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APPLICATION OF COMPUTED FINANCIAL RATIOS IN FRAUD DETECTION MODELLING: A STUDY OF SELECTED BANKS IN NIGERIA

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ABSTRACT

The study examines the application of computed financial ratios in fraud detection modeling using existing Financial Ratio Models with a view to detecting their capabilities in application in Nigerian banking system. Data were collected from published accounts and reports of 20 sampled banks between 2004 -2008, a 5 year period- preceding year and the fraud year. Logistic Regression was used in analyzing the collected data. The study revealed 16 significant ratios out of 29 financial ratios used for the study as being capable of aiding detection of fraud in the financial statements of banks. Consequently, it is recommended that auditors who are eager to look into the possibility of detecting false financial statements can adopt it and save endless time in search for possible red flags

Keywords: Financial Ratios, Fraud, Modeling, Banks, Logistic Regression, Nigeria.

INTRODUCTION

The recent banking scandals involving the Chief Executives of banks in Nigeria, where they were accused of irregular financial reporting and corporate governance dysfunctions confirmed to the depth of financial statement fraud in Nigeria. These banks were living on bubble capital, coupled with high debt portfolios that were not disclosed in their financial statements. For instance, in these banks - Oceanic Bank, Union Bank, Afribank, Finbank and Intercontinental Bank - out of a total loan portfolio of 2.8 trillion naira had aggregate non-performing loans of 1.143 trillion naira, a whopping 40.81% of the total. Margin loans granted for investment in the capital market stood at 456.28 billion naira and exposure to oil and gas sector stood at 487.02 billion naira. Under this dispensation, fraud have grown in scope, nature, methodology and dimensions as the banking industry advances. The rate, frequency and volume of financial losses have been a major source of concern to the regulatory agencies (Kanu and Okorafor, 2013)

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With all these credits, lending dried up and the capital market took a huge hit as the money market that support its meteoric rise halted. The banks immediately came face to face with capital-liquidity problems (Osisioma and Osisioma, 2009). Shareholders and depositors funds were wiped away due to bad loans in many banks and they (these banks) were kept liquid by the special expanded discounted window then opened. By July 2009, the five banks had outstanding balance of 127.85 billion naira at the Expanded Discount Window (EDW), while their net guaranteed inter-bank loans stood at 253.50 billion naira. The cost implication of these financial statement fraud are usually staggering and monumental. In 2009 for instance, the Central Bank Nigeria (CBN) in response to these financial mess doled out a total sum of 620 billion naira, that is, 420 billion naira in the first instance and 200 billion naira subsequently to the rescued banks.

Globally, the average estimated loss by organizations from economic crime is 2,199,930 billion dollars over a two-year period (Price Waterhouse Coopers (PWC) (2003)). The Association of Certified Fraud Examiners (2004) estimated that about six percent of firms' revenue or 660 billion dollars are lost per year as a result of occupational fraud. Equally, there were over 2,422 (and over 10 billion naira) reported cases of attempted or successful frauds and forgeries in the banking industry between 2007 and 2008 (NDIC, 2007-2008). Because of the failures of auditors to detect financial statement fraud/management fraud have resulted in corporate firms sustaining colossal and unimaginable losses. Further, accounting firms have incurred significant legal expenses over the past few years defending cases filed by third parties. The big six alone which include KPMG, Ernest & Young, Price Water House Coopers (PWC), Deloite Touche, and Arthur Anderson had between 1990-1993 paid out over 1 billion dollars to settle cases related to fraud. The 'big six' spent these sums in respect of Ernest and Young (400 million dollars in 1992) and Arthur Anderson (65 million dollars in 1993) settlements to the resolution trust corporation and this is why in their joint statement in 1992 titled "The litigation crisis in the United States: Impact on the accounting profession", equal up to 11 percent of audit revenues. (Glover and Aono, 1995)

These are compounded by the failure of fraud alert in form of red flags to show extreme weakness and deficiency in many respects. Attempts have been made in the past to develop models for detecting financial statement fraud. For example, a conceptual model for detecting management fraud was developed by Loebbecke and Willingham (1988). This model provides analytical procedure for detecting the risk of management fraud. It also has the capability to assess the likelihood of existence of management fraud. The authors believed that management fraud occurs when condition exists for fraud to occur and management has the motivation and attitude to commit fraud. However, these models are said to be inadequate in fraud detection because they were developed in the contexts that were quite different from the Nigerian environment, mainly in Europe and North America. Some of the Nigerian studies that attempted to make up for the weakness of the foreign models were done in the 1990s. For example, Jimoh (1993) attempted the adaptation of earlier international models for bank distress to produce an early warning model

