International Journal of Finance and Accounting 2014, 3(1): 37-48
DOI: 10.5923/j.ijfa.20140301.05

Forecasting Bank Failure in Nigeria: An Application of Enhanced Discriminant Model

P. O. Adeyeye[1,*], J. A. Oloyede[2]

[1]Rufus Giwa Polytechnic, Owo, Ondo State, Nigeria
[2]Ekiti State University, Ado-Ekiti, Nigeria

Abstract This study provides a test of early warning model using an enhanced linear discriminant model to forecast the rate of bank failure in Nigeria. The study combines principal component analysis (CPA) with discriminant analysis (DA) to carry out the estimation. The data set of the analysis contains 11 bank-specific variables of 21 banks out of the 24 banks operating as deposit money banks in Nigeria between 2007 and 2009, a period during which some of the banks were nationalised and some others engaged in merger and acquisition and their identities became subsumed in their respective preferred investors. The empirical analysis reveals that the warning signal so developed produces a robust result yielding overall classification accuracy of 95.2 per cent. The discriminant model can correctly predict the financial status of about 20 banks out of 21 sampled banks respectively. In fact, the model accurately predicted the status of 6 banks out of 7 failed banks included in the model. Even the one not correctly predicted was appropriately identified as misclassified. The implication of this is that discriminant analysis is a good predictor of a bank's failure and employing the model will enable an early detection of problems that could engender remedial actions to prevent a bank from failing. This is a very promising result as it indicates its invaluable usefulness for regulators in assessing the health status of banks of interest.

Keywords Bank failure, Discriminant model, Factor analysis, Principal component analysis, Early warning signal

1. Introduction

A critical examination of the Nigerian economy in the recent past reveals that there has been a dramatic change in the banking environment from the time Structural Adjustment Programme (SAP) was introduced in 1986 till the present time than any other sector of the economy. Since the commencement of the deregulation, there was tremendous growth in the number of banks operating in the country as a result of the increased ease of entry into the field of banking under deregulation. This brought radical changes especially as ownership and control of financial institutions are concerned (Bello [1]).

However, according to Sobodu and Akiode sighted in CBN [2], the banking environment that emerged from the reform was inefficient, riskier, illiquid and generated lower return on assets relative to the pre-reform period. Besides, banking institutions were been subjected to one squeeze or the other by the introduction of some measures to sanitize their operations which adversely affected some of them. The adoption of such measures like prudential guidelines, statement of accounting standards and the use of stabilization securities to mop up excess liquidity in the system, though sometimes imperative, exposed many weak banks and threatened them with insolvency. Some banks which had earlier posted fat profits started to mop up excess liquidity which also pushed some marginal banks to illiquidity. In extreme cases of illiquidity, there was near panic as some of the banks were unable to meet depositors' demand. Consequently, the banks embarked upon distress borrowing in the interbank market at exorbitant rates (Imala [3], CBN [2]).

According to Adeyeye, Fajembola, Olopete and Adedeji [4], all the foregoing combined to create a challenging and precarious financial environment as the financial conditions of many banks worsened significantly, which compelled the authorities to take decisive steps to resolve public confidence in the financial system and ensure efficient payments system. Indeed, between 1991 and 2004, the banking system witnessed series of systemic distress occasioned by the sudden increase in the number of banks, their sizes and the noticeable weakness in their operations as well as the poor state of the Nigerian economy, which resulted in liquidation of many banks. During the period, the number of banks classified as distressed were about 52. Specifically, the CBN revoked the licenses of 31 banks: 4 in 1994, 1 in 1995 and 26 in 1996 (CBN[5], NDIC[6], NDIC[7], Sanusi [8], Toby [9]).

Mindful of the deteriorating condition of the industry, the CBN decided to streamline the regulatory framework and strengthen its supervisory capacity in order to forestall the re-emergence of systemic distress and facilitate the

* Corresponding author:
adeyeyepo@gmail.com (P. O. Adeyeye)
Published online at http://journal.sapub.org/ijfa

attainment of strong, competitive and reliable financial markets that meet international best practices. To this end, according to Adeyeye [10], the CBN took some decisive actions aiming at successful consolidation of the banking industry in Nigeria. The emerging consolidation initiative of the CBN with its attendant mergers and acquisition unprecedented in the history of Nigerian banking system ended up reducing the number of banks from 89 to 25 banks (see *Appendix A1*).

Furthermore, by October 2009, another set of 8 out of the surviving 24 banks (see *Appendix A3*) had their respective chief executives and executive directors sacked for what the CBN called "undue exposure to toxic assets, general weakness in risk management and corporate governance", which definitely are signs of systemic failure of the banks concerned (CBN [11]). While three of them were completely liquidated and their assets and liabilities taken over by the CBN and ultimately transferred to other new outfits as 'bridge banks', five others engaged in merger and acquisition syndrome whereby their identities were subsumed in their respective preferred investors. For instance, the nationalised Spring Bank Plc had its name changed to Enterprise Bank Ltd, Bank PHB Plc became Keystone Bank Ltd while Afribank Plc became Mainstreet Bank Ltd. On the other hand, Intercontinental Bank Plc was taken over by Access Bank, Oceanic Bank Plc was taken over by Ecobank Bank Plc, Equitorial Trust Bank Plc was acquired by Sterling Bank while Finbank Plc was merged with FCMB Plc (CBN [11], Adeyeye, Ayorinde and Ajinaja [12], Adeyeye [10]).

The foregoing is no doubt a gory picture of a system that is expected to be significantly germane to the economic development of a nation. It can then be clearly seen why the banks are highly regulated and supervised by the regulatory authorities in order to minimize the risks and costs of bank failure and equally ensure a safe and sound banking system. It is against this background that this study seeks to use a combination of factor analysis and linear discriminant framework to test the probability of bank failure in Nigeria.

1.1. Motivation for the Study

Prediction of bank failure is important to financial regulators including the Central Bank of Nigeria (CBN) and National Deposit Insurance Corporation (NDIC). The collapse and failure of a bank could have devastating consequences on the entire banking system and a widespread repercussion on the whole economy at large. Very often, bank failures do not occur spontaneously but are usually due to prolonged period of financial distress. Hence, it is desirable to have an early warning system that identifies potential failing or high-risk banks going through financial distress.

