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A Statistical Prediction of Likely Distress in Nigeria Banking Sector Using a Neural Network Approach

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Abstract**—**One of the most significant threats to the economy of a nation is the bankruptcy of its banks. This study evaluates the susceptibility of Nigerian banks to failure with a view to identifying ratios and financial data that are sensitive to solvency of the bank. Further, a predictive model is generated to guide all stakeholders in the industry. Thirty quoted banks that had published Annual Reports for the year preceding the consolidation i.e. year 2004 were selected. They were examined for distress using the Multilayer Perceptron Neural Network Analysis. The model was used to analyze further reforms by the Central Bank of Nigeria using published Annual Reports of twenty quoted banks for the year 2008 and 2011. The model can thus be used for future prediction of failure in the Nigerian banking system.

Keywords**—**Bank, Bankruptcy, Financial Ratios, Neural Network, Multilayer Perceptron, Predictive Model.

I. Introduction

THE importance and relevance of the Banking industry to any economy is based on its main intermediary role expected to be professionally, morally, legally and statistically played as a central position in the financial system.

Banks act as intermediaries for efficient transfer of resources from surplus to deficit units. For the banks to be able to perform efficiently and contribute meaningfully to the development of the economy, the industry must be safe, sound and stable.

An efficient and effective banking sector of the economy is essential not only for the promotion of efficient intermediary role but also for the protection of depositors, encouragement of healthy competition, maintenance of confidence in, and stability of the system and protection against systemic risk and collapse.

Following the deregulation of the Nigerian financial sector in 1986, the banking industry witnessed remarkable growth both in the number of deposit money banks (DMBs) and other types of financial institutions. However in the late 1980s, Nigerian banking institutions faced many challenges, including increased competition and harsh economic conditions. Against this background, the incidence of financial sector distress, induced by under-capitalisation, deteriorating asset quality, poor management, liquidity crises, and a high degree of non-performing loans characterized the banking industry in Nigeria. Bank failure threatens the economic system as a whole, see [5].

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Reference [9] said that a question of explaining bank failures constitutes perhaps one of the greatest concerns to stakeholders in the banking sector. Reference [7] also explained that one of the most significant threats of a national economy is the bankruptcy of its banks. Such bankruptcy will create a serious funding and confidence crisis that threaten the whole economy. The problem of distress in the financial sector, including outright bank failure, has been observed in Nigeria as far back as 1930 when the first bank failure was reported see [6]. The rot in the banking system is well documented and it did not start yesterday. The stress has been there, see [12].

It is therefore of significant importance for the regulatory bodies, the Central Bank of Nigeria (CBN) and Nigeria Deposit Insurance Cooperation (NDIC) to issue early warning signals to all stakeholders in the event of unpreventable insolvency or financial distress of individual banks or in the industry as a whole.

A. Problem Background

Banking thrives on confidence. The bank that lacks public confidence is a dead bank. The consequences of distress of a bank can be disastrous creating synergy effect on the industry. There will be loss of confidence and trust in other banks that are still viable within the banking sector. It will further create capital flight, financial hemorrhage and stagnation of the economy. Reference [10] mentioned connivance of the CBN officials with the management of offending banks to break the laws, as additional factor leading to distress in the banks. CBN in 2004 reported that the distress phenomenon in the Nigerian banking industry re-occurred in 1989 and 1998 with greater intensity than before, thereby increasing the entropy of the industry. It was reported that not less than 45 banks were classified as distressed and 31 of them had been liquidated by 1998. Therefore predicting bank financial failures is crucial to prevent or reduce the incoming negative effects on the economic system. Fundamentally, there exists a problem of classifying and categorising the banks as healthy or non healthy, see [5]. This is expected to be done early enough to inform stakeholders in the banking sector.

B. Objectives of the Study

The banks do not fail overnight. It is thus necessary to:

i. Identify the ratios along with the associated financial data that are sensitive to the determination of the solvency of a bank in Nigeria.
ii. Construct the solvency prediction model that can be used in the assessment and evaluation of the financial stability in the banking industry

iii. Use the financial and accounting data that are available in the annual report of the various banks to evaluate the future financial situation and monitor the solvency of any other selected bank.