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suitable for identification of problem banks in Nigeria. Given the considerable shifts in the operating environment (from analogue to digital environment), the continued adequacy of these models become doubtful. These issues created a lacuna in the literature showing the need to develop a more robust, flexible and friendly fraud detection models suited for the Nigerian environment. Thus, the study is set to assess computed financial ratios with a view to determine whether they can help in fraud detection in the financial statements. The rest of this paper is arranged thus: following the introduction is the review of related literature in Section II, methodology is contained in Section III, results/discussion of findings is in Section IV while Section V is conclusion and policy consideration.

Review of Related Literature

Fraudulent financial reporting according to Kaminski *et al.* (2004) is a matter of grave social and economic concern. Recent news abound with corporate fraud scandals (e.g. Cadbury, African Petroleum, Enron, WorldCom, Bank's chief executives in Nigeria, etc). Such problems are critical problems to the external auditors because of the potential legal liability for failure to detect false financial statements and because of the damage to professional reputation that results from public dissatisfaction about undetected fraud. Following this, intense pressure have been mounted on auditors to detect false financial statement and uncover the trail of fraud, for example, Statement of Auditing Standards (SAS) No 82 and (AICPA, 1997) requires auditing firms to detect management fraud. This obviously increases the need to detect management fraud effectively.

The above statement describes fraud and its characteristics, indicates conditions under which fraud is more likely to occur and requires auditors to make an assessment of the risk of material misstatement due to fraud. We therefore can see that auditor's response to financial statement fraud is important and most essential. This is captured by Palmrose (1987) as cited by Summers and Sweeney (1998) when they argued that failure to detect financial statement fraud during the course of an audit can result in both damage to the auditor's reputation and significant litigation costs. Further to this, Makkawi and Schick (2003) observed that the costs will not only affect auditors in terms of litigation costs but equally on other financial statement users and the capital market systems. Evidence of this according to them is indicated by the current confidence of investors over the credibility of financial reporting and further reinforces the role of auditors in the society to provide reasonable assurance about the reliability and dependability of the financial information. For auditors to assiduously achieve this height, the audit standard directs auditors to consider risk factors ("red-flags") relating to fraudulent reporting. This risk assessment is intended to influence the choice of audit procedures during an audit planning despite these identified risk factors by SAS 82. Auditors actually need to capture these for comprehensiveness in their approach to detecting financial misstated statements. In attempt to close the expectation gap between the auditors and the public, a remarkable model in financial distress prediction according to Spathis (2002) was developed by (Altman, 1968; Altman, 1983) where Z-score was used as a control variable to

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investigate the difference in fraudulent financial statement distress and non-fraudulent financial statement. The use of Z-score is accompanied by some limitations as it was in use about 43 years ago to develop a corporate failure prediction model for USA manufacturing sector. It is nevertheless still used today in many studies as reported by Summers and Sweeney (1998). However, its non application to the financial sector is a gross inadequacy in the coverage of the model. This may possibly be due to the opacity of financial company's balance sheet and their frequent use of off-balance sheet items.

Related to the above model were those developed by Ohlson (1980) model as cited by Lenard and Alam (2009) used logistic regression, which is of the form: 1/(1+e^{-y}), where the equation for Y was conducted as follows:

$$Y = -132 – 0.407(LOGTA) + 6.03(TLTA) – 1.43(WCTA) + 0.0757(CLCA) – 2.37(NITA) – 1.83(FUTL) + 0-.285(INTWO) – 1.72(OENEG) \quad \ldots equation1$$

Where LOGTA = log of total assets, TLTA = total liabilities divided by total assets, WCTA = working capital divided by total assets, CLCA = current liabilities divided by current assets, NITA = net income divided by total assets, FUTL = funds provided by operations divided by total liabilities, INTWO = 1 if net income is negative for the last 2 years (0 otherwise), and OENEG = 1 if total liabilities are greater than total assets (0 otherwise). Ohlson (1980) developed three models with prediction accuracy of 92 to 96 percent. Ohlson also described an analysis of the cut-off point for his model, the point which minimized the sum of errors was 0.038, suggesting that a score or a value higher than that indicated a bankrupt company.

