



# RATIONALISATION RED FLAGS AND LIKELIHOOD OF FRAUD DETECTION IN NIGERIA

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## ABSTRACT

*The broad objective of this study is to ascertain the impact of rationalisation red flags as prescribed by SAS.99 in relation to the fraud triangle on the likelihood of fraud detection in Nigeria. The specific objectives of this study are to determine the effects of rationalisation red flags proxies: quality of earnings; and effective cash tax rate on the likelihood of fraud detection in Nigeria. This study used secondary data sourced from audited annual reports of quoted companies in the Nigeria Stock Exchange and a sample size of sixty-five (65) companies were used for a six-year period of 2009-2014. The variables were derived by making necessary computations using information reflected on the face of financial statements to derive our figures not explicitly stated on the face of the financial statements. The probit regression estimation analyses on the pooled data shows that Rationalization red flags such as quality of earnings and effective cash tax rate on the average cannot aid the likelihood of fraud detection in Nigeria. It is however recommended that forensic accountants should as a matter of necessity pay close attention to our findings in this study and make use of SAS.99 qualitative and quantitative proxies red flags when carrying fraud examination.*

## I. INTRODUCTION

The Association of Certified Fraud Examiners (ACFE, 2012) reported a high percentage of fraud that occurs globally. ACFE (2012) reported and analyzed 1388 fraud cases the world over and classified these fraud cases into three groups that include; asset misappropriation, corruption, and financial statement fraud. It was observed that asset misappropriation has the most cases with more than 86 percent of fraud cases but caused the lowest range of loss at US\$ 120000 on the average. On the contrary, financial statement fraud involved less than 8 percent of the fraud cases, but the majority of losses were related to this category with US\$ 1 million on the average. This statistics underlines the perceived challenges associated with fraud detection in financial statements, even though the conventional audit procedure will normally issue an unqualified opinion relating to claims made by management in the financial statements.

The American Institute of Certified Public Accountants, AICPA (2002), in an acknowledgement of the challenges faced by forensic auditors in the course of fraud detection, established the Statement of Auditing Standards (SAS) No.99; consideration for fraud in financial statements, which auditors are expected to use as tools in the course of detection of fraud in financial statements. The standard issued 42 red flags that the auditors should look out for in the course of trying to detect fraud. However the red flags were aligned into the elements of fraud triangle and because the red flags are qualitative in nature, it makes it difficult for auditors to use scientific modeling in detecting financial statement fraud except where necessary proxies are adopted. Few empirical studies like those of Skousen, Smith and Wright (2008), in the United States of America, Amara, Amar, and Jarbou (2013) in France, and Aghghaleh, Iskandar, and Mohamed (2014) in Malaysia.



Fraud detection is the act of uncovering the phenomenon of theft, conversion and concealment. Fraud detection becomes necessary where prevention of fraud fails in an organization, hence the need for the forensic accountant to be equipped with the requisite skills in detection of fraud cannot be overemphasized. The detection techniques deployed by a forensic accountant is a function of the kind of fraud occurring in the organisation. Fraud detection approaches basically involves documentation and independent checks of special transactions (Hopwood, Young & Leiner, 2013), but due to the continuous proliferation of sophisticated crimes across the globe, the issue of fraud detection appears to have gone beyond mere documentation and independent checks of special transactions. Enofe, Ibadin, Audu and Izevbigie (2014) observed that despite the high increase in fraud rate in Nigeria, the vehicle for investigating and prosecuting fraudster and fraudulent activities are still very limited.

Meanwhile in an attempt to ease the fraud detection problems, the American Institute of Certified Public Accountants (AICPA) in October 2002 established the Statement of Auditing Standards (SAS) No. 99, which deals with consideration of fraud in financial statements. The SAS No. 99 in a bid to address the obvious challenges faced by forensic accountants in the detection of fraud, listed about 42 red flags (mostly qualitative) which are subsumed into the fraud triangle model developed by Cressey (1953), so as to guide forensic accountants in the course of fraud detection exercise. However, studies carried out by researchers on the nexus of these red flags and fraud detection in Nigeria and other African countries such as (Hegazy & Kassem, 2010; Koornhof & Plessis, 2000; Ogwueleka, 2011), have scarcely used quantitative proxies in representing these red flags. The objective of this study is to examine the nexus between rationalisation red flag and likelihood of fraud detection, with emphasis on quantitative proxies as basis for measurement of variable of interest.