Furthermore, as noted above, 8 of the existing 24 banks operating as money deposit banks in Nigeria were sanctioned in one way or the other due to the triple problem of huge concentrations in their exposure to certain sectors of the economy, a general weakness in risk management and poor corporate governance (CBN [11]). This development generated mixed reactions from the general public.

Hence, this study seeks to adopt a veritable hybrid early warning model that is capable of predicting the level of performance of a bank with a view to using it to empirically justify (or debunk) the 2009 decision of CBN. According to Adeyeye [10], the potential advantages of such an early warning model include, but not limited to, the following:

(i) The early warning model could contribute significantly to strengthening the process of on-going banking supervision by the regulatory authorities, and that supervisors are likely to work towards refining the systems further in order to improve their accuracy and predictive power.

(ii) It could definitely assist regulators/supervisory authorities to best achieve their mandate as timely identification of problem banks and appropriate intervention may result in fewer bank failures, smaller losses to depositors and less disruption to the payment mechanism.

(iii) It could assist in making various government macroeconomic policies to be better focused to achieve desirable results through the banking system.

(iv) It could equally constitute a basis for critical self-assessment by banks so that they could take remedial action in good time to arrest the problem.

1.2. Research Question

Following the above discussion, the following research questions require further investigation, which will form the basis for this study.

(i) What is the impact of bank-specific attributes on the probability that a bank would fail or survive?

(ii) To what extent do economic factors impact on a bank's probability of failure?

1.3. Objectives and Hypothesis of the Study

The primary purpose of this study is to use an enhanced discriminant model to test, given publicly available financial data, the probability of bank failure in Nigeria. In achieving this objective, we intend to:

(i) examine the impact of both economic factors and peculiar bank characteristics on the probability that a bank would fail or survive.

(ii) adapt and modify the existing discriminant model to classify the financial status of banks in Nigeria.

(iii) use the predictive ability of the model to forecast the possibility of bank failure in Nigeria.

In the light of the foregoing set objectives, it is hereby hypothesised that:

H_0: The probability that a bank would fail or survive is not significantly dependent on some bank-specific characteristics and economic factors.

2. Empirical Literature

Numerous empirical studies have been published in an attempt to measure bank performance and hence predict the probability of its failure. For instance, Altman [13] used multiple discriminant analysis (MDA) technique to estimate a bankruptcy prediction model. The MDA is a statistical technique used to classify a categorical dependent variable having more than two categories, and using it as predictors for a number of independent variables. Beaver [14] used the MDA to construct a predictive algorithm based on five key financial ratios. These include: working capital to total assets, retained earnings to total assets, earnings before interest and taxes to total assets, market value equity to book value of total debt and sales to total assets. He further used these ratios to calculate Z-score, which formed one of the first statistical off-site models for predicting bankruptcies. However, according to Vilen [15], the Z-score model has been disputed greatly. For example, Boritz [16] found as many as 65 different financial ratios used as predictors in bankruptcy studies. Moreover, while Hamer [17] argued that ratios selected for the analysis do not have notable effect on the model's ability to predict failure, Karels and Prakash [18] suggested quite opposite, encouraging researchers to carefully select the financial ratios to include to the model, in order to improve prediction accuracy. Furthermore, Hol, Sjur and Nico [19] criticised the Z-score model for "searching" for right variables to establish the model. They also argued that in the absence of a strong conceptual model scarce bankruptcy information was statistically "used up" by searching procedures.

Among the statistical techniques analysing and predicting bank failures, discriminant analysis (DA) was the leading technique for many years (Karels and Prakash[18], Haslem, Scheraga and Bedingfield [20]. There are three sub-categories of DA: linear, multivariate, and quadratic. One drawback of DA is that it requires a normal distribution of regressors. When regressors are not normally distributed, maximum likelihood methods, such as Logit, can be used (Martin [21]; Ohlson [22], Kolari, Glennon, Shin and Caputo [23] and Demyanyk [24]. DA is a tool for analysing cross-sectional data. If one needs to analyse time series data on bank firm, or loan defaults, hazard or duration analysis models can be used instead of DA models (Cole and Gunther [25], Lane, Looney and Wansley [26] and Molina [27]).

Blums [28] developed a D-score model using forward selection process in a relaxed Gambler's ruin and Merton model context. It took advantage of the most recent financial data for middle market publicly traded firms and used multi-year observations per firm. But, he opined that comparison between the results of various previous researchers is fruitless.

Tam and Kiang [29] compared the power of linear discriminant analysis (LDA), Logit, K-nearest neighbour, interactive dichotomizer 3(ID3) feed forward neural network on bank failure prediction problems. They find that DA outperforms the others for a two-years-prior training sample.

3. Model Specification

This study adapts the linear discriminant analysis (LDA) method used in a recent study by Adeyeye *et al* [4]. Linear discriminant analysis is a conventional method for discriminant feature extraction. The main idea is to find a feature transformation which maximises the covariance of feature metrics between classes, while minimising the covariance of feature metrics within each class (Gao, Ding and Wu [30], Xu and Wang [31]).

In the discriminant analysis it is considered that any bank a is characterized by *a* vector of elements that are measurements of the independent variables (11 in this study). For two populations (failed and non-failed banks) it is assumed that the independent variables are distributed within each group according to multivariate normal distribution with different means but equal dispersion matrices.

The objective of this method is to obtain the linear combination of the independent variables that maximizes the variances between the populations relative to within-group variance. Technically, the use of the discrimination function corresponds to the way that the regression line is used in regression analysis, the only difference lying in the fact that the discriminant line helps in the estimation of whether the dependent variable possesses one or another non-metric characteristic (i.e. failed banks taking on the value of 1 and non-failed banks taking on the value of 0 in our present study). Hence, the *discriminant* function is hereby specified:

$$D_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} +, \cdots, + \beta_k x_{ik} + \mu_i \quad (1)$$

where D_i signifies the discriminant scores for bank *i*.

D_i = is the dependent variable for bank i (i.e. the odds that bank i would be insolvent and therefore fail).