In a related development, Persons (1995) as cited in Lenard and Alam (2009) equally applied logistic regression and performed an analysis of determining the best "cut-off" score for the model that minimized type I (accepting results as correct when they are actually incorrect) and type II (rejecting results as incorrect when they are actually correct) errors. The study presented two models, one for the preceding year and one for the fraud year. In the model for the financial ratios in the fraud year, the most successful cut-off probability was 0.6018, meaning that a value equal to or greater than 0.6018 indicated a fraudulent company. The equation for Y in that model is as follows:

$$Y = 1.3935 + 2.7837(TLTA) + 1.8746(CATA) – 0.6807(SATA) – 0.2418(LOGTA), \ldots equation2$$

Where TLTA = total liabilities divided by total assets, CATA = current assets divided by total assets, SATA = sales divided by total assets, and LOGTA = log of total assets.

A conceptual model for detecting management fraud by Loebbecke and Willingham (1988) attempted to provide analytical procedure for detecting the risk of management fraud. This they developed by dividing the process of assessing the likelihood of existence of management fraud into three components: condition, motivation and attitude. They believed that management fraud

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occurs when condition exists for fraud to occur and management has the motivation and attitude to commit fraud. The model is expressed thus; P(mf) = F(c, m, A). Where: P (mf) represents auditor's assessment of probability of a material misstatement due to fraudulent financial reporting, and C, M, and A represents the client's conditions, managements motivation and management attitudes respectively.

Loebbecke *et al.* (1989) were actually developed from the original model presented in Loebbecke and Willingham (1988) in response to suggested factors in SAS 53 and observed the presence of at least 71% of all the three components. The 1989 results therefore showed at least one factor from each of the three components for about 86% therefore making the model a robust indicator for the existence of management fraud. The problem with this model was that it provided no useful analytical procedure for planning an audit as well as no proportional weighing scheme capable of determining the relative importance of the individual factors that indicates management fraud. However, these models mentioned above were developed in contexts that were quite different from the Nigeria environment, therefore may not be adequate for Nigeria situation and in the areas they were applied. Secondly, these models did not extend their research work to the banking industry which is imperative now in Nigeria. This is because of the recent pervasive record of false financial statement fraud in banks in Nigeria where bank chiefs live on bubble capital, giving false impression about their actual state coupled with huge amount of bad loans in their portfolios not disclosed. The need to extend the research across to these areas in Nigeria becomes imparative. About two decades ago, precisely in the 90s in Nigeria, a model was made for fraud detection which tried to make up for the weaknesses of the foreign models. Thus, Adekanye (1992) made efforts to determine factors which are critical to the performance of banks in Nigeria. It was discovered that some factors peculiar to Nigerian systems that impede significantly on bank performance, include: capital adequacy, asset quality, liquidity, managerial efficiency, loan portfolio, revenue sources, revenue application, bank location, bank size, liability match, regulation and national economic variables, and the study also added other factors such as ownership, location of bank headquarters, absence of board room squabbles.

In a related development, Jimoh (1993) attempted the adaptation of earlier international models for bank distress to produce an early warning model suitable for identification of problem banks in Nigeria. In this, he settles for maximum likelihood model. Data for his analysis were collected from bank examination reports, Nigeria Deposit Insurance Corporation (NDIC) published annual accounts on key financial variables such as total deposits of banks, total assets, total loans and advances, etc. A sample size of 53 commercial banks was used in the study. Initial finding of the study showed that five financial ratios are the important discriminating variable. These are risk, liquidity, asset quality, ownership and return to total assets. The high point of this study was that it was able to identify three more banks on the verge of distress in addition to eight that have been officially classified as distressed at the end of 1991.

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These works despite the fact that they made up the gaps created by alien models can be argued not to be adequate for fraud detection in the present milieu due to the following:

i. The research suffers from the traditional limitations of qualitative models for determining bank distress. This is because qualitative factors such as quality of bank management, corporate governance practices and absence or presence of boardroom squabbles were not included in the model.

ii. The model was only available and useful to sophisticated users like bank supervisors and examiners who for obvious reasons kept their results to themselves. The unsophisticated investors are left in the lush.

iii. The study's claim to have used the logistic regression in grouping problem and non-problem banks is unacceptable because its use of t-test statistics infers that ordinary least square regression rather than logistic regression which requires z-test statistics was used.

iv. The level of sophistication in crime in the 90s is extremely lower than what is obtainable today as a result, it is highly doubtful if models developed in such crime environment would be suitable to detect and predict crime in a highly volatile and kinetic crime environment of the 21st century with increased use of information and communication technology.

