revenue growth on shareholder wealth creation for 38 companies listed in the Nairobi Securities Exchange (NSE) for a period of ten years, the study was descriptive-correlational, it was found that there was a positive and significant relationship between revenue growth and shareholder wealth. The study's conceptual scope was limited to value creation (not reporting integrity) and did not use a fraud-detection model, like the F-Score. This study aims to tackle this question by examining growth in revenues as a potential indicator of increased fraud risk, instead of as a performance metric.

Al-Rizky et al. (2024) studied the relationship between financial target and the possibility of fraud in the financial statements using the Vousinas Hexagon Fraud analysis and fraud measured using the F-Score model. Panel data regression with purposive sampling was used with the results of each industry listed on the Indonesia Stock Exchange (IDX) during 2017 to 2022, which was limited to 16 non-financial state-owned enterprises (SOKES) to obtain results that financial target has a positive effect on fraud potential. The study however was only for non-financial state owned enterprises, and excluded any unusual transactions or other operational anomalies. The present study investigates the out-of-the-ordinary transactions within the context of a sectoral analysis of listed Nigerian financial firms with the F-Score model.

Puspaningrum et al. (2024) applied purposive sampling with 143 observations and regression panel data to determine the effect that collusion has on the indicators of financial statement fraud of infrastructure companies listed on the Indonesia Stock Exchange (IDX) in 2020-2022, the results of the study showed that collusion had a positive effect on the indicators of financial statement fraud of infrastructure companies listed on IDX in 2020-2022. The study was limited to interpersonal collusion, and did not include unusual or non-recurring transactions, or financial institutions. In the present study, the same is attempted by sectorial focus and by following the F-Score model to directly evaluate the unusual transactions.

Salim et al. (2024) based on a fraud-hexagon perspective, sampled 15 insurance companies listed on the Indonesia Stock Exchange (2019-2022), used the F-Score model and logistic regression to find factors that influenced corporate fraud, opportunity, rationalization and ego significantly influenced financial statement fraud, whereas stimulus, capability and collusion did not. The study focused on insurance companies and analyzed only six broad behavioural elements, not specifically unusual transactions, which limits generalizability. The present study, therefore, addresses this deficiency by operationalizing the unusual transactions in the F-Score framework of banking and non-banking companies in Nigeria.

Based on the F-Score model, the audit committee as a moderating variable, the empirical evidence obtained by Riyanti and Trisanti (2021) showed that collusion has a positive impact on potential financial statement fraud in Indonesian state-owned companies (2016-2020). Rather than looking at red flags such as strange transactions, the study focused on governance and behavioural aspects. The current study fills this gap by investigating the impact of unusual transactions, measured using financial data of firms, on fraud risk detection in Nigeria.

Wicaksono and Suryandari (2021) validated the impact of financial targets on fraudulent financial reports by using the fraud hexagon theory and sampling of 41 mining companies listed on the Indonesia Stock Exchange in the years 2017 to 2019, which amounted to 123 analysis units, using panel regression analysis technique, the results found that financial targets had positive and significant effects on fraudulent financial reports. The study only examined motivational aspects of fraud, not transaction-based aspects, and focused only on the mining sector, which is very different from financial institutions. The focus of the current study is placed on unusual transactions, which is measured using the F-Score model, building upon this literature.

For the banking companies listed on the Indonesia Stock Exchange (ISX) in the period 2017-2021, the sample used was 215 companies, which was analyzed using SPSS 25, the authors concluded that the financial targets did not significantly affect the reporting of fraudulent financial reporting. The study looked at financial objectives only, without taking into account indicators like unusual transactions, and failed to disaggregate the sector for comparison. The present study aimed to address these gaps by using a sectoral approach and applying the F-Score model to predict whether an unusual transaction is a fraud or not as a quantitative measure of fraud.

2.3 Theoretical Review

2.3.1 Fraud Hexagon Theory

As an extension of the Fraud Triangle (Cressey, 1953) and Fraud Diamond (Wolfe & Hermanson, 2004), Vousinas (2019) suggested the Fraud Hexagon theory. The Fraud Triangle focuses on the three elements of pressure, opportunity and rationalization in the context of fraud, and the Fraud Diamond introduces capability as a fourth dimension. You has added two more elements: arrogance and collusion, creating a six-element model that encompasses the multifaceted conditions of behavior, organization, and structure that can contribute to fraudulent activities in today's corporations (Vousinas, 2019). Its core premise is that fraud is not caused by a single element, but rather is a combination of various internal and external factors that allow an individual or organization to indulge in dishonest financial activities.

