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Predicting Bank Failure in Nigeria using Principal Component Analysis and D-Score Model

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Abstract

In this study, we coupled principal component analysis with discriminant model to predict the probability of bank failure in Nigeria. Our empirical analysis reveals that the warning signal so developed 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. The analysis of the regression model 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 (healthy) and failed banks. However, variables for management quality and other bank characteristics like economic conditions and staff productivity are potentially not important predictors of financial problems in Nigerian banks but might make a difference for the group of banks that are facing difficulties. The research methodology employed in this study could be applied to other financial and non-financial sectors of the economy.

Keywords: Bank failure prediction, D-score model, principal component analysis, early warning signal, Nigerian banking crisis

1. Introduction

The task of maintaining a safe and sound banking system wholly rests on the central banks and deposit insurance corporations in many countries (Nyong, 1994). This is carried out with a view to preventing, or at least, minimising bank failures. This should be seen as being consistent with stabilisation goal which suggests that given the institutional structure, failure of banks should be prevented lest it precipitates a run on other banks, a development that may lead to a significant reduction in the money supply and could eventually lead to depression (Mayer, 1980). For instance, large-scale bank failures consequent on a run on banks limit the ability of banks to create money, jeopardise the payment mechanism and disrupt bank lending activities. The disruption of their lending activities may lead to a decline in investment and hence, a depression results.

In similar vein, since banks serve as conduits through which stabilisation policy is transmitted to the economy at large, generalised bank failures impair the continued usefulness of the banking system as a conduit for macroeconomic stabilisation policies. In fact, the impact of an unhealthy financial system, particularly the banking sector would definitely leave nobody untouched including the government, the regulatory authorities, the bankers themselves as well as the banking public. It is against this background that this study seeks to evolve a veritable and testable criterion for measuring the performance of banks and use the framework to predict the probability of failure.

1.1 Objectives and Hypothesis of the Study

Generally, banks' probability of failure is our main focus in the study. Specifically, the objective of this study is to combine principal component analysis with discriminant score in predicting the probability of bank failure in Nigeria. In achieving this objective, we intend to:

(i) examine the impact of bank-specific attributes and economic factors on the probability that a bank would fail or survive.
(ii) adapt and modify some existing early warning models for measuring the performance of banks in Nigeria.
(iii) use the predictive ability of the model to forecast the possibility of bank failure.

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 significantly dependent on some bank-specific attributes and economic factors.

1.2 Justification for the Study

Incessant systemic distress syndrome in the banking sector over the years is worrisome and thus calls for a pressing need for assessing the performance of banks to enhance early identification of those that show signs of ill-health so that preventive measures could be undertaken to prevent ultimate failure. Justification for the study is equally premised on the fact that there is no other auspicious time to embark on such a research like this other than now for some obvious reasons:

First, the research work will not only complement other research works earlier done in the same area, but also improve upon them by using appropriate econometric early warning model to predict the level of bank performance in Nigeria.

Second, in the Nigerian banking landscape, the regulatory authority (i.e. the Central Bank of Nigeria) reported in the second quarter of 2009 that some banks have continued to display signs of failure despite the earlier financial reforms in the banking sector that saw the emergence of 24 out of the existing 89 banks operating in the country before the reforms. Specifically, 8 of the banks 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, 2009). Hence, adopting a veritable early warning model that is capable of predicting the level of performance of a bank will definitely be in order. This will enable the investing public to be wary of where they invest their resources and the regulatory authorities intervene early enough before much damage is done to the economy and thus achieving their goal of maintaining stability in the banking system and generating continued confidence by the public in the system.

2. Empirical Literature

Attempts to measure bank performance and hence predict the probability of its failure are bedevilled by the absence of any coherent yardstick as a result of which various approaches have been adopted by various researchers. An assessment of bank performance as noted by Ojo (1992) poses some difficulties because of the nature of bank objectives (often conflicting) against which an assessment has to be made. In assessing the performance of a bank therefore, apart from considering quantitative factors, some other qualitative factors have to be considered as well.