Methodology

The population of the study consists of 24 banks as at 2004 capitalization programme in Nigeria. Data were collected from published accounts and reports from the 20 banks whose financial statements were available at the time of the study (2004 – 2008). The banks include: Access Bank Plc, AfribankPlc, Diamond Bank Plc, EcobankPlc, FCMB Plc, Fidelity Bank Plc, FinbankPlc, GTB Bank, IBTC, Stanbic Bank Plc, Intercontinental Bank, First Bank Plc, Oceanic Bank Plc, Bank PHB Plc, Skye Bank Plc, Sterling Bank Plc, UBA Plc, Union Bank Plc, Wema Bank Plc, and Zenith International Bank Plc.

Fraud that were caught by auditors and/or firm and subsequently corrected within the company are not revealed publicly nor frauds that were not discovered and therefore not available for study. This is why it is difficult in investigation in the banking and insurance sector and were often excluded from most study, Kaminski *et al.* (2004) observed these exclusions. For the purpose of this work, the CBN classification of problem and non-problem banks provided an encouraging platform for the computed ratio predictivity in detecting financial statement fraud. In the circumstances therefore, problem and non problem banks of asset base not below 25 billon naira and within the same time period and operational in the same industry and environment were chosen for this study. The study compared data from the total population made up of both problem and non problem bank for a 5 year period- the preceding year and the fraud year. Secondly, problem and non problem bank were equally pair-matched for this assessment. Thus the study was more comprehensive, looking at extended ratios over the period using logistic regression modeling.

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Results/ Discussions

Link Function: Logistic

Response Information

Variable	Value	Count	
STATUS	1	65	(Event)
	0	35	
	Total	100	

Table-1. Logistic Regression Analysis For Unequal Population

Predictor	Coef	SE Coef	Z	P	Odds Ratio	95% CI Lower	95% CI Upper
Constant	1.11990	3.83304	0.29	0.770			
X1	7.43142	4.83939	1.54	0.125	1688.20	0.13	22222443.98
X2	0.756965	1.17676	0.64	0.520	2.13	0.21	21.40
X3	-6.16962	2.89954	-2.13	0.033	0.00	0.00	0.61
X4	-0.949963	0.747331	-1.27	0.204	0.39	0.09	1.67
X5	-2.42971	15.1774	-0.16	0.873	0.09	0.00	7.31247E+11
X6	7.17211	18.5012	0.39	0.698	1302.59	0.00	7.30052E+18
X7	1.36492	4.83934	0.28	0.778	3.92	0.00	51535.59
X8	-1.11497	1.05579	-1.06	0.291	0.33	0.04	2.60
X9	30.5070	30.3301	1.01	0.314	1.77429E+13	0.00	1.16552E+39
X10	-0.206906	3.57841	-0.06	0.954	0.81	0.00	903.96
X11	-30.4338	19.6438	-1.55	0.121	0.00	0.00	3191.13
X12	1.02102	1.46803	0.70	0.487	2.78	0.16	49.32
X13	15.6204	5.92497	2.64	0.008	6079414.21	55.01	6.71883E+11
X14	12.3386	7.41963	1.66	0.096	228339.74	0.11	4.72389E+11
X15	-2.35711	4.64569	-0.51	0.612	0.09	0.00	852.73
X16	-1.46904	1.39517	-1.05	0.292	0.23	0.01	3.54
X17	-0.705621	1.63157	-0.43	0.665	0.49	0.02	12.09
X18	-37.2496	20.4324	-1.82	0.068	0.00	0.00	16.41
X20	2.75339	2.97200	0.93	0.354	15.70	0.05	5316.18
X21	-0.576148	2.61902	-0.22	0.826	0.56	0.00	95.31
X23	-14.8028	6.84557	-2.16	0.031	0.00	0.00	0.25
X24	0.801382	0.862728	0.93	0.353	2.23	0.41	12.09

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X25	-0.888118	2.14252	-0.41	0.678	0.41	0.01	27.42
X26	-3.38096	2.76735	-1.22	0.222	0.03	0.00	7.71
X27	4.69805	8.30003	0.57	0.571	109.73	0.00	1.27486E+09
X28	-0.333630	7.11225	-0.05	0.963	0.72	0.00	811296.18
X29	-5.77496	2.66861	-2.16	0.030	0.00	0.00	0.58

Log-Likelihood = -39.551

Test that all slopes are zero: G = 50.388, DF = 27, P-Value = 0.004

Goodness-of-Fit Tests

Method	Chi-Square	DF	P
Pearson	78.7992	68	0.174
Deviance	79.1016	68	0.168
Hosmer-Lemeshow	4.5910	8	0.800