Out of the total of six elements, two of them are closely related to the focal elements of this paper. Fraud stresses the point that it takes individuals with both technical skills and knowledge to perpetrate fraud and sufficient position and authority to take advantage of weaknesses. In Nigerian financial institutions, there are senior executives who have an in-depth knowledge of complicated financial instruments or who have an intimate understanding of a lack of oversight, which may have the ability to commit or conceal a fraud - this study indirectly captures this 'capability' through the phenomenon of accounting anomalies like Revenue Growth (RG) where inflated and/or unsustainable growth figures may be 'made' easier by managers who have the technical ability to manipulate earnings.

Rationalization is a psychological process by which fraudsters make their unethical actions seem acceptable; this can include seeing accounting manipulation as methods to protect the investor, to save jobs or to boost confidence in the market in financial firms. While not explicitly measurable, aspects of rationalization (and closely related arrogance: that the manager is above internal controls or above the regulatory requirements) can be seen in Unusual Transactions (UT) in which the manager will rationalize non-standard accounting practices as “necessary adjustments” or simply ignore the standard accounting practice altogether.

Empirical challenges to the Fraud Hexagon identify its benefits and some of its drawbacks. Brennan (2020) and Nindito (2020) suggest that arrogance and collusion can give a more realistic picture of fraud in corporate environments in which executives often hold a dominant position and manipulate others within the group. Liu et al. (2022), however, remind us that certain dimensions of the model are more abstract, like rationalization and collusion, and are more difficult to operationalize in quantitative models, while Omar and Bakar (2021) point out that the development of the model has been limited in developing economies, and that it is necessary to carry out contextualized studies like the one in this paper. The Fraud Hexagon Theory is relevant to the study because it comprehensively explains the Fraud Risk Factors in Nigerian listed financial firms: By aligning RG with capability and UT with rationalisation/arrogance, the study employs a strong theoretical base to explain the interaction between the behavioural and structural weaknesses that increase the level of fraud risk in the financial firms.

3. Methodology

3.1 Research Design

The study was a quantitative research because it enables the use of objective measurement tools to measure accounting red flags (revenue growth and unusual transactions) and its impact on fraud risk detection among listed financial firms in Nigeria. In this quantitative setting, the study used a causal (explanatory) design; the ex-post facto approach was used because the data used for the study was historical data from the annual reports and financial statements of listed financial firms in Nigeria (2014 - 2024) which the researcher had no control over. To add to this, a panel research design was also adopted to ensure the cross-sectional and time-series nature of the data was captured, as this increased the robustness of any causal inferences, by controlling for unobservables across firms and over time, and by separating any variation in the data by sectoral characteristics (banking and non-banking firms) and time-related shocks (such as regulatory reforms).

The study is grounded in an objective ontology and the related concept that fraud risks and the accounting red flags associated with fraud risks, such as unusual increases in revenue, are real and observable, rather than subjective constructs, in the financial statements of listed companies. In terms of epistemology, the study is based on the positivism perspective, which focuses on collecting data in the form of facts that can be observed, measured, and empirical data in financial statements that have been audited to explain the cause and effect that occurs in the financial sector so that the results can be generalized, and the method used is econometric analysis, including the panel regression method. From an axiological perspective, the study is value-neutral, using only secondary data that are publicly available in audited annual reports and regulatory documents, and using strong standard errors so that the findings are reliable, transparent and free from personal bias of the researcher.

The population of this study included all the 43 listed financial institutions in Nigeria which include both banking and non-banking financial institutions as classified by the Nigerian Exchange Group (NGX). Since the population was relatively small and manageable, a purposive sampling technique was used and only firms with complete data for the study period (2014-2024) were included in the study.

Table 1: Population and Sample of the Study

Sector	Population	Sample	Justification for Selection
Banking (Deposit Money Banks)	17	17	No firm was excluded
Non-Banking (Insurance and Other Financial Services)	26	25	1 firm excluded due to incomplete reporting between 2014-2024
Total	43	42	Final sample for analysis

Source: Author's compilation, 2025.