## II. CONCEPTUAL LITERATURE

### Likelihood of fraud detection

Kou, Lu and Sinvongwattana (2004) defined fraud detection as the act of identifying fraud as quickly as possible once it is perpetrated. The authors maintained that fraud detection has been implemented by a number of methods which include artificial intelligence, statistics, and data mining. However, Bierstaker, Brody, and Pacini (2006) identified fraud prevention and detection techniques to include but are not limited to: fraud policies, firewalls, employee reference checks, vendor contract reviews and

sanctions, financial ratio analysis, telephone hot lines, password protection, digital analysis and other forms of software technology, fraud vulnerability reviews, and discovery sampling. According to Yücel (2012) understanding the factors that cause fraud and accordingly defining primary areas to conduct detailed examination by estimating the riskiest accounts is the way to detect fraud in the most effective manner. Auditors follow various indicators (red flags) and employ different methods in detecting fraud and manipulations.

Bolton and Hand (2002) sees fraud detection as a mechanism for early identification of fraud upon its occurrence, and that failure of fraud prevention leads to fraud detection. They propose a continuous use of fraud detection because of the inability to easily determine the failure of preventive controls. They opined that fraud detection is still evolving and that perpetrators are most likely to adopt different approaches as management try to put in place more robust fraud detection techniques. Othman, Aris, Mardziyah, Zainan, and Amin (2015) opine that fraud detection should be continually used and worked upon because fraud is always evolving. Othman *et al.* (2015) pointed to the fact that the conventional fraud detection approach like auditing is no longer sufficient in fraud detection and only enabled fraud to be detected, if ever after a lag period, maintaining that this development result in colossal loss and potential loss of goodwill. Some tools commonly used to measure the likelihood of fraud in an organization are the Beneish M-score and Altman Z-score.

### Beneish M-Score model

Jansen, Ramnath, and Yohn (2012) opined that identifying earnings management is important for financial statement users to assess current economic performance, to predict future profitability, and to determine firm value. The M-Score was modeled by Professor Messod Beneish. It is a mathematical model that adopts some financial metrics to identify the extent of company's earnings. The M-Score is similar to the Z-Score except that the M-Score concentrates on estimating the extent of earnings manipulation instead of determining when a company becomes bankrupt. The M-Score comprise of eight ratios that capture either financial statement distortions that can result from earnings manipulation or indicate a predisposition to engage in earnings manipulation (Beneish and Nichols, 2005). Warshavsky (2012) indicates that companies with higher Beneish scores are more likely to be manipulators. Mahama, (2015) stated that one of the advantage of the M-score is that the treatment sample consists of firm that have indeed managed



earnings and that determination is independent of abnormal accrual models (Beneish, 1998).

The Beneish (1999) model is presented mathematically as follows:

$$M = -4.84 + 0.920DSR + 0.528GMI + 0.404AQI + 0.892SGI + 0.115DEPI - 0.172SGAI + 4.679ACCRUALS - 0.327LEVI$$

Where,

$$DSRI = (\text{Receivables}_t / \text{Sales}_t) / (\text{Receivables}_{t-1} / \text{Sales}_{t-1})$$

$$GMI = ((\text{Sales}_{t-1} - \text{Sold Goods of Costs}_{t-1}) / \text{Sales}_{t-1}) / ((\text{Sales}_t - \text{Sold Goods of Costs}_t) / \text{Sales}_t)$$

$$AQI = (1 - ((\text{Current Assets}_t + \text{PPE}_t) / \text{Total Assets}_t)) / (1 - ((\text{Current Assets}_{t-1} + \text{PPE}_{t-1}) / \text{Total Assets}_{t-1}))$$

$$SGI = \text{Sales}_t / \text{Sales}_{t-1}$$

$$DEPI = (\text{Depreciation}_{t-1} / \text{Depreciation}_{t-1} + \text{PPE}_{t-1}) / (\text{Depreciation}_t / \text{Depreciation}_t + \text{PPE}_t)$$

$$SGAI = (\text{SGA Expenses}_t / \text{Sales}_t) / (\text{SGA Expenses}_{t-1} / \text{Sales}_{t-1})$$

$$TAT = (\text{Change in Working Capital}_t - \text{Change in Cash} - \text{Change in Income Tax Payable}_t - \text{Depreciation \& Amortisation}_t) / \text{Total Assets}_t$$

$$LEVI = ((\text{LTD}_t + \text{Current Liabilities}_t) / \text{Total Assets}_t) / ((\text{LTD}_{t-1} + \text{Current Liabilities}_{t-1}) / \text{Total Assets}_{t-1})$$