X_{ij} = matrix of independent variables describing the performance of individual bank i, $i = 1, 2, 3, \ldots, n$

β_0 = intercept

β_j = coefficient vectors of parameters to be estimated, $j = 1, 2, 3, \ldots, k$

μ_i = error term

For the discriminant model, the classification of the banks under study into the failed or non-failed group is based on the optimum cut-off score (C), which is calculated as stated in *Equation* (2) below.

$$C = \frac{N_N D_F + N_F D_N}{N_N + N_F} \quad (2)$$

where

C = cut-off score

N_N = number of the non-failed banks

N_F = number of the failed banks

D_N = average score for non-failed banks

D_F = average score for failed banks

The classification is based on the following procedure:

If D-score > C, the bank is classified to the non-failed group.

If D-score $\leq C$, the bank is classified to the failed group.

The relevant financial ratios computed measure the various characteristics of behaviour and performance of individual banks under study (see *Appendix A4*). These include capital adequacy, liquidity sufficiency, asset quality and profitability, management quality, operating efficiency, credit policy, public confidence, staff productivity and economic conditions under which the banks operate. For the purpose of the study, the ratio of total liquid assets to total deposits is used to measure liquidity, two ratios, net income to total assets and net income to equity capital, are used to measure profitability. Also, two ratios, capital to total deposits and capital to total risk weighted assets, are used to measure capital adequacy/sustenance while management quality is measured by the ratio of total expense to total assets. Two ratios, total loans to total deposits and total loans to total assets, are equally used to measure asset quality / credit risk. Furthermore, the growth rate of total assets is used as proxy for economic conditions, while the addition of total deposits and total customers' advances divided by total number of employees to measure staff productivity and earnings per share to measure public confidence respectively.

3.1. Estimation Technique

The objective of our analysis is not only prediction but also reliable estimation of the parameters in which case serious multicollinearity could pose a problem because it is capable of generating large standard errors of the estimators. To solve the problem, we employed factor analysis. Specifically, to run the factor analysis, we used principal component analysis (PCA) method.

The PCA helps us to explore and understand the underlying patterns of relationship between the financial ratios used in the study, while the purpose of factor analysis is to categorise variables (financial ratios) into subgroups sharing common characteristics. By applying the PCA to the financial data, the important financial factors (5 in the present study), which can significantly explain the changes in financial conditions of the banks, were determined. Factor scores were estimated for each of the bank with respect to the five factors determined and these scores were used as independent variables in estimating the discriminant model. The five factors extracted are: factor F_1 represents economic conditions and productivity; factor F_2 represents credit risk and liquidity structure; factor F_3 represents management competence and asset quality, while factor F_4 represents productivity structure and factor F_5 represents capital adequacy and earnings structure respectively.

The other objective of the PCA is to calculate factor scores for each of the banks according to the five factors determined. In PCA, all financial ratios are standardized, with a mean of 0 and the standard deviation of 1 according to *Equation* (3):

$$Z_{ij} = \frac{R_{ij} - \mu_j}{\sigma_j} \quad i = 1, \cdots, 11 \qquad i = 1, \cdots, 21 \qquad (3)$$

Estimated factors can be expressed as a function of the observed original variables (ratios in our present study). In order to estimate the *k*th factor score (F_{ik}) for bank *i*, *Equation* (4) was used below:

$$F_{ik} = \sum w_{jk} Z_{ij}, \qquad k = 1, \ 2, \ 3 \qquad (4)$$

where:

w_{jk} = the factor score coefficient for the *k*th factor and *j*th ratio and

Z_{ij} = the standardized value of the *j*th ratio for bank *i*.

The study relies on *SPSS 17* to generate the D-score output. *SPSS 17* was chosen largely because it treats discriminant analysis as a method for classifying data and is capable of putting it into a subset of methods that also include clustering methods. *SPSS 17* econometric software is equally known for its high degree of consistency, reliability and dependability.

3.2. Data Sources

The sample set of the study covers the periods 2007, 2008 and 2009 respectively and contains financial ratios of 21 banks (see *Appendix A*3) out of the total 24 that were operating as Money Deposit Banks (MDBs) in Nigeria during the period. The reason is not far-fetched. One, Societe Generale Bank, which is one of the 25 surviving banks after the consolidation exercise is yet to start full banking operation even up till now. Two, the data for the remaining three banks (i.e. Equitorial Trust Bank Plc, Nigerian International Bank Ltd. and Standard Chartered Bank Ltd were not included in the study because there were too many omitted variables in their available data. All the 21 banks under review are listed on the Nigerian Stock Exchange (NSE). 11 financial ratios for both the failed and non-failed banks were computed using data collected from annual financial reports of individual banks. For reliability and consistency, the data were compared with the ones contained in the NSE's *Factbook*.

4. Empirical Results

Some of the diagnostic tests conducted include the means and standard deviations of the financial ratios for the two groups (*failed* and *non-failed* banks), significance tests for the equality of group means for each ratio and *F* statistics and their observed significance levels. Of the parameters for the 11 variables, only 3 are significant at 5% level and 1 is significant at 10% level while the remaining 7 are insignificant. In other words, the significant level is relatively small for only four of the eleven ratios under consideration, namely: capital-to-total risk-weighted assets (CARAS), total loans-to-total deposits (LNDEP), total loans-to-total assets (LOTAS), and earnings per share (EPS) respectively. Hence, the null hypothesis that two group means are equal is rejected at 5% significant level for these ratios.

Table 1. Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.710	82.255	10	.000

Source: Authors' calculations

The other test statistics calculated in *Table* 1 is Wilk's Lamda (λ) which is the ratio of the within-groups sum of squares to the total sum of squares.

Wilks' Lamda indicates how well the categories are separated. The smaller the statistics, the better the separation. It takes the value between 0 and 1 ($0 \le \lambda \le 1$). $\lambda = 1$ means all observed group means equal. Values close to 0 occur when within-groups variability is small compared to the total variability. That is, most of the total variability is attributable to differences between means of the groups. It is observed that the groups' means of all our variables are most different for non-failed and failed banks.

In the principal component analysis (PCA), five common factors (F_i) as earlier identified were extracted. To decide how many factors needed to represent the financial data, percentages of total variances explained by each factor were estimated (eigenvalues).