The study relied exclusively on secondary data obtained from the annual reports and audited financial statements of listed financial firms in Nigeria covering the period 2014 to 2024, accessed through the Nigerian Exchange Group (NGX) database, company websites, and regulatory filings with the Central Bank of Nigeria (CBN), the National Insurance Commission (NAICOM), and the Securities and

Exchange Commission (SEC). A structured data-extraction template was designed to systematically capture revenue growth (RG) from year-on-year changes in revenue, and unusual transactions (UT) from related-party transaction disclosures, alongside the components required to compute the F-Score. Data were cross-checked against multiple sources, including the NGX Factbook and CBN statistical bulletins, to minimize extraction errors.

3.1 Model Specification

The parent thesis from which this paper is drawn estimated a single joint model of four accounting red flags on fraud risk detection:

$$F\text{-SCORE}_{it} = \beta_0 + \beta_1 RG_{it} + \beta_2 UT_{it} + \varepsilon_{it}$$

where This paper reports and discusses only the RG and UT coefficients, standard errors, and p-values from that same jointly-estimated four-variable model, consistent with standard practice of reporting a focused subset of a multivariate model's own estimated coefficients. No separate two-variable regression was re-run or re-estimated for this paper; the coefficients presented in Section 4.4 are identical to those obtained in the thesis's original joint estimation.

3.6 Variable Measurement

Table 2: Variable Measurement

Variable	Measurement	Source
Fraud Detection (F-Score model)	F-Score = RSST Accrual + Financial Performance	Dechow et al. (2011); Jannah et al. (2022); Inayah & Chariri (2024)
Unusual Revenue Trends	$(\text{Revenue}_t - \text{Revenue}_{t-1}) \div \text{Revenue}_{t-1} \times 100$	ISA 240.A33
Unusual Transactions (UT)	$\text{Related-Party Transactions} \div \text{Total Assets}$	ISA 240.A37

Source: Author's compilation, 2025.

The F-Score is computed as RSST Accrual plus Financial Performance, where RSST Accrual = (Working Capital + Non-Current Operating Assets and Liabilities + Financial Assets and Liabilities) ÷ Average Total Assets, and Financial Performance = Change in Receivable + Change in Inventories + Change in Sales + Change in Earnings, each scaled by Average Total Assets or its relevant base as specified in the F-Score formula.

3.7 Technique for Data Analysis

Descriptive statistics and correlation analysis were first conducted to provide an overview of the data distribution and preliminary variable relationships. Panel data regression analysis was then employed as the main analytical technique, given the dataset's combination of cross-sectional and time-series information. The choice between Fixed Effects (FE) and Random Effects (RE) estimators was guided by the Hausman specification test, while the Breusch-Pagan Lagrangian Multiplier (LM) test assessed the appropriateness of random effects over pooled Ordinary Least Squares (OLS). A series of diagnostic procedures was applied: the Shapiro-Wilk test for normality, the Variance Inflation Factor (VIF) for multicollinearity, the Modified Wald/Breusch-Pagan test for heteroskedasticity, the Wooldridge test for serial correlation, the Pesaran test for cross-sectional dependence, and the Levin-Lin-Chu test for unit roots. Where diagnostic results indicated violations of classical regression assumptions, robust standard errors were applied.

4.1 Descriptive Statistics

Table 3: Descriptive Statistics (F-SCORE, RG, UT)

Sector	Statistic	F-SCORE	RG	UT
Banking	Mean	22.57906	0.0692941	24.2418
Banking	Std. Dev.	72.8554	0.4114977	73.8202
Banking	Min	-0.12	-0.552	0.078
Banking	Max	659.812	3.904	659.791
Non-Banking	Mean	16.00228	1.076891	19.61436
Non-Banking	Std. Dev.	38.50508	15.00657	51.18436
Non-Banking	Min	-0.146	-9.422	0
Non-Banking	Max	277.455	242.921	453.699
Overall	Mean	18.66431	0.6690541	21.48737
Overall	Std. Dev.	55.07497	11.58282	61.32683
Overall	Min	-0.146	-9.422	0

Overall	Max	659.812	242.921	659.791
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Source: STATA version 17, 2025.