### Red flags

The American Institute of Certified Public Accountants, AICPA (2002) submitted in its Statement of Auditing Standard, SAS No. 99, that auditors are expected to use 42 red flags in financial statement audits to detect fraudulent financial reporting. The list of 42 red flags found in SAS No. 99 is categorized under pressure, opportunity and rationalization. Abdullahi and Mansor (2015) defined red flags as a systematic way of detecting the symptoms or any signs of fraudulent activities within the organizational settings, they opined that the red flags found in SAS No. 99 is arranged based on the fundamental concept of fraud triangle, which encompasses: pressure, opportunity, and rationalization.

Abdullahi and Mansor (2015) extended the red flags beyond the 42 prescribed by SAS No.99 by identifying some red flags under the fourth element of fraud diamond theory as follows: Pressure red flags includes excessive personal debt; Material lifestyle with lower earning; Excessive gambling; Undue family, organization, and or community prospects; Alcohol or drugs addiction among the employees; Perceived differential and inequality treatment; Antipathy of superiors, intimidation and frustration with job; Pressures from the employee's peer group and clique; Greediness of the employee; and Social, working and other environmental distresses.

According to Abdullahi and Mansor (2015), opportunity red flags include close relationship between suppliers and other key people within and outside the organization; Organizational failure to orienting employees on the measures uses to eradicate fraudulent act; Frequent and excessive replacement of key employees due to retrenchment, firing and retiring; Lack of job rotation, regular vacation or transfer of key

employees within the organization; Inadequate personnel-screening policies when employing a new employee for the replacement; Lack of general and precise personnel policy; Improper record of commendation on personnel dishonest act and other disciplinary actions; Lack of executive disclosures and examinations; A dishonest or overlapping of duty by the dominant management; frequent operation in an unfavorable climate; Lack of supervision and attention paid to details of the job; Inadequate compensation scheme;

Others opportunity red flags include inadequate training programs; Related party transactions; A complex organizational structure; Lack of effective internal auditing staff; use of several auditing firms or changes auditors frequently; providing irrelevant data to the auditors and lack of required information; Use of various legal firms or changes legal counsels repeatedly; An organization that uses large number of different bank accounts; Continuous problems with various regulatory agencies; Large year-end and unusual transactions or unbalanced transactions; An inadequate internal control system or no enforcement of the existing internal controls; Lack of proper accounting records and inadequate accounting personnel; An organization that inadequately disclosed questionable or unusual accounting practices; and Too much familiarity with operations. Rationalization red flags includes an employee's inconsistent behaviour; Lack of personal ethics and morality; A wheeler-dealer personality; A strong desire to beat the system; Employee's criminal or questionable historical background; and a poorly recommended employee with poor financial status. Capacity red flags include having exercising an excessive power; Job or work overlapping; Too much



power to coerce other employees; Ability to pursued others; Too much resistance to stresses; Ability to convincingly deceive and tell lies; Too much egoism and over confidence; Specialization in one function for a long duration; and Confidence of risk bearing

Koornhof and Plessis (2000) maintained that red flags are seen as those events, conditions, situations, pressures, opportunities, threats or personal characteristics that may increase the risk of management fraud, suggesting that the access that auditors have to the organization books allow them to use a broad spectrum of red flag indicators.

## REVIEW OF EMPIRICAL LITERATURE

### *Rationalisation red flags and fraud detection*

Koornhof and Plessis (2000) examined the perception of investors and lenders on red flagging as an indicator of financial statement fraud. They carried out a survey by administering questionnaire to investors and lenders in South Africa with a view to ascertaining the usability of fraud red flags and also attempted to find out the opinions of respondents on the relevance of the individual red flags. The study reveals that lenders and investors in South Africa are obviously aware of the benefits of red flags as early fraud symptoms. However Koornhof and Plessis observed that there was absence of distinction among the different categories of red flags that were based on the nature of red flags, an indication of a lack of structural approach in questionnaires/checklists.