Table 2. Eigenvalues of the Factors

Factors	Value	Variances (%)	Cumulative (%)
*F*1	2.161549	0.1965	0.1965
*F*2	2.058816	0.1872	0.3837
*F*3	1.718981	0.1563	0.5399
*F*4	1.273103	0.1157	0.6557
*F*5	1.029833	0.0936	0.7493
*F*6	0.808492	0.0735	0.8228
*F*7	0.657611	0.0598	0.8826
*F*8	0.644406	0.0586	0.9412
*F*9	0.360748	0.0328	0.9740
*F*10	0.199913	0.0182	0.9921
*F*11	0.086548	0.0079	1.0000

Source: Authors' calculations

Table 2 presents the estimated factors and their Eigenvalues. Here financial ratios are expressed in standardized form with a mean of 0 and standard deviation of 1. Eleven (11) financial ratios as listed earlier were used in the study; then each ratio's standardized variance is 1 and the total variance is11. In line with the suggestion of Rencher (2002), only those factors that account for variances greater than 1 (eigenvalue > 1) were included in the model. Factors with variances less than one are not better than a single ratio, since each ratio has a variance of 1. Hence the first five factors were included in the model. Factor (F_1) is the most important dimension in explaining changes of financial conditions of banks. It explains 19.65% of the total variance of the financial ratios. Factors F_2 to F_5 explain 18.72%, 15.63%, 11.57% and 9.36% of the total variance respectively. The estimated five-common factor model explains 74.93% of total changes of financial conditions for the Nigerian commercial banks.

Table 3 presents the factor score coefficient matrix (w_{jk}) estimated by the PCA.

Table 3. Factor Score Coefficients Matrix (w_{jk})

Ratios	F1	F2	F3	F4	F5
ASGR	**0.730470**	-0.154530	0.028150	-0.114660	0.014907
CARAS	-0.031074	-0.003307	-0.190384	-0.038593	**0.676487**
CATAS	0.024522	0.077163	0.270794	-0.009071	**0.648387**
EPS	0.210870	-0.081324	-0.085565	0.205146	**0.247560**
EXAS	0.172632	-0.372273	**0.584976**	0.071638	-0.029588
LNDEP	-0.046344	**0.712931**	0.058686	-0.007888	0.066809
LOTAS	-0.108111	0.188169	**0.708776**	-0.021235	0.029646
NIECAP	0.102397	-0.050082	0.010786	**0.683762**	-0.037692
NITA	-0.183669	0.056753	0.012765	**0.664430**	-0.001361
SPRO	**0.571674**	0.414357	-0.083784	0.145254	-0.045346
LADEP	-0.075585	**-0.322265**	-0.164340	0.086342	0.225289

Source: Authors' calculations

To make for easy interpretation of the financial factors, the Orthogonal Varimax factor rotation method with Kaiser Standardization was adopted in the PCA as suggested by Cambas, Cabuk and Suleyman [32]. Convergence was achieved after 12 iterations. This method minimizes the number of variables that have high loadings on a factor. *Table* 4 presents the factor loadings.

Table 4. Factor Loadings

Code	Ratios	F1	F2	F3	F4	F5
R1	ASGR	0.730470				
R2	SPRO	0.571674				
R3	LNDEP		0.712931			
R4	LADEP		-0.322265			
R5	EXAS			0.584976		
R6	LOTAS			0.708776		
R7	NIECAP				0.683762	
R8	NITA				0.664430	
R9	CARAS					0.676487
R10	CATAS					0.648387
R11	EPS					0.247560

Source: Authors' calculations

It should be noted that variables in *Table* 4 with large loadings for the same factors are grouped and negligible loadings less than 30 per cent are omitted. Estimated factor represents a specific characteristic of each of the banks under consideration.

The first factor (F_1) represents economic conditions and staff productivity (ratios R_1 and R_2). This underscores the significance of favourable economic conditions and staff productivity. Increases in the score of economic condition and staff productivity factors have a positive value on a bank. Obviously, favourable economic conditions lessen the cost of production; increase the ease of doing business and increase productivity. When a bank employs relatively more experienced and qualified personnel coupled with conducive work environment staff productivity will be enhanced.

The second factor (F_2) consists of two ratios (R_3 and R_4) representing credit risk and liquidity structure of a bank respectively. However, while R_3 factor has positive loading, R_4 shows a negative loading. Banks facing decreasing profitability tend to take excessive credit risk (a high and rising loan-to-deposit ratio) in order to bolster their profits leading to greater liquidity risk. An increase in the score of the credit risk factor (R_3) has a positive value on a bank, meaning that, an increase in the value of this ratio will lead to increase in the score of this factor, which may increase the failure risk of a bank and may eventually cause its financial failure. However, ratio R_4 (liquidity structure) has less than average negative loading on the second factor (F_2). This result supports the theoretical expectation of the study, which earlier anticipated that there would be an inverse relationship between probability of a bank failing and variables measuring liquidity. Increase in the value of this ratio (liquidity ratio) will reduce the score of the liquidity factor and greatly reduce the risk of failure. In essence, the smaller the values of the liquidity factor of a bank the greater its ability to meet depositors' demands and other maturing obligations and the less likely it is to fail.

The third factor (F_3) consists of two ratios (R_5 representing management quality and R_6 representing asset quality) representing management and asset quality of a bank respectively. Both have positive loadings on the third factor and hence indicate positive impact on a bank. The quality of management determines the soundness of credit policy and the quality of loan portfolio. This shows that higher management competence and good asset quality reduce the failure risk.

The forth factor (F_4) represents the profitability structure of a bank. An increase in the score of the profitability factors (R_7 is the ratio of net income to total assets and R_8 is the ratio of net income to equity capital) have a positive value on a bank, meaning that, an increase in the value of these ratios will lead to increase in the score of the profitability factor and lower failure risk. The greater the profitability of a bank, the less likely it is that it will fail.