Fraud detection, measured by the F-Score, was on average higher in banks (22.58) than in non-banking firms (16.00), underscoring that banks tend to show more fraud-related warning signals. The wide variability within banks, with fraud scores rising as high as 659.81, suggests that while some banks operated within normal risk boundaries, others were deeply exposed to fraudulent practices—an extreme variation linked to the highly complex nature of banking operations, large transaction volumes, and regulatory pressures that create opportunities for manipulation. Non-banking firms, though showing lower average F-Scores, still reached a maximum of 277.46, indicating that fraud risk is significant but generally less severe than in banks.

Revenue growth presents a different picture. Non-banking firms achieved much higher average growth (1.08) compared to banks (0.07), reflecting more aggressive expansion strategies outside the traditional banking space, but with excessive volatility, ranging from -9.42 to 242.92. Such instability often signals possible earnings manipulation, where firms inflate revenues to attract investors or conceal financial distress. Banks demonstrated relatively modest and stable growth, reducing the likelihood of overt revenue manipulation but potentially concealing understated performance risks.

Unusual transactions were more prevalent in banks, averaging 24.24 compared to 19.61 in non-banking firms, reflecting a higher incidence of irregular accounting activities in banks, potentially involving complex financial instruments, off-balance-sheet items, or manipulation of loan classifications. The very high maximum of 659.79 in banks compared to 453.70 in non-banks suggests that banks are more vulnerable to extreme cases of irregularities that, if unchecked, can escalate into full-blown financial scandals. For non-banking firms, although unusual transactions were relatively lower on average, the wide variability still indicates that irregularities recur and could be linked to opportunistic behaviours such as related-party transactions.

4.2 Correlation Analysis

The correlation analysis examined the strength and direction of the relationships between fraud detection (F-Score) and revenue growth (RG) and unusual transactions (UT) across the banking, non-banking, and overall financial sectors, providing preliminary insight into whether these red flags move together with fraud risk.

Table 4a: Correlation Matrix for Banking Sector (F-SCORE, RG, UT)

	F-SCORE	RG	UT
F-SCORE	1.0000		
RG	-0.0590	1.0000	
UT	0.9791*	-0.0575	1.0000

Table 4b: Correlation Matrix for Non-Banking Sector (F-SCORE, RG, UT)

	F-SCORE	RG	UT
F-SCORE	1.0000		
RG	0.3604	1.0000	
UT	0.6458	-0.0281	1.0000

Table 4c: Correlation Matrix for Overall Financial Sector (F-SCORE, RG, UT)

	F-SCORE	RG	UT
F-SCORE	1.0000		
RG	0.1904	1.0000	
UT	0.8552	-0.0206	1.0000

Source: STATA version 17, 2025.

For the banking sector, the correlation between revenue growth (RG) and F-Score was weak and negative (-0.0590), suggesting that revenue expansion in banks does not strongly contribute to the detection of fraud risk and may not be a reliable early-warning signal, possibly owing to the stable but regulated nature of revenue generation in Nigerian banks. Unusual transactions (UT), by contrast, displayed a very strong and statistically significant positive correlation with F-Score (0.9791*), highlighting transaction irregularities as the most important red flag for detecting fraud in banks—plausibly explained by the complexity of banking operations, where manipulations such as inflating loan values or engaging in off-balance-sheet arrangements often lead directly to elevated fraud scores.

In the non-banking sector, revenue growth (RG) was positively correlated with F-Score (0.3604), indicating that rapid revenue increases in non-banking firms are associated with a higher likelihood of fraudulent reporting, possibly reflecting manipulation of revenue figures to create an impression of strong growth. Unusual transactions (UT) also had a positive correlation with F-Score (0.6458), suggesting that, as in banking, irregular accounting practices remain a major driver of fraud detection, although the magnitude is lower than in banks, implying a relatively less dominant role in the less complex non-banking transaction environment.

For the financial sector as a whole, revenue growth (RG) was positively correlated with F-Score (0.1904), though the relationship was comparatively modest, suggesting that firms experiencing revenue increases tend to show slightly higher fraud risk without revenue growth alone being a reliable standalone indicator. Unusual transactions (UT) demonstrated a strong positive correlation with F-Score (0.8552), confirming that across both banks and non-banking firms, transaction irregularities are the most consistent and powerful indicator of fraud detection—a universal red flag for fraudulent activities in Nigerian financial firms regardless of sector.

4.3 Diagnostic Tests

Before proceeding with panel regression, the dataset was subjected to a series of diagnostic tests to ascertain its suitability for robust econometric modelling.