Moyes, Lin, Landry, and Vicdan (2006) in a study on internal auditors' perceptions of the effectiveness of red flags to detect fraudulent financial reporting, investigated the level of effectiveness of the forty-two (42) red flags prescribed by SAS 99 for detecting fraudulent financial reporting. Moyes *et al.* (2006) submitted that the professional practices framework of the Institute of Internal Auditors (IIA, 2005) expects internal auditors to deter, detect, investigate and report fraud, maintaining that though statement of auditing standard (SAS) No. 99 expect external auditors to use fraud red flags in the auditing of financial statement, but that the internal auditors also use them in conducting compliance, operational and conventional audit. Moyes *et al.* (2006) however found out that out of the 42 red flags, 15 were found to be more effective, 14 were rated to be effective, while 13 were observed as ineffective as probable of the presence of fraud. According to Moyes *et al.* (2006) SAS No. 99 categorizes the forty-two (42) red flags into three elements of the fraud triangle—“opportunities,” “pressures,” and “rationalizations.” Based on their findings, it was observed that internal

auditors consistently rated red flags categorized as “opportunity” and “rationalizations” as more effective in detecting falsified financial statements than red flags labeled “pressures.”

Ogwueleka (2011) examined the relevance of data mining application in credit card fraud detection system, using the neural network. The study adopted an unsupervised method neural network (NN) architectural design for the credit card detection system, and was applied to the transactions data to generate four clusters of low, high, risky and high-risk clusters. With the aid of self-organizing map neural network (SOMNN) technique, the study was able to resolve the problem of optimal classification of each transaction into its associated group, based on the fact that prior output was unknown. However, Ogwueleka (2011) opined that the receiver-operating curve (ROC) for credit card fraud (CCF) detection watch, without any false alarms was able to detect a significant 95% of fraud cases unlike other statistical models and the two-stage clusters, which is a clear indication that the CCF performs better and CCF detection watch is in tandem with other fraud detection software.

Bhusari and Patil (2011) carried out a study of hidden Markov model in credit card fraudulent detection. Bhusari and Patil (2011) asserted that in the existing credit card fraud detection business processing system, fraudulent transaction will be detected after transaction is done, but showed in this study that credit card fraud can be detected using Hidden Markov Model during transactions, maintaining that the Hidden Markov Model helps to obtain a high fraud coverage combined with minimal false alarm rate.

Amara, Amar, and Jarboui (2013) investigated the impact of the elements of fraud triangle on the detection of fraud in the financial statements. Using data related to a sample of 80 French companies in the SBF 250 for the period 2001 to 2009 and logistic regression method, their findings shows that the performance issues exerted on the manager which culminate in pressure precipitate the perpetration of fraud in the financial statements. While other factors related to financial difficulties (debt, liquidity) and the size of auditing firm are not associated with the detection of fraud.

## THEORETICAL FRAMEWORK

### *Fraud Triangle Theory (Donald Cressey, 1950)*

Donald Cressey in 1950 developed the fraud triangle theory as a way of investigating the root causes of fraud and published the fraud triangle theory for the first time in 1953 in his journal title other people's



money (Abdullahi & Mansor, 2015). Cressy in 1950, attempted to provide answers on why people commit financial crimes by examining 250 criminals in a period of 5 months and concluded that: trust violators, having a financial problem that is non-shareable and having knowledge or awareness that this problem can be secretly resolved by a violation of the position of financial trust, gave birth to the theory of fraud triangle which comprises of elements such as pressure, opportunity and rationalization.

Ruankaew (2013) argued that before an employee makes sub-optimal/fraudulent decisions, the tripod elements of fraud triangle which includes pressure, opportunity, and rationalization are preconditions which must be satisfied. He noted that pressure relates to the triggering factor that leads to unethical behaviors, maintaining that those who perpetrate fraud are usually under pressure arising from various circumstances, which in most cases will involve financial stress. Similarly, Ruankaew submitted that perpetrator believes that opportunity exist irrespective of the reality of such opportunity, citing that fraudulent actions is a function of low level of risk. On the other hand, rationalization is a calculated attempt by perpetrator to justify his/her action before the eventual execution of the fraudulent actions. Hopwood, Young and Leiner (2013) defines fraud triangle as a means of assessing the risk that a particular individual may commit fraud. They opine that the triangle consist of three elements which includes pressure/motive, opportunity and rationalization. This means that in the use of use of model for fraud detection, an understanding of the workability of the theory of fraud triangle is very important.