The fifth factor (F_5) consists of three ratios, R_9, R_{10} and R_{11}. The first two representing capital adequacy/sustenance (ratios of capital to total assets and capital to total risk weighted assets respectively) while the third representing earnings structure. Since the factor loading of R_{11} (earnings per share or EPS) is relatively small (0.24756) and below our specified benchmark (30%), we simply ignore it, though positive, this is so, given that earnings (profitability) have been adequately captured under F_4. An increase in the score of the capital adequacy factor has a positive value on a bank. An increase in the value of this factor is an indication of a bank's ability to sustain the losses due to risk exposures in the bank's capital. Hence, the greater its value the greater will be the bank's financial strength and the lower will be its failure risk.

4.1. The Discriminant Model

As earlier stated, the objective of this method is to obtain the linear combination of the independent variables that maximizes the variances between the populations relative to within-group variance. *Table A5* in *Appendix A* shows both pooled within-groups correlations between discriminating variables and standardized canonical discriminating functions. The linear combination of the factors scores provide for each bank a discriminant score (D-score), according to the estimated canonical discriminant model shown in the following equation:

$$D_i = -0.19F_{1i} - 0.102F_{2i} + 0.18F_{3i} + 0.213F_{4i} + 0.9F_{5i} \quad (5)$$

Equation (5) is the D-score for bank a and F_1 to F_5 represents the economic conditions/staff productivity, credit risk/liquidity, management competence/asset quality, profitability and capital adequacy/earnings structure of bank a respectively.

One of the basic assumptions of a discriminant analysis is that the covariance matrices must be equal; implying that observed differences between groups are attributable to random chance. If this precondition of equality is not fulfilled, that is, if the null hypothesis of covariance matrix equality is rejected, then, strictly speaking, a linear discriminant function is not appropriate.

Also, *Table A5* shown in *Appendix A* presents the covariance matrix and correlation matrix for the pooled-within groups matrices. The results show clearly that the precondition of equality was perfectly met. The covariances of the groups under consideration were in fact identical. The covariance matrix has 19 degree of freedom. Thus the null hypothesis of covariance matrix equality cannot be rejected.

A proper significance test for assessing the equality of covariance matrices is Barlett's chi-square approximation (Canbas *et al* [32]. In order words, all of the diagonal elements of the corresponding matrix are equal to 1 and the rest of the elements are equal to 0 and any correlations do not exist between the ratios. *Table A*4 shows that most of the ratios show correlation to each other.

However, *SPSS 17* used to carry out our analysis supplies a more sophisticated and complex test, called Box' M. It is an F-test, assessing for the equivalence of the covariance matrices for multivariate samples (Schmidt and Hollensen [33]). The Box's M test assumes multivariate normality and is supposedly very sensitive, meaning that, a high *p*-value will be a good, although informal, indicator of equality, while a low *p*-value (highly significant result) may in practical terms be a too-sensitive indicator of inequality. *Table* 5 shows the results of Box's M statistic. The obvious inequality within group covariance is appropriately appreciated by the size of the Box's M value and the corresponding significance value of less than 1%.

Table 5. Box's Test of Equality of Covariance Matrices

Box's M		1408.013
F	Approx.	24.287
	df1	55
	df2	84940.206
	Sig.	.000

Source: Authors' calculations

In order to evaluate effectiveness of the estimated discriminant model, the model statistics were calculated in *Table* 6. An effective discriminating model is one that has much between-group variability of D-scores when compared to within-group variability of D-scores. Coefficients of the discriminant model are chosen so that the ratio of between-groups to within-groups sum of squares of D-scores is as large as possible. Any other linear combination of the predictor variables will have smaller ratio.

Table 6. The Statistics of the Estimated Discriminant Model

Eigenvalue	Canonical Correlation	Wilks' Lambda
.835	.539	.710

Source: Authors' calculations

The *Eigenvalue* statistic presented in *Table* 6 is the ratio of the between groups to within-groups sum of squares of D-scores. Eigenvalue of 0.835 shows that the estimated discriminant model has moderately high discriminating ability. Canonical correlation is a measure of degree of association between D-scores and the group variable that is coded 1 for failed banks and 0 for non-failed banks, which is moderately low at 0.539. Furthermore, the Wilk's Lambda of 0.710 shows that most of the total variability is attributable to differences between the means of D-score of the groups. *Table* 7 below shows the calculated D-scores for each of the banks under study.

Table 7. Estimated Discriminant Scores and Classification Results

Case Code	Actual Group	Year – 1		Year – 2		Year – 3	
		D-Scores	Predicted Group	D-Scores	Predicted Group	D-Scores	Predicted Group
		1.152	0	.399	0	-.594	0
B2	0	1.380	0	.344	0	-.398	0
B3	1	-3.984	1	-1.963	1	2.450	1
B4	0	.986	0	.368	0	-.334	0
B5	0	1.367	0	.430	0	-.505	0
B6	0	1.386	0	.320	0	-.517	0
B7	0	.899	0	.422	0	.115	0
B8	1	-.563	1	.391	0**	-.407	0**
B9	1	-2.339	1	.363	0**	-.362	0**
B10	0	1.031	0	.375	0	-.372	0
B11	0	.579	0	.275	0	-.327	0
B12	0	.560	0	.402	0	-.223	0
B13	1	-1.940	1	.258	0**	3.907	1
B14	0	.240	0	.453	0	-.364	0
B15	1	-4.015	1	.405	0**	-.398	0**
B16	1	.458	0**	-.934	1	-.459	0**
B17	1	-1.919	1	-4.217	1	.133	0**
B18	0	1.034	0	.405	0	-.445	0
B19	0	.607	0	.014	0	-.105	0
B20	0	2.108	0	1.057	0	-.332	0
B21	0	.976	0	.432	0	-.462	0
Classification Results			95.2%		81.0%		76.2%

Source: Authors' calculations
** Misclassified case

There is an improvement in the estimated D-score and classification results reported for year –2 (year 2008). Specifically, it is observed that all the 21 banks except 3 banks, namely, B3, B16, and B17, had scores less than the optimum cut-off score of 0. This is an indication that there was a significant improvement in the financial conditions of most of the banks in year 2008 compared with the preceding financial year. Again, the 3 banks with negative D-scores failed to significantly improve their financial conditions during the period under consideration and D-model correctly classified them as belonging to the *failed-group*. It should equally be noted that misclassified cases reduced marginally from 5 to 4 involving B8, B9, B13 and B15 respectively. In essence, Union Bank Plc, Bank PHB Plc, Finbank Plc and Intercontinental Bank Plc were misclassified as belonging to the *non-failed group* when in actual fact they belong to the *failed group*. The overall classification accuracy improved from 76.2 in year –1 (year 2007) to 81% in year –2 (year 2008).