Table 5: Shapiro-Wilk Normality Test (F-SCORE, RG, UT)

Variable	Obs	W	V	z	Prob>z
F-SCORE	462	0.32227	212.329	12.834	0.00000
RG	462	0.03844	301.250	13.672	0.00000
UT	462	0.34289	205.869	12.760	0.00000

All three variables depart significantly from normality (Prob > z = 0.0000 at 1%). The non-normality of the F-Score—a composite fraud-detection measure—suggests that fraudulent versus non-fraudulent observations are concentrated in particular ranges rather than evenly spread, possibly reflecting systemic tendencies among Nigerian financial firms toward similar manipulation techniques during certain periods; the non-normality of RG and UT similarly implies irregular growth patterns and unusual transaction flows symptomatic of opportunistic reporting. These violations necessitated the robust estimation techniques applied in the regression analysis.

Table 6: Multicollinearity Test (VIF) — RG and UT

Variable	Banking VIF	Banking 1/VIF	Non-Banking VIF	Non-Banking 1/VIF	Overall VIF	Overall 1/VIF
RG	1.02	0.976038	1.06	0.943062	1.02	0.979514
UT	1.01	0.987235	1.00	0.995293	1.00	0.997444

All VIF values for RG and UT are well below the conventional threshold of 10, with tolerance (1/VIF) above 0.94 in every sector, confirming that revenue growth and unusual transactions are independent, non-redundant fraud indicators in the joint model across all three sectors. No multicollinearity concern was identified.

Table 7: Heteroskedasticity Test (Modified Wald/Breusch-Pagan-Cook-Weisberg, χ^2 -distributed)

	Banking	Non-Banking	Overall
Chi ²	701,609.55	5,236,471.33	3,262,959.93
Prob > Chi ²	0.0000	0.0000	0.0000

The null hypothesis of homoskedasticity was rejected in all three sectors ($p = 0.0000$), indicating non-constant residual variance and that the effect of accounting red flags on fraud detection varies across firms. Robust standard errors were therefore applied throughout to correct for heteroskedasticity and ensure reliable estimates.

Table 8: Serial Correlation Test (Wooldridge Test for Autocorrelation in Panel Data)

	Banking	Non-Banking	Overall
F-Statistic	58.883	0.017	0.380
Prob > F	0.0000	0.8960	0.5409

The Wooldridge test rejected the null hypothesis of no serial correlation for banking ($p = 0.0000$), suggesting that fraud risk indicators in banks follow persistent patterns rather than occurring randomly. For non-banking ($p = 0.8960$) and overall ($p = 0.5409$), the null could not be rejected, indicating that fraud risk indicators occur more randomly over time in those samples, often triggered by situational rather than structural factors.

Table 9: Pesaran Test for Cross-Sectional Independence

	Banking	Non-Banking	Overall
F-value	0.118	0.404	-0.666
Prob	0.9057	0.6864	0.5054
Average absolute value	0.259	0.304	0.308

The null hypothesis of cross-sectional independence could not be rejected in any of the three sectors (all p-values well above 0.05), indicating that fraud-related shocks in one firm do not systematically spill over to others. Fraud risks in Nigerian financial firms therefore appear firm-specific and contained rather than contagious, validating the treatment of firms as relatively independent units in the modelling framework.

Table 10: Levin-Lin-Chu Unit-Root Test for F-SCORE

	Banking	Non-Banking	Overall
Unadjusted t-statistic	-22.8139	-8.1319	-1.7e+02
Adjusted t-statistic	-17.9806	4.1959	-1.8e+02
Prob-value	0.0000	1.0000	0.0000

For banking, both unadjusted and adjusted t-statistics were strongly negative ($p = 0.0000$), confirming that F-Score is stationary and that fraud-detection signals among Nigerian banks remain stable and predictable over time. For non-banking, the adjusted statistic turned positive (4.1959, $p = 1.0000$), a failure to reject the unit-root null, indicating that F-Score is non-stationary and fraud-detection signals are less predictable in that subsector. For the overall pooled sample, both statistics were again extremely negative ($p = 0.0000$), confirming stationarity and strengthening the reliability of the pooled regression results.