C. Scope and Limitation of the Study

Thirty quoted banks that had published Annual Report for the year preceding consolidation i.e. 2004 were selected. Further, six quoted banks that had published annual Report for the year preceding the present CBN reforms in the banking sector i.e. 2008 were selected to test run the model and justify the bankruptcy status of the selected banks. Further studies were conducted for 2011.

D. Significance of the Study

The problems of distress in the banking sector always have a major devastating blow on the whole economy. Only viable banks can impose the stability and confidence of all stakeholders in the economy. It is therefore sufficient to predetermine statistically and futuristically possible distress or insolvency in the banking industry in other to forecast effectively the direction of the national economy.

Thus there is need to generate an empirical model that all stakeholders can use to assess distress status of a bank in Nigeria, thereby predicting possible failure of a bank in the nearest future.

II. Literature Review

Conceptually, a bank is considered distressed if it is illiquid or insolvent. A bank is illiquid when it can no longer meet its liabilities as they mature for payment, i.e., it is in breach of contractual obligations. It is insolvent when the value of its realizable assets is less than the total value of its liabilities, implying a case of negative net worth.

Reference [18] insisted that banks have to perform well in order to deliver better returns in compensating depositors for their money. Hence a question of explaining bank failures constitutes perhaps one of the greatest concerns of the stakeholders in the banking sector of the economy. Reference [7] stated that one of the most significant threats of a national economy is the bankruptcy of its banks, since it creates a serious funding and confidence crisis that threaten the whole economy.

Nevertheless, the spectra of distress still haunts the industry, prompting CBN to sack five managing directors of Nigerian banks on August 14, 2009 and also injected ~~N~~420billion into the affected banks to prevent systemic failure in the industry.

A. Models Relevant to the Study

Solvency as indicator of the banking system soundness is a difficult concept to measure and a number of variables contributed to it, some qualitative. However with quantitative techniques, the following are the models relevant to the research.

1. Logistic regression model is useful for situations in which it is expected to predict the presence or absence of each independent variable.
2. Multivariate Discriminant analysis. This is based on the assumption that the two classes have Guassian distribution with equal covariance matrics and considering many variables.
3. Neural Network (multilayer Perceptron). The goals of the training process is to find the set of weight values that will cause the output from the Neural Network to match the actual target values as closely as possible, see [15]. Once the network weights are initiated, the network is ready for the training and usage. It considers the interdependency among the variables

III. Research Methodology

Bank bankruptcy studies have passed through many stages. The pioneers of the empirical approaches are [4], [2] and [13] Reference [4] was one of the first researchers to study the prediction of bankruptcy using financial statement data. However his analysis is very simple in that it is based on studying one financial ratio at a time and on developing a cut-off threshold for each ratio.

The approaches by [2] and [13] are essentially linear models that classify between healthy and bankrupt firms using financial ratios as inputs.

Reference [2] used the classical multivariate discriminant analysis technique. It is based on applying the Bayes classification procedure, under the assumption that the two classes have Gaussian distributions with equal covariance matrix. Reference [14] cited [8] who used logit Regression Model, Reference [1] employed multiple Discriminant Analysis. Reference [7] employed financial ratios along with logistic Regression Model as also [9].

References [17], [11], [19], [3] and [18] employed various models of Artificial Neural Network for predicting future failure in the financial industry.

Reference [16] employed Artificial Neural Network along with multiple Regression analysis.

This study employed Neural Network (multiplayer Perceptron) analysis but using Multivariate Discriminant Analysis as benchmark or support.

Altman used the following ratios in his model:

1. Working capital to total Asset
2. Retained earrings to total Asset
3. Earning before, interests to total Asset
4. Market capitalization to total debts
5. Sales to total Asset.

Altman generated z score using the ratios above as the variables. The model is regularly modified. Hence, Altman's Z score varies with type of industry.

Reference [15] showed that various combination or modification of Altman ratios can be used to generate a predictive model. Hence the following ratios were obtained and use for this research work:

Ratios used in the Model (Variables)

$$\mathbf{X_1} = \frac{T_6}{T_2}$$

$$\mathbf{X_2} = \frac{T_{11}}{T_2}$$

$$X_3 = \frac{T_4}{T_2}$$
$$X_4 = \frac{T_8}{T_{12}}$$
$$X_5 = \frac{T_1}{T_2}$$
$$X_6 = \frac{T_9}{T_{13}}$$
$$X_7 = \frac{T_5}{T_3}$$
$$X_8 = \frac{T_4}{T_1}$$
$$X_9 = \frac{T_4}{T_6}$$