Extensive research has been conducted to develop formal models that successfully predict bankruptcy based on financial and accounting data. For example, Beaver (1966 and 1968) made comparisons of selected ratios for failed and non-failed firms. Altman (1968) uses multiple discriminant analysis technique to estimate a bankruptcy prediction model. Wilcox (1973) derives and tests a bankruptcy prediction model based upon a Markov process sometimes referred to as the 'gambler's ruin problem'. The model estimates the probability that future cash outflows will exceed the firm's financial resources based upon its historical performance. The Altman and Wilcox models have generally been developed and tested on a matched-pair sample of healthy and bankrupt firms. Their reportedly good performance is certainly influenced by testing on a population where 50 per cent of the firms are known to have entered bankruptcy. This procedure has been described as an autopsy of diseased firms rather than as a prediction of business failures (Benishay, 1973, Dietrich and Kaplan, 1982).

The performance evaluation of banks has been based on the CAMEL rating system. This has been extensively employed by regulatory authorities like CBN and NDIC (Nnanna, 2004, Bello, 2005 and Omankhanlen, 2011). Based on the relevant parameters, appropriate financial ratios are developed for depicting the conditions of the banks. In line with this, Osaze and Anao (1990) posit that corporate performance can be investigated in terms of profitability, liquidity, leverage (long-term solvency) and activity (efficiency of operations) ratios. Adekanye (1992) agrees with these variables but added potential and actual growth as an important measure of bank performance. He therefore suggests that quality and quantity of service should be a further measure.

Moreover, good as the CAMEL rating is, writers and analysts seemed not too comfortable with the method mainly because of the inherent tendency to give the same prescription for different ailments (Eriki, 1997). Furthermore, according to Eriki, "given the strategic and sensitive financial role of banks in an economy, the use of CAMEL alone to identify distressed banks calls for some statistical and quantitative up-date. Equally important is the fact that the CAMEL rating is a blanket measure of determining distress, the ratios being computed independently, the CAMEL does not indicate the group of banks that are likely to be distressed to enable early warning and the need to adopt pre-emptive measures to forestall possible distress. Eriki seems to cast a shadow on the predictive ability of the method by asserting that it has no futuristic significance. It is against this obvious flaws of the CAMEL rating system that he used the Z-score rating in order to identify the bank that could be classified as failed, poor performing (grey) and good performing. The Z-score rating system was invariably based on the same parameters as CAMEL. Perhaps the biggest problem for all bankruptcy studies has been the lack of a strong theoretical framework. Hol, Westgaard and Wijst (2002) criticise 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.

Jimoh (1993) develops two early warning models, the cluster and logit models, to identify the critical factors that adequately predict bank's insolvency. However, good as the models are, as pointed out by Nyong (1994), there are certain important methodological and interpretational inconsistencies inherent in the study that may seriously diminish the usefulness of the results for policy purposes. Thus in an attempt to complement and improve upon Jimoh's efforts, Nyong in the same article, develops a linear multiple discriminant analysis using logit model to address the obvious shortcomings of the former. His study is significant in three areas: first, it provides a vigorous analysis of solving methodological and interpretational problems in classification models. Second, it uses alternative model to effectively identify problem and non-problem banks. Third, it examines the condition for optimality in the use of the model and validates the model using an enlarged sample of Nigerian banks. Other Nigerian scholars that employ multiple discriminant analysis in predicting bank failure include Adefila (2002), Olaniyi (2006) and Olaniyi (2007); their studies appear too simplistic for any meaningful academic contribution to existing knowledge on the present subject under study.

Among the statistical techniques analysing and predicting bank failures, discriminant analysis (DA) was the leading technique for many years (e.g. Karels and Prakash, 1985; Haslem, Scheraga and Bedingfield, 1992). 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 (see Martin, 1977; Ohlson, 1980; Kolari, Glennon, Shin and Caputo, 2002 and Demyanyk, 2008). 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 (see Cole and Gunther, 1995, Lane, Looney and Wansley, 1986 and Molina, 2002, among others).

Canbas, Cabuk and Kilic (2005) propose an integrated early warning system (IEWS) that combines DA, Logit, Probit, and principal component analysis (PCA), which can help predict bank failure. First, they use PCA to detect three financial components that significantly explain the changes in the financial condition of banks. They then employed DA, Logit and Probit regression models. By combining all these together, they construct an IEWS. The authors use the data for 40 privately owned Turkish commercial banks to test the predictive power of the IEWS, concluding that the IEWS has more predictive ability than the other models used in the literature.