According to Kassem and Higson (2012), the question of why people commit fraud was first examined by Donald Cressey, a criminologist, in 1950. He pointed out that his research was about what drives people to violate trust. He interviewed 250 criminals

over a period of 5 months whose behaviour met two criteria: (1) the person must have accepted a position of trust in good faith, and (2) he must have violated the trust. He found that three factors must be present for a person to violate trust and was able to conclude that: "Trust violators when they conceive of themselves as having a financial problem which is non-shareable, have knowledge or awareness that this problem can be secretly resolved by violation of the position of financial trust, and are able to apply to their own conduct in that situation verbalisations which enable them to adjust their conceptions of themselves as trusted persons with their conceptions of themselves as users of the entrusted funds or property". The three factors were non-shareable financial problem; which is the pressure, opportunity to commit the trust violation, and rationalisation by the trust violator. When it comes to non-shareable financial problem, Cressey stated "Persons become trust violators when they conceive of themselves as having incurred financial obligations which are considered as non-socially sanctionable and which, consequently, must be satisfied by a private or secret means". The theoretical framework upon which this work is anchored on is the theory of fraud triangle.

### III. METHODOLOGY

The secondary source of data collection was used. This was achieved from the annual reports of the respective companies and the Nigeria Stock Exchange Fact Books for a six (6) year period from 2009-2014, thus making it a panel data collection of sixty-five (65) companies. The study used probit regression as it expects a functional relationship between the pressure red flag and the likelihood fraud detection. The model adapted from the work of Aghghaleh, Iskandar and Mohamed (2014) is stated and operationalized as follows:

$$\text{Fraud} = \beta_0 + \beta_1 \text{SALAR} + \beta_2 \text{LEV} + \beta_3 \text{AUDCSIZE} + \beta_4 \text{BRDSIZE} + \epsilon$$

.....Eqn. 3.1

The model is adapted in this study as follows:

$\text{DLFD}_{it} = F$  (pressure (SALAR, LEV), opportunity (AUCSIZE, BRDSIZE), rationalization)

Grove and Cook (2004) put forward two additional quantitative red flags not yet considered in fraud detection models which were incorporated into this model and classed under rationalization. The additional quantitative red flags are: Quality of

earnings and the effective cash tax rate, which they denoted as follows:

*Quality of earnings (QOE)* = (Operating cashflows/Net income); with a red flag benchmark of <2

*Effective cash tax rate (ECR)* = GAAP: Accrual basis: (Total income tax expense/Net income before taxes) or



Cash basis: (Total income tax paid/Net income before taxes)

With a red flag benchmark of >2

Thus the fraud detection model adapted from Aghghaleh, Iskandar and Mohamed, (2014) for this study is:

$DLFD_{it} = F$  (pressure (SALAR, LEV), opportunity (AUCSIZE, BRDSIZE), rationalization (QOE, ECR)), However, because our dependent variable; likelihood of fraud detection ( $Dlfd_{it}$ ) is measured using dummy variables on the Beneish M-score metrics, we used probit regression model for our estimate as follows:

$$DLFD_{it} = \beta_0 + \beta_1 SALAR_{it} + \beta_2 LEV_{it} + \beta_3 AUCSIZE_{it} + \beta_4 BRDSIZE_{it} + \beta_5 QOE_{it} + \beta_6 ECR_{it} + \epsilon_{it} \dots \dots \dots \text{Eqn. 3.2}$$

Where:

$DLFD_{it}$  = Likelihood of fraud detection of company i in year t.

$SALAR_{it}$  = Sales to Accounts receivables of company i in year t.

$LEV_{it}$  = Total debt to Total assets of company i in year t.

$AUCSIZE_{it}$  = Number of audit committee members of company i in year t.

$BRDSIZE_{it}$  = Number of board of directors members of company i in year t.

$QOE_{it}$  = Quality of earnings of company i in year t.

$ECR_{it}$  = Effective cash tax rate of company i in year t.