The estimated D-scores and classification results for year –1 (year 2009) improves significantly in all parameters. With an improved classification accuracy of 95.2%, the model predicted accurately that banks B3 (Afribank Plc), B8 (Union Bank of Nigeria Plc), B9 (Bank PHB Plc), B13 (Finbank Plc), B15 (Intercontinental Bank Plc) and B17 (Spring Bank Plc) respectively had negative D-scores and were categorised as belonging to the *failed-group*. Indeed, all these banks belonged to the group of 8 banks earlier reported to have been identified by the Central Bank of Nigeria as showing serious signs of distress and some of which were actually ‘nationalised’ while others have already been merged or taken over by more viable banks in the system. Again, it should be noted that the only misclassified case in year –1 of the model involves Oceanic International Bank Plc (B16) which was misclassified as belonging to the *non-failed group* when in actual fact; it belongs to the categories of *failed-group* of banks already taken over by Ecobank Bank Plc. The significant improvement in the classification results for year –1 (2009) over the previous two years (year 2008 and 2007) suggests an increasing predictive power of the model as more recent data are used in the estimation.

From the foregoing, the D-model is able to predict with high degree of accuracy the strained financial condition of 6 out of the 7 *failed* banks included in the model and it was equally able to report that the seventh bank (Oceanic International Bank Plc) was actually misclassified. This shows the predictive ability of the model.

On the other two banks namely, B19 (Unity Bank Plc) and B20 (Wema Bank Plc) whose respective boards were ordered by CBN to recapitalise latest by June 20, 2010, the model shows that they were actually doing well as they both had positive D-scores in year –1 and –2 respectively. Although Unity Bank Plc had a marginal D-score of 0.014 (the least on *Table* 7) in year –2, it had D-score of 0.607, which is clearly higher than four other banks that were classified as belonging to the *non-failed group* on *Table* 7, Wema Bank Plc had the strongest estimated D-scores of 1.057 and 2.108 in year –1 and –2 respectively compared with other banks included in the model. Perhaps the CBN had other reasons other than technical insolvency why it ordered the respective management of those two banks to recapitalise within a stipulated time.

5. Summary and Conclusions

In this study we coupled principal component analysis with D-score model to predict the probability of bank failure in Nigeria. Our empirical analysis reveals that this combination produces a robust result with high prediction accuracy. This is a very promising result as it indicates its invaluable usefulness for regulators in assessing the health status of banks of interest.

All variables identified in the study have the expected signs. Twenty per cent of the significant predictive variables measure the credit risk of the banks under study. This makes sense as credit risk is by far the most significant source of risk in the banking industry. Another forty per cent of the variables measures profitability of the banks. This may not be unconnected with the fact that unprofitable banks have higher risk of running into financial difficulties. Furthermore, twenty per cent of the important explanatory variables measure bank characteristics related to capital adequacy. Most interestingly, variables for management quality and other bank characteristics like economic conditions and staff productivity are potentially not important predictors of financial problems for the entire population of banks but might make a difference for the group of banks that are facing difficulties. Banks with effective and efficient management quality have a higher probability of surviving periods of financial crisis.

The analysis of the D-score model so far indicates that the measures of profitability, liquidity, credit risk and capital adequacy are the key predictive financial ratios. In other words, differences in profitability, liquidity, credit risk (asset quality) and capital adequacy (sustenance) are found to be the major distinguishing characteristics between the non-failed and failed banks.

6. Suggestions for Further Studies

Applying the research methodology employed in this study to a more comprehensive data set that actually enables the estimation of default prediction models for operational banks could potentially reveal additional insights into the processes that force financial distress of banks.

Also, the research methodology used in this study may equally apply to other financial and non-financial sectors of the economy.

Appendix A

Table A1. Component Members of Consolidated Banks in Nigeria as at January 1, 2006

	Bank	Members of the Group
1.	Access Bank Nigeria Plc	Access Bank, Marina Int'l Bank & Capital Bank International
2.	Afribank Nigeria Plc	Afribank Plc and Afribank Int'l (Merchant Bankers)
3.	Diamond Bank Plc	Diamond Bank , Lion Bank and African International Bank
4.	EcoBank Nigeria Plc	EcoBank Plc
5.	Equitorial Trust Bank Plc	Equitorial Trust Bank Ltd and Devcom Bank Ltd
6.	First City Monument Bank Plc	First City Monument Bank, Coop Development Bank, Nigeria-American Bank and Midas Bank
7.	Fidelity Bank Plc	Fidelity Bank, FSB International Bank and Manny Bank
8.	First Bank of Nigeria Plc	First Bank Plc, MBC International Bank & FBN (Merchant Bankers)
9.	First Inland Bank Plc	First Atlantic Bank, Inland Bank (Nigeria) Plc, IMB International Bank Plc and NUB International Bank Limited
10.	Guaranty Trust Bank Plc	GT Bank Plc
11.	IBTC-Chartered Bank Plc	IBTC, Chartered Bank Plc and Regent Bank Plc
12.	Intercontinental Bank Plc	Intercontinental Bank Plc, Global Bank Plc, Equity Bank of Nigeria Limited and Gateway Bank of Nigeria Plc
13.	Nigeria International Bank Limited (Citi Group)	Nigeria International Bank limited
14.	Oceanic Bank International Plc	Oceanic Bank International Plc and International Trust Bank
15.	Platinum-Habib Bank Plc (Bank PHB)	Platinum Bank Limited and Habib Nigeria Bank Limited
16.	Skye Bank Plc	Prudent Bank Plc, Bond Bank Limited, Reliance Bank Limited, Cooperative Bank Plc and EIB International bank Plc
17.	Spring Bank Plc	Citizens International Bank , ACB International Bank, Guardian Express Bank, Omega Bank, Trans International Bank and Fountain Trust Bank
18.	Stanbic Bank of Nigeria Ltd	Stanbic Bank of Nigeria Limited
19.	Standard Chartered Bank Ltd	Standard Chartered Bank Limited
20.	Sterling Bank Plc	Trust Bank of Africa Limited, NBM Bank Limited, Magnum Trust Bank, NAL Bank Plc and Indo-Nigeria Bank
21.	United Bank for Africa Plc	United Bank for Africa Plc, Standard Trust Bank Plc and Continental Trust Bank
22.	Union Bank of Nigeria Plc	Union Bank of Nigeria Plc, Union Merchant Bank Limited, Broad Bank of Nigeria Limited and Universal Trust Bank Nigeria Plc
23.	Unity Bank Plc	Intercity Bank Plc, First Interstate Bank Plc, Tropical Commercial Bank Plc, Centre-point Bank Plc, Bank of the North, New African Bank, Societe Bancaire, Pacific Bank and New Nigerian Bank
24.	Wema Bank Plc	Wema Bank Plc and National Bank of Nigeria Limited
25.	Zenith Bank Plc	Zenith Bank Plc