Factors (Data)

T_1 = Gross Earnings
T_2 = Total Assets
T_3 = Customers' Deposit
T_4 = Earning before Tax
T_5 = Cash and Short Term Funds
T_6 = Working Capital
T_7 = Earning after Tax
T_8 = Total Equity
T_9 = Loans and advances
T_{10} = Dividend paid
T_{11} = Retained Earnings
T_{12} = Liabilities (without Equity)
T_{13} = Current Assets

Cash and Short Term Funds = Customers' Deposit – Loans and Advances to Customers
Current Asset = Total Asset – Fixed Asset
Working Capital = Current Asset – Customers' Deposit

IV. Interpretation of Results

In this research, 30 banks were analyzed based on their 2004 financial standings before the consolidation of banks. 15 failed banks and 15 non-failed banks were analyzed. 6 banks out of the non-failed banks were added using their 2008 financial account ratios to ascertain their solvency percentages. Hence the total cases for the analysis summed up to 36.

A failed bank is coded as 0, while a non-failed bank is coded as 1.

The names of the selected failed banks are:

1. MARINA INT BANK LTD
2. PACIFIC BANK PLC
3. BOND BANK
4. METROPOLITANT BANK LTD
5. SOCIETY GENERALE BANK LTD
6. TRADE BANK PLC
7. HALLMARK BANK PLC
8. TRIUMPH BANK PLC
9. CITY EXPRESS BANK
10. ASSURANCE BANK NIG LTD
11. NNB INTL BANK LTD
12. BROAD BANK LTD
13. GUARANTY EXPRESS BANK LTD
14. NATIONAL BANK OF NIG LTD
15. MANNY BANK NIG PLC

While the names of the selected non-failed banks are:

1. ZENITH BANK PLC
2. FIDELITY BANK PLC
3. GUARANTY TRUST BANK PLC
4. OCEANIC BANK INTL NIG PLC
5. FIRST BANK OF NIG PLC
6. DIAMOND BANK LTD
7. WEMA BANK PLC
8. FCMB PLC
9. ACCESS BANK NIG PLC
10. UBA PLC
11. ECOBANK
12. UNION BANK OF NIG PLC
13. INTERCONTINENTAL BANK PLC
14. STERLING BANK PLC
15. FIRST ATLANTIC BANK PLC

TABLE I
2004 Financial Positions of Banks using the Model Above to Compute Z Score

BANK	Z SCORE
MARINA INT BANK LTD	0.51
PACIFIC BANK PLC	0.84
BOND BANK	0.55
METROPOLITANT BANK LTD	1.15
SOCIETY GEN BANK LTD	0.60
TRADE BANK PLC	0.06
HALLMARK BANK PLC	1.08
TRIUMPH BANK PLC	0.01
CITY EXPRESS BANK	1.04
ASSURANCE BANK NIG LTD	0.54
NNB INTL BANK LTD	0.28
BROAD BANK LTD	0.41
GUARANTY EXPRESS BANK LTD	-28.78
NATIONAL BANK OF NIG LTD	0.49
MANNY BANK NIG PLC	0.65
ZENITH BANK PLC	1.53
FIDELITY BANK PLC	1.03
GUARANTY TRUST BANK PLC	1.55
OCEANIC BANK INTL NIG PLC	1.44
FIRST BANK OF NIG PLC	1.35
DIAMOND BANK LTD	1.33
WEMA BANK PLC	1.11
FCMB PLC	1.52
ACCESS BANK NIG PLC	1.22
UBA PLC	1.34
ECOBANK	1.17
UNION BANK OF NIG PLC	1.17
INTERCONTINENTAL BANK PLC	0.82
STERLING BANK PLC	0.59
FIRST ATLANTIC BANK PLC	1.42

The 2008 financial ratios of 6 selected banks were added into the analysis for predictions of their financial status and the probability of becoming failed banks. The names of the 6 selected banks are:

1. FIRST BANK PLC
2. UNION BANK PLC
3. UBA PLC
4. OCEANIC BANK PLC
5. INTERCONTINENTAL BANK PLC
6. ZENITH BANK PLC

Predictions

The Neural network and the Discriminant Analysis can be used to test for probability of failure of 6 selected banks mentioned above. The result is shown in the table below:

TABLE II
PROBABILITY OF FAILURE IN PERCENTAGE (USING 2008 FIGURES)

SN	BANK	DISCRIMINANT ANALYSIS (%)	NEURAL NETWORK (%)	AVERAG E (%)
1	FBN	0.01	0.00	0.005
2	UBN	0.00	0.00	0.00
3	UBA	0.45	0.00	0.225
4	OCEANIC	0.00	0.00	0.00
5	ICB	0.00	0.00	0.00
6	ZB	0.00	0.00	0.00

The above result of the 6 selected banks shows that none of them is likely to fail. This concludes that the 6 selected banks based on their 2008 audited financial records are not likely to fail.