Table 11: Hausman Test

	Banking	Non-Banking	Overall
Chi ²	3.04	1.20	2.46
Prob > Chi ²	0.5511	0.8779	0.6527

Across all three sectors, the Hausman probability values were well above the 5% threshold, so the null hypothesis that the random-effects estimator is consistent could not be rejected—indicating that Random Effects is preferred over Fixed Effects in every sector.

Table 12: Breusch and Pagan Lagrangian Multiplier (LM) Test for Random Effects

	Banking	Non-Banking	Overall
Chibar ²	0.00	2.73	7.75
Prob > Chibar ²	1.0000	0.0493	0.0027

For banking, the LM test failed to reject the null ($p = 1.0000$), indicating that the panel structure adds little beyond pooled regression, so Robust Pooled OLS was adopted as the final banking estimator. For non-banking ($p = 0.0493$) and overall ($p = 0.0027$), the null was rejected, indicating important unobserved firm-level heterogeneity, so Robust Random-Effects GLS was adopted for both models—consistent with, and complementing, the Hausman results above.

4.4 Regression Results and Test of Hypotheses

Table 13: Panel Regression Results

	Banking (Robust Pooled OLS)		Non-Banking (Robust RE-GLS)		Overall (Robust RE-GLS)	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
RG	-0.9930157	0.518	0.9881153	0.000	1.00245	0.000
UT	0.8097228	0.000	0.5015352	0.004	0.779253	0.000
Constant	7.524651	0.208	-4.363977	0.722	-12.87501	0.394
N (Obs)	187		275		462	
F-Statistic	50.94		11046.17		13020.62	
Prob > F	0.0000		0.000		0.000	
R-squared	0.7905		0.5791		0.8311	

Source: STATA version 17, 2025.

Consistent with the diagnostic results in Section 4.3, the Banking model was estimated as Robust Pooled OLS, while the Non-Banking and Overall models were estimated as Robust Random-Effects GLS. For the banking sector, the model produced an R-squared of 0.7905 ($F = 50.94$, $p = 0.0000$), indicating that about 79% of the variation in fraud detection is jointly explained by the model's

predictors. For the non-banking sector, the R-squared was 0.5791 ($F = 11,046.17$, $p = 0.000$), explaining about 58% of the variation. For the overall pooled sample, the R-squared was 0.8311 ($F = 13,020.62$, $p = 0.000$), explaining about 83% of the variation—the strongest fit of the three models.

Test of H_{01} (Revenue Growth):

In the banking sector, RG carried a negative coefficient (-0.993) but was statistically insignificant ($p = 0.518 > 0.05$); the null hypothesis H_{01} is therefore not rejected for banking. In the non-banking sector, RG was positive and highly significant (0.988 , $p = 0.000 < 0.05$); H_{01} is therefore rejected for non-banking. In the overall sector, RG remained positive and highly significant (1.002 , $p = 0.000 < 0.05$); H_{01} is therefore rejected for the overall model. Revenue growth is thus a sector-conditional red flag: unsustainable revenue growth is strongly associated with elevated fraud risk in non-banking firms and in the pooled financial sector, but not in the more tightly regulated banking sub-sector.

Test of H_{02} (Unusual Transactions):

In the banking sector, UT was positive and highly significant (0.810 , $p = 0.000 < 0.05$); H_{02} is therefore rejected for banking. In the non-banking sector, UT remained positive and significant (0.502 , $p = 0.004 < 0.05$); H_{02} is therefore rejected for non-banking. In the overall sector, UT was positive and highly significant (0.779 , $p = 0.000 < 0.05$); H_{02} is therefore rejected for the overall model. Unusual transactions are therefore the only one of the two focal red flags (and, more broadly, the only accounting red flag examined across the parent thesis's full four-variable model) that is statistically significant in every sector, confirming its status as the single most consistent predictor of fraud risk detection in Nigerian listed financial firms.

5. Discussion of Findings

5.1 Revenue Growth (RG) and Fraud Risk Detection.

As in the non-banking and overall financial service sectors, an increase in revenue growth is found to have a positive and significant effect on fraud risk detection, consistent with empirical evidence to the effect that growing revenues, if fast or unsustainable, increases manipulation tendencies. According to Al-Yahyaee et al. (2024), strong growth in revenue increases the incentive for management to engage in earnings management, at the expense of earnings quality and increasing vulnerability to earnings manipulation by management, and Adepoju and Ibrahim (2025) found that, under weak monitoring, abnormal increase in revenue may lead to accounting distortions even if sustainable growth improves transparency. Also, revenue growth may enhance shareholder value but may at the same time motivate misreporting as a result of market or regulatory pressure (Munyua and Kamau 2022). So, if the revenue growth is too much for a company, not backed by real operations, it is a red flag for manipulation, especially in non-banking companies where revenue recognition policies are more flexible than in the banking companies.