Source: (1) CBN Annual Reports[34], (2) Dabiri[35]

Table A2. List of Eight Banks with Signs of Systemic Failure as at 2009

S/N	Name of Bank	Present Status
1.	Afribank Plc	Nationalised to become Mainstreet bank Ltd
2.	Intercontinental Bank Plc	Acquired by Access Bank Plc
3.	Union Bank of Nigeria Plc	Retains its original name
4.	Oceanic International Bank Plc	Acquired by Ecobank Plc
5.	Finbank Plc	Merged with FCMB Plc
6.	Spring Bank Plc	Nationalised to become Enterprise Bank Ltd.
7.	Bank PHB Plc	Nationalised to become Keystone bank Ltd.
8.	Equatorial Trust Bank Plc	Acquired by Sterling Bank

Table A3. Sample of Banks used in the Study and their Codes

B6	United Bank for Africa Plc
B7	Sterling Bank Plc
B8	Union Bank of Nigeria Plc
B9	Bank PHB Plc
B10	Diamond Bank Plc
B11	Ecobank Nigeria Plc
B12	Fidelity Bank Plc
B13	Finbank Plc
B14	First City Monument Bank Plc
B15	Intercontinental Bank Plc
B16	Oceanic Bank International Plc
B17	Spring Bank Plc
B18	Stanbic IBTC Bank Plc
B19	Unity Bank Plc
B20	Wema Bank Plc
B21	Zenith Bank Plc

Source: Author's conjecture

Table A4. Variables in the Model

Code	**Variables**	**Financial Ratio**
R1	Economic Conditions	Growth Rate of Total Assets (ASGR)
R2	Staff Productivity	Advances + Deposits/No of Employees (SPRO)
R3 R6	Credit Risk/Asset Quality	Total Loans/Total Deposits (LNDEP) Total Loans/Total Assets (LOTAS)
R4	Liquidity	Total Liquid Assets/Total Deposits (LADEP)
R5	Management Quality	Total Expense/Total Assets (EXAS)
R7 R8	Profitability	Net Income/Equity Capital (NIECAP) Net Income/Total Assets (NITA)
R9	Capital Adequacy/Sustenance	Capital/Total Risk Weighted Assets (CARAS)
R10	Capital Adequacy/Sustenance	Capital/Total Assets (CATAS)
R11	Public Confidence	Earnings per share (EPS)

Source: Author's conjecture

Table A5. Pooled Within-Groups Matrices[a]

		LADEP	NITA	NIECAP	CARAS	EXAS	LNDEP	LOTAS	ASGR	SPRO	EPS
Covariance	LADEP	.076	.009	.147	.022	-.010	.018	-.008	-.010	-6557.326	-.126
	NITA	.009	.049	.976	.000	-.004	.014	-.003	.020	-602.667	.030
	NIECAP	.147	.976	53.113	-.280	.026	.093	-.176	-.616	275202.079	-3.252
	CARAS	.022	.000	-.280	.115	-.004	-.020	-.018	-.001	263.277	.086
	EXAS	-.010	-.004	.026	-.004	.008	-.005	.003	.008	-253.265	.023
	LNDEP	.018	.014	.093	-.020	-.005	.049	.003	-.009	12248.101	.276
	LOTAS	-.008	-.003	-.176	-.018	.003	.003	.013	.016	-5150.296	-.025
	ASGR	-.010	.020	-.616	-.001	.008	-.009	.016	.096	-28656.304	.016
	SPRO	-6557.326	-602.667	275202.079	263.277	-253.265	12248.101	-5150.296	-28656.304	2.060E10	197039.451
	EPS	-.126	.030	-3.252	.086	.023	.276	-.025	.016	197039.451	12.743
Correlation	LADEP	1.000	.145	.073	.239	-.392	.302	-.259	-.120	-.166	-.129
	NITA	.145	1.000	.604	.006	-.205	.291	-.137	.289	-.019	.038
	NIECAP	.073	.604	1.000	-.113	.039	.058	-.215	-.273	.263	-.125
	CARAS	.239	.006	-.113	1.000	-.142	-.264	-.464	-.014	.005	.071
	EXAS	-.392	-.205	.039	-.142	1.000	-.231	.245	.298	-.019	.069
	LNDEP	.302	.291	.058	-.264	-.231	1.000	.116	-.125	.387	.350
	LOTAS	-.259	-.137	-.215	-.464	.245	.116	1.000	.472	-.319	-.061
	ASGR	-.120	.289	-.273	-.014	.298	-.125	.472	1.000	-.645	.014
	SPRO	-.166	-.019	.263	.005	-.019	.387	-.319	-.645	1.000	.385
	EPS	-.129	.038	-.125	.071	.069	.350	-.061	.014	.385	1.000

a. The covariance matrix has 19 degrees of freedom.
Source: Author's calculations
Legend: LADEP = Total liquid Assets/Total Deposits, NITA = Net Income/Total Assets, NIECAP = Net Income/Equity Capital, CARAS = Capital/Total Risk Weighted Assets, EXAS = Total Expense/Total Assets, LNDEP = Total Loans/Total Deposits, LOTAS = Total Loans/Total Assets, ASGR = Growth Rate of Total Assets, SPRO = Advances + Deposits/No of Employees and EPS = Net Income – Dividends/Outstanding Shares

REFERENCES

[1] Bello, Y. A., 2005, "Banking system consolidation in Nigeria and some regional experiences: Challenges and prospects", Bullion, Central Bank of Nigeria, Vol. 29, No. 2, April/June, p. 46-53.