For further predictions of future banks failure, we could use the model below

$$Z = 2.589x_1 + 1.238x_2 + 7.354\, x_3 - 0.326\, x_4 - 7.032x_5 + 0.192\, x_6 + 0.995\, x_7 + 0.074x_8 - 3.532\, x_9.$$

TABLE III
2008 FINANCIAL POSITIONS OF BANKS USING THE MODEL ABOVE TO COMPUTE Z SCORE

BANK	Z
FBN	1.83
UBN	1.94
UBA	1.80
OCEANIC	1.99
ICB	2.01
ZB	1.87

TABLE IV
QUARTILE OF 2004 AND 2008 FINANCIAL POSITIONS OF BANKS COMPUTED ABOVE

3rd Quartile	1.46
2nd Quartile	1.13
1st Quartile	0.58

Decision Rule for Z Prediction

Based on the decision rule that

$Z < 0.58$	-	Bankruptcy region
$0.58\ Z < 1.13$,	-	High Bankruptcy potential
$1.13\ Z < 1.46$	-	Low Bankruptcy potential
$Z \geq 1.46$	-	Strong bank (no sign of bankruptcy)

This depicts that as Z approaches zero (0) or negative value, bank approaches bankruptcy tendency.

TABLE V
2011 FINANCIAL POSITIONS OF BANKS USING THE MODEL ABOVE TO COMPUTE Z SCORE

BANK	Z-SCORE
FBN	1.74
UNITY BANK	1.73
UBA	1.79
STANDARD CHARTERED BANK	2.04
FCMB	2.01
ZENITH BANK	1.71
DIAMOND BANK	2.00
ACCESS BANK	1.80

V. FINDINGS, SUMMARY, CONCLUSION AND RECOMMENDATIONS

It is well accepted that banking industry play major and indispensable role in the social, financial and economic development of any country. The projection of future development and sustainable financial institutions must be considered as the fundamental basis for national development.

The banking institutions occupy a central position in the financial system in any economy. Banks act as intermediaries for efficient transfer of resources from surplus to deficit units. For banks to be able to perform efficiently and contribute meaningfully to the development of the economy, the industry must be safe and sound.

Unfortunately the banking industry out of other financial institutions, have witnessed more strain and stress than others.

To tackle the emerging problems and enhance the confidence of members of public investors and other stakeholders, a strong capital base along with predictive process of future time to failure are fundamental conditions that will precede a sound banking system and thereby lead to viable and virile economy.

Notwithstanding, the existing financial regulatory body CBN, NDIC, EFCC etc., each one is yet to develop a very sound model which can determine accurately and adequately the financial capability of the bank to fulfill all its obligations. Present liquidation processes are not quantitatively or statistically biased. Emergence of Mega banks in Nigeria even suggests that the failure of any of them could have far more serious and long-lasting adverse effects on the economy than the failure of small banks. Consequently, a thorough understanding of the underlying causes of bank distress in Nigeria is not only relevant but predictive ability to pre-empt distress crucial and essential. This will help to prevent re-emergence of distress in the banking sector of the economy. The various species of the virus stigmatized as corruption need to be eradicated completely from the financial institutions (banks) if this seems impossible from the economy as whole.

In this study, neural network (artificial intelligence approach) presented in this research work, provides bank bankruptcy prediction model useful for early warning signals, which can be used for prediction of time to failure and evaluation of financial capability of Nigerian banking industry so as to protect the general public against the consequences of bank failure.

Therefore, the advantages of this study can be summarized as follows:

(1) The result may be used to help promote sound supervisory standards and develop an efficient prediction model that could serve regulatory objectives.
(2) The results/models generated can be used as reference for supervisors to monitor and predict the solvency of banks as well as their time to failure.
(3) The results/models generated can provide the disclosure of financial information to the new policy holder before they sign contracts.