Measures of Association:

(Between the Response Variable and Predicted Probabilities)

Pairs	Number	Percent	Summary Measures	
Concordant	1985	87.3	Somers' D	0.75
Discordant	286	12.6	Goodman-Kruskal Gamma	0.75
Ties	4	0.2	Kendall's Tau-a	0.34
Total	2275	100.0		

Link Function: Logit

Response Information

Variable	Value	Count
STATUS	1	35
	0	35
	Total	70

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Table-2. Logistic Regression Analysis For Equal Population

Predictor	Coef	StDev	Z	P	Odds Ratio	95% CI Lower	95% CI Upper
Constant	3.380	5.918	0.57	0.568			
X1	17.08	10.24	1.67	0.095	2.62E+07	0.05	1.35E+16
X2	2.260	1.892	1.19	0.232	9.58	0.23	390.99
X3	-5.355	5.530	-0.97	0.333	0.00	0.00	240.71
X4	-1.068	1.346	-0.79	0.428	0.34	0.02	4.81
X5	-33.89	38.67	-0.88	0.381	0.00	0.00	1.59E+18
X6	31.11	73.33	0.42	0.671	3.23E+13	0.00	*
X7	4.54	12.20	0.37	0.710	93.90	0.00	2.28E+12
X8	-0.914	1.539	-0.59	0.553	0.40	0.02	8.18
X9	16.01	59.87	0.27	0.789	8.96E+06	0.00	*
X10	0.441	7.223	0.06	0.951	1.55	0.00	2.19E+06
X11	-20.64	27.08	-0.76	0.446	0.00	0.00	1.22E+14
X12	0.415	2.648	0.16	0.875	1.52	0.01	271.81
X13	14.691	7.888	1.86	0.063	2.40E+06	0.46	1.24E+13
X14	6.01	12.65	0.47	0.635	407.09	0.00	2.39E+13
X15	0.102	6.654	0.02	0.988	1.11	0.00	5.11E+05
X16	-0.370	1.273	-0.29	0.771	0.69	0.06	8.37
X17	-1.430	2.672	-0.53	0.593	0.24	0.00	45.06
X18	-104.83	52.86	-1.98	0.047	0.00	0.00	0.29
X20	-1.564	4.792	-0.33	0.744	0.21	0.00	2507.85
X21	-2.233	3.996	-0.56	0.576	0.11	0.00	270.26
X23	-8.24	11.54	-0.71	0.475	0.00	0.00	1.76E+06
X24	-0.8643	0.6846	-1.26	0.207	0.42	0.11	1.61
X25	6.065	5.676	1.07	0.285	430.42	0.01	2.92E+07
X26	-20.21	12.94	-1.56	0.118	0.00	0.00	174.67
X27	20.56	17.31	1.19	0.235	8.49E+08	0.00	4.58E+23
X28	-15.29	13.90	-1.10	0.271	0.00	0.00	1.55E+05
X29	-6.250	4.800	-1.30	0.193	0.00	0.00	23.51

Log-Likelihood = -23.655

Test that all slopes are zero: G = 49.731, DF = 27, P-Value = 0.005

Measures of Association:

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(Between the Response Variable y and Predicted Probabilities x)

Pairs	Number	Percent	Summary Measures	
Concordant	1127	92.0%	Somers D	0.84
Discordant	96	7.8%	Goodman-Kruskal Gamma	0.84
Ties	2	0.2%	Kendalls Tau-a	0.43
Total	1225	100.0%		

DISCUSSIONS

Table 1 shows the logistic regression analysis on unequal population made up of all the sampled problem and non problem banks. The result reveals that the following financial ratios marked X_3, X_{13}, X_{23} and X_{29} with P-Values of 0.033, 0.008, 0.031 and 0.030 are less than the critical P-Value of 0.05. Hence, we posit that these financial ratios are significant in fraud detections. Additionally, it discovered in the Odd Ratio column that the following financial ratios X_1, X_2, X_9, X_{13}, X_{14}, X_{20}, X_{24} and X_{27} are significant with high predicitivity for fraud detection in the work. In these circumstances therefore, both the P-Value and Odd ratio evaluation, are not correlated but jointly significant. Following this however, the result showed that the test has 87.3% concordance which implies the percentage of assurance in using the resulting financial ratios.