$\epsilon_{it}$  = stochastic error term

$\beta_1 - \beta_6$  = Regression coefficients

### Data Analyses and interpretation

The result of the descriptive statistics in Table 1 the appendices shows the statistics of three hundred and ninety (390) recorded observations from annual reports of sixty-five (65) companies listed on the Nigeria stock exchange for a period of six years (2009-2014). It shows that the Likelihood of Fraud Detection (LFD), which is the main variable of interest as it is the dependent variable has a mean value of 0.400000, while its standard deviation is 0.490527, it has a Jarque-Bera value of 65.45139. Sales to Accounts receivables (SALAR) has the highest mean value of 19.20881 and a standard deviation of 107.0200. Total debt to Total assets (LEV) has a mean value of 0.078203 and standard deviation value of 0.123877, Number of audit committee members (AUCSIZE) has a mean value of 5.123077 and standard deviation of 1.658578, while Number of board of directors' members (BRDSIZE) has a mean value of 9.107692 and standard deviation of 3.942217. Quality of earnings (QOE) and Effective cash tax rate (ECR) have mean values and standard deviation values of 0.700000, 0.112821 and 0.458846, 0.316780 respectively. Sales to Accounts receivables (SALAR) has the highest Jarque-Bera value of 281810.6. All other variables but Number of audit committee members (AUCSIZE), Number of board of directors' members (BRDSIZE) and Quality of earnings (QOE) exhibited positive skewness.

Table 2 in the appendices shows the association among the variables employed in our study. It shows that the Likelihood of Fraud Detection (LFD) has a low positive relationship with Sales to Accounts receivables (SALAR), Total debt to Total assets (LEV),

Number of audit committee members (AUCSIZE), and Number of board of directors' members (BRDSIZE) with correlation coefficient values of 0.081614, 0.094254, 0.207911 and 0.146497 respectively, and a negative relationship with Quality of earnings (QOE) and Effective cash tax rate (ECR) with a correlation coefficient values of -0.059391 and -0.009926 respectively. Sales to Accounts receivables (SALAR) has low positive and negative relationship with Total debt to Total assets (LEV), Number of audit committee members (AUCSIZE), Number of board of directors' members (BRDSIZE), and Quality of earnings (QOE), Effective cash tax rate (ECR) with a correlation coefficient values of 0.063967, 0.047406, 0.015589 and -0.001598, -0.036860 respectively.

Total debt to Total assets (LEV) has low positive and negative relationship with Number of audit committee members (AUCSIZE), Number of board of directors' members (BRDSIZE), Effective cash tax rate (ECR) and Quality of earnings (QOE) with correlation coefficient values of 0.135642, 0.041877, 0.093380 and -0.063596 respectively.

Number of audit committee members (AUCSIZE) has low positive and negative relationship with Number of board of directors' members (BRDSIZE), Effective cash tax rate (ECR) and Quality of earnings (QOE) with correlation coefficient values of 0.716672, 0.046896 and -0.208079 respectively. While Number of board of directors' members (BRDSIZE) has negative and low positive relationship with Quality of earnings (QOE) and Effective cash tax rate (ECR) with a correlation coefficient values of -0.138421 and 0.010831 respectively.



Table 3 in the appendices shows the result of probit regression estimate. It has a McFadden R-squared value of 0.045772, an indication that about 4% of the likelihood of fraud detection on the average, is jointly explained by Sales to Accounts receivables (SALAR), Total debt to Total assets (LEV), Number of audit committee members (AUCSIZE), Number of board of directors' members (BRDSIZE), Quality of earnings (QOE) and Effective cash tax rate (ECR) while the balancing 96% is captured in the stochastic error term ( $\epsilon_{it}$ ). This means that the model has a low predictive power. However, with an LR statistic value of 24.02800 and Prob (LR statistic) value of 0.000516, the model on the average can be said to be statistically significant at 95% confidence interval. This means that there exists a significant relationship between likelihood of fraud detection and all explanatory variables which includes Sales to Accounts receivables (SALAR), Total debt to Total assets (LEV), Number of audit committee members (AUCSIZE), Number of board of directors' members (BRDSIZE), Quality of earnings (QOE) and Effective cash tax rate (ECR).

The results of our estimate show that quality of earnings have a probability value of 0.7826, hence not significant at 95% confidence interval. This means on the average, that the quality of earnings cannot aid the likelihood of fraud detection in Nigeria.

The results of our estimate show that effective cash tax rate has a probability value of 0.7203, hence not significant at 95% confidence interval. This means on the average, that effective cash tax rate cannot aid the likelihood of fraud detection in Nigeria.