[2] CBN, "Recent reforms in the Nigerian banking industry: issues and challenges", being a paper delivered by the Research and Statistics Department of Central Bank of Nigeria on the occasion of a study visit to the Bank by some students on 4th May 2006.

[3] Imala, Odufu I., 2005, "Challenges of banking sector reforms and bank consolidation in Nigeria", Bullion, Central Bank of Nigeria, 29(2), April/June, 25-36.

[4] Adeyeye, P. O., Fajembola, O. D., Olopete, M. O. and Adedeji, D. B., 2012, "Predicting bank failure in Nigeria using principal component analysis and D-Score model", Research Journal of Finance and Accounting, IISTE, 3(8), 159-170, Sept.

[5] CBN, Annual Report and Statement of Accounts, 1998.

[6] NDIC, "Review of developments in banking and finance in the third quarter of 1995". NDIC Quarterly, 5(3), September, 1-13, 1995.

[7] NDIC, "An overview of the role of the Nigerian Deposit Insurance Corporation (NDIC) in the sanitisation of the banking sector", NDIC Quarterly, 8(1/2), March/June, 1-34, 1999.

[8] Sanusi, J. O. Keynote address delivered at the 5th Annual Finance Correspondents and Business Editors Seminar in Owerri and published in the Bullion, Central Bank of Nigeria, 28(1), January/March, 3-4, 2004.

[9] Toby, A. J., 1999, "Analysis of the Financial Performance of Public Enterprise Banks", First Bank Review, 7(15), December.

[10] Adeyeye, P. O., "Prediction of bank failure in Nigeria: a test of early-warning models", an unpublished doctoral thesis, Ekiti State Univeristy, Ado-Ekiti, March 2013.

[11] CBN, "Developments in the banking system in Nigeria", Press Release, 14th August, 2009.

[12] Adeyeye, P. O., Ayorinde, O. O. & Ajinaja, T., "Effects of the proposed removal of CBN Autonomy on the Nigerian economy: An Informed Analysis", International Journal of Business and Management Review (IJBMR), 1(2), 79-88, June 2013.

[13] Altman, E. I., "Financial ratios, discriminant analysis and the prediction of corporate bankruptcy", Journal of Finance, 589-609, Sept. 1968.

[14] Beaver, W. H., 1966, "Financial ratios as predictors of failure. Empirical research in accounting: Selected studies", Supplement to Journal of Accounting Research, 71-111.

[15] Vilen, Markus, 2010, "Predicting Failures of Large U.S. Commercial Banks", an Economics Masters' Thesis, Aalto University School of Economics.

[16] Boritz, J. E., 1991, "The "going concern" assumption: Accounting and auditing implications", Toronto, Canada: The Canadian Institute of Chartered Accountants (CICA).

[17] Hamer, M. M., 1983, "Failure prediction: sensitivity of

classification accuracy to alternative statistical methods and variable sets", Journal of Accounting and Public Policy, 2(4), 289-307.

[18] Karels, G. V. and Prakash, A. J.,1987, "Multivariate normality and forecasting of business bankruptcy", Journal of Business Finance and Accounting, 14(4).

[19] Hol, S., Sjur W. and Nico van der Wijst (version 2002) Capital structure and the prediction of bankruptcy, Working Paper.

[20] Haslem, J. A, Scheraga, C. A. and Bedingfield, J. P., 1992, "An analysis of the foreign and domestic balance sheet strategies of the U.S. Banks and their association to profitability performance", Management International Review, First Quarter.

[21] Martin, D., 1977, "Early warning of bank failure: a logit regression approach", Journal of Banking and Finance, 1:249–76.

[22] Ohlson, J. A., 1980, "Financial ratios and the probabilistic prediction of bankruptcy", Journal of Accounting Research, 18, 109–31.

[23] Kolari, J, Glennon D., Shin H. and Caputo M., 2002, "Predicting large US commercial bank failures", Journal of Economics and Business, 54(4):361–87.

[24] Demyanyk, Y., 2008, "Quick exits of subprime mortgages", Federal Reserve Bank of St. Louis Review, 92(1).

[25] Cole, R and Gunther J. A., 1995, "CAMEL rating's shelf life", Federal Reserve Bank of Dallas Review, 13–20.

[26] Lane, W. R, Looney S. W. and Wansley J. W., 1986, "An application of the Cox proportional hazards model to bank failure", Journal of Banking and Finance, 10: 511–31.

[27] Molina, C. A., 2002, "Predicting bank failures using a hazard model: The Venezuelan banking crisis", Emerging Market Review, 2:31–50.

[28] Blums M. (2004) "D-Score: bankruptcy prediction model for middle market public firms. [Online]. Available: www. mineapolisfed.org/mea/contest/2004papers/blums.pdf

[29] Tam, K. Y. & Kiang, M. Y., 1992, "Managerial Applications of Neural Networks: The Case of Bank Failure Predictions. Management Science", 38(7), 926-947

[30] Gao, J., Ding, X. & Wu, Y., 1999, "On improvement of multiple discriminant analysis model of discriminative feature extraction", IEEES SMC '99 Conference Proceedings, 2, 12-15.

[31] Xu, X. & Wang, Y., 2009, "Financial Failure Prediction using Efficiency as a Predictor. Science Direct, 36, 366-373.

[32] Canbas Serpil, Cabuk, Altan, Kilic, Suleyman Bilgin, 2005, "Prediction of commercial bank failure via multivariate statistical analysis of financial structures: The Turkish case", European Journal of Operational Research, 166:528–46.

[33] Schmidt, Marcus J. and Hollensen, Svend, 2006, "Marketing Research: An International Approach", Pearson Education Limited, England.

[34] CBN Annual Reports, 2005.

[35] Dabiri, W. B., 2007, "Banking Reforms and Consolidation: The Nigerian Experience", University of Ibadan Alumni Annual Lecture.