In contrast, the negative, yet non-significant, result in the banking industry is different from the results of other studies like Al-Yahyaee et al. (2024) which found that high revenue growth was correlated with financial manipulation generally. This difference can be attributed to contextual and regulatory differences, with Nigerian banks subject to CBN prudential guidelines that have higher disclosure and audit and compliance requirements, while non-banking institutions enjoy more freedom in accounting distortions. The absence of an insignificant banking result does not therefore mean that there is no fraud risk but rather that revenue based indicators are less likely to detect fraud when governance and monitoring is more robust.

The patterns correspond with the Fraud Hexagon Theory, where the growth in revenue and the ability dimension coincide—managers with the ability to count and organise the business to inflate or unsustainable growth figures may be able to do so. In the non-banking sector, where internal controls and regulatory oversight are comparatively less well entrenched, it is possible for capable managers to rationalise manipulative accounting to preserve investor confidence, while in banking, it is not as easy for capable managers to go around the regulatory monitoring and independent auditing and internal controls, to weaken the relationship between revenue growth and fraud detection. The results therefore substantiate the contextual flexibility of the Fraud Hexagon Theory; revenue growth can trigger ability to perpetrate fraud in environments with less strict regulation, but less so in the environment of Nigeria's banking industry with strong regulations.

5.2 Unusual Transactions (UT) and Fraud Risk Detection

That unusual transactions have a positive and significant effect on fraud risk detection is comparable with previous empirical research showing that unusual transactions are associated with fraudulent reporting, most strongly in the banking sector. Al-Rizky et al. (2024) revealed that the dimension of

financial targets significantly affect the risk of financial statement fraud, as firms try to inflate their performance to meet such targets, and Salim et al. (2024) validated the role of opportunity and rationalization dimensions in the financial statement fraud of insurance companies, which is in line with unusual transactions as an operational manifestation of these behavioral dimensions. Collusion's positive influence on fraudulent reporting – it means that there is a positive relationship between collusion and the increase of fraudulent reporting, which means that the increase of collusion will also increase fraud, as was stated by Puspaningrum et al. (2024); and transactional nature of fraud that is the financial pressures give rise to fraudulent reporting as stated by Wicaksono and Suryandari (2021). This finding is consistent with the current study's conclusion that the irregular or non-recurring transactions are important red flags for fraud detection.

Achmad et al. (2023) on the other hand produced contrasting results, due to methodological and sectoral differences: The results were obtained based on a single-variable regression model that did not consider transaction-level anomalies, and the sectoral differentiation used in the present study was not used. The sectoral comparative design of the current study, however, indicates that the intensity of unusual transactions (and hence fraud detection) is greater in the case of banks because of the complexity of their operations, more and widespread interbank transactions and multi-level transaction structure.

The current study's findings are well rooted in the Fraud Hexagon Theory, where unusual transactions are the practical manifestation of rationalization and arrogance: individual rationalize non-standard accounting practices as “necessary adjustments” or demonstrate a lack of adherence to standard accounting conventions on the assumption that they will not be detected by oversight mechanisms. This is especially true in banking, where the number of transactions is high, and the systems are highly digitalized, allowing for people with the means to hide their manipulative activity in unusual transactions. In line with this interpretation, empirical studies conducted by Riyanti et al. (2021), Salim et al. (2024) and Puspaningrum et al. (2024) strongly support the notion that collusion and pressure usually occur in the form of transactional anomalies. These theoretical elements are operationalized in the use of the F-Score model, which quantifies the contribution of such irregularities to fraud risk detection, thus testing the Fraud Hexagon Theory in the banking and non-banking financial services sectors in Nigeria.