Out of the fifteen banks selected as failed banks, 7 of them completely failed on or before the deadline of banks consolidation in 2005 and 8 of them almost failed before they were acquired by big banks making the total failed banks to be 15. On the other hand, 15 healthy banks were selected. 30 banks in all were used for the analysis proper.

The conclusions of this research are as follows:

i. Ratios vis-a-vis financial data that are sensitive to solvency of banks have been identified and they are:
- x_4 = Total Equity/Liabilities (without Equity)
- x_3 = Earnings before Tax/Total Assets
- x_1 = Working capital/Total Assets
- x_9 = Earnings before Tax/Working Capital
- x_8 = Earnings before Tax/Gross Earnings

ii. The solvency prediction model, that can be used in the assessment and evaluation of financial stability in the Banking industry is given below by:

$$Z = 2.589x_1 + 1.238x_2 + 7.354\, x_3 – 0.326\, x_4 – 7.032x_5 + 0.192\, x_6 + 0.995\, x_7 +0.074x_8 - 3.532\, x_9$$

iii. The financial and accounting data that are available in the Annual Report of the selected banks have been used to evaluate their financial situation and also to monitor their solvency. The results of the selected banks showed that they not distress according to the book records as follows:
- First Bank of Nigeria Plc (FBN): FBN has 0.005% chance of failure. The solvency prediction model also produced Z score of 1.83 making it to fall in the region of strong banks with no sign of bankruptcy.
- Union Bank of Nigeria Plc (UBN): UBN has 0% chance of failure. The solvency prediction model also produced Z score of 1.94 making it to fall in the region of strong banks with no sign of bankruptcy. It shows a better position than FBN.
- United Bank for Africa Plc (UBA): UBA has 0.225% chance of failure. The solvency prediction model produced Z score of 1.80 making it to fall in the region of strong banks with no sign of bankruptcy. It is less position compared to First Bank and Union Bank.
- Oceanic Bank Plc: Oceanic has 0% chance of failure. The solvency prediction model produced Z score of 1.99 making it to fall in the region of strong banks with no sign of bankruptcy. It shows better positioned compared to FBN, UBN and UBA.
- Intercontinental Bank Plc (ICB): ICB has 0% chance of failure. The solvency prediction model also produced Z score of 2.01 making it to fall in the region of strong banks with no sign of bankruptcy. It is the strongest among the six selected banks.
- Zenith Bank Plc (ZB): ZB has 0% chance of failure. The solvency prediction model also produced Z score of 1.87 making it to fall in the region of strong banks with no sign of bankruptcy. It is placed above First Bank and UBA.

Predicting failure due to whatever cause prevents further losses, it also prepares one to checkmate the impending loss and misallocation of resources, coupled with the fact that changing in policy, voluntary liquidation or any other method of eliminating losses at an early date are preferable to bankruptcy from both social and economic view points.

The following are the recommendations in order to predict failure, prevents loses due to bankruptcy, prepares one to checkmate the impending loss due to misallocation of resources and help Central Bank of Nigeria (CBN) to monitor financial position of banks:

i. Ratios (vis-a-vis financial data) such as the ratio of Equity to Book value of Total Debt, Earnings before Tax to Total Assets, Working capital to Total Assets, Earnings before Tax to Working Capital and Earnings before Tax to Gross Earnings are very sensitive to solvency of banks and these ratios should be monitored closely by financial analysts, investors, auditors and most especially Central Bank of Nigeria (CBN).

ii. The future position of banks could be monitored using the solvency prediction model that was formulated to predict, assess and evaluate the financial stability of banks in the Banking industry in Nigeria. The model is expressed by:

$$Z = 2.589x_1 + 1.238x_2 + 7.354\, x_3 – 0.326\, x_4 – 7.032x_5 + 0.192\, x_6 + 0.995\, x_7 + 0.74x_8 - 3.532\, x_9$$

iii. The financial and accounting data of 2008 and 2011 such as are available in the Annual Report of the selected banks have been used to evaluate their financial situation and also to monitor their solvency. The results of these selected banks which shows no sign of bankruptcy, implies that all the banks are very healthy. CBN from time to time at least every year should carry out a routing programme to check the financial positions of all existing banks in the country. The records of the banks must be a sincere true and fair position of the banks.

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