Table II equally shows the logistic regression analysis on equal population/ matched pair sample of problem and non-problem banks. The result of the test shows P-Value of 0.04 which is less than the untied value of 0.05 and indicated that resulting financial ratios under the odd ratio as having strong predictivity and significance in fraud detection modeling. These include:- X_2, X_7, X_{10}, X_{12}, X_{14}, X_{15} and X_{25}. The test recorded 92% concordance which implies the degree of percentage assurance in the test using these financial ratio in the work.

From Table I and II, the study identified 16 financial ratios out of 29 applied financial ratios as being significant for fraud detection predictivity in unequal and equal population respectively. The results were in line with prior studies by Spathis (2002), Liou (2008)and Jimoh (1993)which noted the essence of financial ratios in fraud detection in published accounts. This is also in line with Ohlson (1980) who noted a predictivity accuracy of 92 – 96% in his work. In the same vein, Kaminski *et al.* (2004) did a seven year work and discovered 16 significant variable out of 21 variables they tested using 79 samples of fraud and non fraud firms.

CONCLUSION

Failures of auditors to detect financial statement fraud have resulted in corporations sustaining colossal and unimaginable losses. These have also resulted in accounting firms incurring

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significant legal expenses in defending cases filed by third parties. Attempts to stop this menace have not yielded a meaningful result as fraud and crime were spotted on the increase across the globe. Auditors' response to financial statement fraud is important and most essential. For auditors to assiduously achieve this height, the audit standard direct auditors to consider risk factors ("red flags") relating to fraud. However, this is not enough as observed by Pincus (1989) when he noted that auditors using red flags did poorly when compared with a group of auditors not using red flags. This he argued is because of length and type of questions often posed in the red flags which do not focus auditors on their targets. The study therefore recommended that auditors should adopt the 16 selected financial ratios in the work which has the potency in detecting false financial statement when applied and cease endless search for red flags advocated for by audit standards.

POLICY CONSIDERATION

The paper has offered an alternative set of financial ratios in fraud detection modeling for determining the likelihood of fraud occurrence. This is predicated on the premise that financial ratios provide early warning signals which corporations should watch closely. Although it does not ensure 100% fraud detection, it offers an indication to vulnerable fraud areas where accounting practitioners and managers are likely to concentrate their audit time and labour than chasing endless red-flags without direction. It is therefore very important that financial sector regulators in Nigeria such as Central Bank of Nigeria, Nigerian Deposit Insurance Corporation of Nigeria and other government agencies should incorporate the outcome of this study to compliment other efforts in combating the spate of fraud occurrence in Nigerian banks.

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APPENDIX: List of Compiled/Manual Ratios Applied In Fraud Detector Modeling: Across A Sample of 20 Banks in Nigeria.

A. Asset Quality Ratios:

1. Non-performing loans/Advances
   Total Loans/Advances.
2. Provision on Non-performing Loans/Advances
   Total Non-performing Loans/Advances.
3. Non-performing Loans/Advances
   Shareholder's Fund.
4. Total Loans/Advances
   Shareholder's Fund.
5. Non-performing Loans/Advances
   Total Current Assets.

B. Earnings & Profitability Ratios:

- Return on capital Employed

6. Profit b/f taxation
   Capital Employed.
7. Return on Equity
   Profit b/f taxation
   Equity
8. Net Interest margin
   Net Interest Income
   Interest income
9. Retained Earnings
   Total Assets
10. Earnings b/f Interest & Tax
    Total Assets
11. Net Income
    Total Assets.

C. Liquidity/Solvency Ratios

12. Total Specified Liquid Assets
    Total Current Liabilities
13. Net Loans
    Total Deposit
14. Inter-Bank takings
    Total Deposit
15. Working Capital
    Total Asset

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16. Working Capital
    Equity
17. Cash
    Current liabilities
18. Account Receivable
    Total Assets

D. Long term Solvency/Leverage Ratio:

19. Long term Liability
    Equity
20. Total Debt
    Current Liabilities
21. Total Debt
    Current Liabilities
22. Preference Stock/Debt/Bond
    Shareholder's Fund.
23. Shareholder's Fund
    Total Deposits
24 Shareholders Fund
    Total Loans/Advances

E. Capital Adequacy Ratio:

24. Total Qualifying Capital
    Total Risk-weighed Assets.
25. Qualifying Capital
    Total Assets

F. Cash Flow Analysis:

26. Capital Flow from Operation
    Total Assets
27. Capital Flow from Operation
    Current Liabilities

G. Trends:

28. Annual Percentage Charge of Gross Interest Margin
29.
30.

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