#### IV. CONCLUSION

This study is an empirical investigation of rationalisation red flags and likelihood of fraud detection in Nigeria. Detection of fraud involves the use of different mechanisms such as fraud models and other methodology. Based on our empirical analyses, finding shows that red flags can aid the likelihood of fraud detection in Nigeria. However, the nature of red flag model to be employed in fraud detection process may vary from industry to industry based on the varying degree of significance of the different red flags in the different corporate industries in Nigeria. The result of this study shows that Rationalization red flags such as quality of earnings and effective cash tax rate on the average cannot aid the likelihood of fraud detection in Nigeria. It is however recommended that forensic accountants should as a matter of necessity pay close attention to our findings in this study and make use of SAS.99 qualitative and quantitative proxies red flags when carrying fraud examination.

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## APPENDIX

Table 1 Descriptive statistics

	LFD	SALAR	LEV	AUCSIZE	BRDSIZE	QOE	ECR
Mean	0.400000	19.20881	0.078203	5.123077	9.107692	0.700000	0.112821
Median	0.000000	4.309185	0.020363	6.000000	9.000000	1.000000	0.000000
Maximum	1.000000	1494.708	0.960651	7.000000	21.00000	1.000000	1.000000
Minimum	0.000000	0.000000	-0.462440	0.000000	0.000000	0.000000	0.000000
Std. Dev.	0.490527	107.0200	0.123877	1.658578	3.942217	0.458846	0.316780
Skewness	0.408248	10.97473	2.114106	-2.091805	-0.093675	-0.872872	2.447612
Kurtosis	1.166667	132.8476	12.19973	6.709489	3.959115	1.761905	6.990804
Jarque-Bera	65.45139	281810.6	1665.834	508.0222	15.51878	74.43311	648.2082
Probability	0.000000	0.000000	0.000000	0.000000	0.000427	0.000000	0.000000
Sum	156.0000	7491.437	30.49898	1998.000	3552.000	273.0000	44.00000
Sum Sq. Dev.	93.60000	4455326.	5.969429	1070.092	6045.477	81.90000	39.03590
Observations	390	390	390	390	390	390	390

*Source: Researchers computation (2016) using Eviews 8.0*

**Table 2 Correlation matrix**

Covariance Analysis: Ordinary

Date: 04/22/16 Time: 10:51

Sample: 1 390

Included observations: 390

<b>Covariance Correlation</b>	<b>LFD</b>	<b>SALAR</b>	<b>LEV</b>	<b>AUCSIZE</b>	<b>BRDSIZE</b>
LFD	0.240000 1.000000				
SALAR	4.273422 0.081614	11423.91 1.000000			
LEV	0.005713 0.094254	0.845862 0.063967	0.015306 1.000000		
AUCSIZE	0.168718 0.207911	8.393005 0.047406	0.027798 0.135642	2.743826 1.000000	
BRDSIZE	0.282564 0.146497	6.560196 0.015589	0.020398 0.041877	4.673925 0.716672	15.50122 1.000000
QOE	-0.013333 -0.059391	-0.078287 -0.001598	-0.003606 -0.063596	-0.157949 -0.208079	-0.249744 -0.138421
ECR	-0.001538 -0.009926	-1.246413 -0.036860	0.003655 0.093380	0.024576 0.046896	0.013491 0.010831

*Source: Researchers computation (2016) using Eviews 8.0*



**Table 3 Regression result output**

Dependent Variable: LFD  
 Method: ML - Binary Probit (Quadratic hill climbing)  
 Date: 04/22/16 Time: 10:48  
 Sample: 1 390  
 Included observations: 390  
 Convergence achieved after 4 iterations  
 Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-1.314037	0.314753	-4.174817	0.0000
SALAR	0.001016	0.000835	1.216795	0.2237
LEV	0.694675	0.522524	1.329462	0.1837
AUCSIZE	0.189917	0.064713	2.934776	0.0033
BRDSIZE	0.002699	0.023438	0.115148	0.9083
QOE	-0.039670	0.143777	-0.275911	0.7826
ECR	-0.074133	0.207040	-0.358063	0.7203
McFadden R-squared	0.045772	Mean dependent var		0.400000
S.D. dependent var	0.490527	S.E. of regression		0.482595
Akaike info criterion	1.320311	Sum squared resid		89.19994
Schwarz criterion	1.391498	Log likelihood		-250.4605
Hannan-Quinn criter.	1.348530	Deviance		500.9211
Restr. deviance	524.9491	Restr. log likelihood		-262.4746
LR statistic	24.02800	Avg. log likelihood		-0.642207
Prob(LR statistic)	0.000516			
Obs with Dep=0	234	Total obs		390
Obs with Dep=1	156			

Source: Researchers computation (2016) using Eviews 8.0