6. Conclusion and Recommendations

In the banking sector, unusual transaction activity is the most significant and positively related to F-Score, indicating the strong association between operational irregularities in Nigerian banks and fraudulent transactions, and the importance of transaction monitoring to banks' fraud prevention efforts. The performance pressure by revenue growth does not seem to affect the growth of revenue in banking, indicating that fraud in banking is more about getting into the transaction level manipulation rather than about the revenue growth. In the non-banking sector, a significant increase in revenue growth and/or unusual transactions elevate the fraud risk – managers could overstate revenues or tweak sales to ensure positive numbers, and unusual transactions heighten the risk. The combined results reinforced these results for the overall financial sector, and for the financial sector generally, both unusual transactions and growth in revenue turned out to be significant contributors. The overall fraud risk in the Nigerian financial institutions is therefore related to unusual transactions and revenue growth, with a sector specific aspect; banks are more vulnerable to unusual activity in their operations, while non-banking institutions are more vulnerable to both unusual activity over transactions and pressure on revenue.

The study suggests that financial firms should pay closer attention to monitoring and auditing of unusual transactions as these were the most consistent and powerful determinants of fraud, as well as first, that the study recommend the need for closer attention to sales price for financial firms as it emerged as an effective predictor and appeared in the largest volume across the board in all samples. Real-time data-analytics and artificial-intelligence tools should be strengthened by banks; all licensed banks should be required by the CBN and the NDIC to have fraud-analytics software via regulatory directives, periodic compliance audits and penalties for non-adoption by the FRCN and SEC for non-banking institutions.

Second, because the growth of revenue has significant impact on fraud detection in the non-banking area, SEC and FRCN should provide more stringent guidelines for the recognition of revenue and conduct forensic audit of revenue streams every quarter, with the inclusion of case studies on earnings manipulation during the mandatory training of the profession by ICAN and ANAN, in addition to the

mandatory disclosures of revenue drivers, benchmarking of income growth against the industry and whistle blowing mechanisms.

Thirdly, the EFCC and ICPC must work with the CBN and SEC in setting up a central Fraud Risk Monitoring Hub to coordinate and assess the suspicious transaction reports and revenue growth anomalies from firms, facilitate the identification of systemic risks through the use of a secure digital platform for real time reporting.

Lastly, external auditors should incorporate unusual transactions and revenues into their audit planning and risk-assessment process and the FRCN, ANAN, and ICAN should update audit standards to require the audit to be a fraud audit, with audit quality inspections and penalties for failure to identify red flags.

7. Implications, Limitations and suggestions for further research

The results have theoretical, practical and policy implications. Theoretically, the study expands and corroborates Fraud Hexagon Theory in Nigerian financial institutions such that the significance of unusual transactions in all three models provides good empirical support for the rationalization/opportunity strand of the theory; likewise, the significance of revenue growth in the non-banking and overall models confirm the relevance of capability/managerial ability in concealing irregularities and manipulating earnings as an independent variable in fraud detection. In practice, the report focuses on the most reliable indicators of fraud – unusual transactions and revenue growth – and offers regulators, auditors and corporate managers sector-specific guidance to help enhance fraud-detection mechanisms within banking and non-banking financial institutions.

Despite the contributions, the study has some limitations. In terms of methodology, it was based on secondary data from published annual reports which may not fully reflect unreported or concealed fraudulent actions and included only F-Score as the measure of the fraud detection; although well-known, the F-Score might not capture some qualitative aspects of fraud, including collusion or unethical management practices. Because there was a larger 4-red-flag model estimated in the parent study, both of the two red flags examined here were included in that larger model; as such, interaction effects between all four red flags are not separately examined here, although the two variables examined in this paper were methodologically valid as a subset-reporting exercise. Heteroskedasticity and cross-sectional dependence were corrected using robust regression methods, but these corrections might not remove all statistical bias caused by performing panel data analysis. The study was also limited to the work of the financial sector and to an 11-year period of data, because of limited resources and time, and it was not possible to access qualitative data like the insider reports.

These restrictions provide opportunities for further research. Other fraud indicators, such as audit fees and executive compensation, could be added to analyze revenue growth and unusual transactions; future studies could also consider analyzing other non-financial sectors, as it is possible that fraud patterns will vary according to sector; future studies could also apply a mixed-methods approach with both quantitative analysis and qualitative evidence from fraud investigation. One would have to have a cross country or regional Sub-Saharan African data set to be able to check if the effects identified here are specific to Nigeria; sophisticated econometric models such as dynamic panel regressions, structural equation modelling, or machine-learning based fraud-detection models would also be useful in testing the robustness of the revenue growth and the unusual-transaction indicators.

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