The foregoing section has undoubtedly reviewed a plethora of different quantitative and qualitative early warning models employed by different researchers in determining the probability of a bank failure in different studies. It is against this background that this study attempts to complement the above reviewed studies by the application of a well-known multivariate statistical technique (principal component analysis) to explore the basic characteristics of the banks under study and equally use discriminant model to construct an early warning model that will enable a prediction of the probability of bank failure and assess the severity of their financial distress in Nigeria.

3. Model Specification

In the D-score model, 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 healthy 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 as specified in *Equation* (4) the only difference lying in the fact that the discriminant line helps in the estimation of whether the dependent variable possess one or another non-metric characteristic (i.e. failed banks taking on the value of 0 and non-failed banks taking on the value of 1 in our present study). Hence, the *discriminant* function is hereby specified:

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

Where D_i signifies the discriminant scores for bank *i* and other variables remain as earlier stated.

D_i = is the dependent variable for bank *i (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, ..., *n*

β_0 = intercept

β_j = coefficient vectors of parameters to be estimated, *j* = 1, 2, 3, ..., *k*

μ_i = error term

Applying the specification of Equation (1) to the bankruptcy prediction model, the explanatory variables $x_{i1}, x_{i2}, \cdots, x_{ik}$ would be financial ratios computed from the financial statements of individual banks under review, and $\beta_1 x_{i1} + \beta_2 x_{i2} +, \cdots, + \beta_k x_{ik}$ is a measure of the financial soundness of the firm. If this measure exceeds a critical value, the firm is assumed to go bankrupt. The critical value of this variable is assumed to vary among individual banks and thus the stochastic term μ_i is introduced. By any choice of a monotonic distribution function for μ this structure will simply imply a constant rate of compensation between variables.

3.1 A Note on the Variables of the Model

This study takes cognisance of the controversial nature of using constructed ratios to make qualitative statements about a going concern. Thus the financial ratios to be used in the study will be combined with additional information related to the peculiarities of each bank under review and the market in which it operates (i.e. economic conditions and staff productivity in each bank).

The relevant financial ratios computed measure the various characteristics of behaviour and performance of individual banks under study. These include capital adequacy, liquidity sufficiency, asset quality and profitability, management quality, operating efficiency, credit policy, staff productivity and economic conditions under which the banks operate.

On *a priori* theoretical expectation about the signs of the parameter estimates of the variables listed above, the probability that a bank will be insolvent and therefore fail is expected to be inversely related to the variables measuring liquidity, profitability, capital adequacy, economic conditions, public confidence and staff productivity. The reason for this position stems from: (i) the higher the liquidity and the better capitalised a bank is, the less likely it is going to fail; (ii) the higher the profitability of a bank, the less likely it is that it will fail; (iii) capital adequacy measures the bank's ability to sustain the losses due to risk exposures in the bank's capital; (iv) increased market stock prices indicate public confidence in a company's future performance with less fear of losing their investment and (v) conducive economic conditions lessen the cost of production, increase ease of doing business and increase productivity.

On the other hand, the probability that a bank will fail is expected to increase with the variables measuring poor management quality, poor credit policy and high credit risk. The reason being that: (i) the quality of management determines the soundness of credit policy and thus the quality of loan portfolio; (ii) poor credit policy will manifest in loan problems, the severity of which is measured by the per cent of non-performing loans or loan loss reserves; (iii) a significant increase in any of these ratios will obviously decrease profitability and thus increase probability of failure; (iv) banks facing decreasing profitability tend to take excessive credit risk (i.e. a high and rising loan-to-assets or loan-to-deposit ratio) in order to bolster their profits.

3.2 Estimation Technique

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.

3.3 Data Sources

The sample set of the study covers the periods 1993-2010 and contains financial ratios of 21 banks out of the total 24 that were operating as Money Deposit Banks (MDBs) in Nigeria during the period. All the 21 banks under review are listed on the Nigerian Stock Exchange (NSE). 11 financial ratios for both the failed and surviving 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

4.1 Principal Component Analysis

The main objective of the principal component analysis (PCA), according to Cambas et al (2005), is to determine the important characteristics which can explain the changes in financial conditions of the banks. PCA was applied to the specified 11 early warning ratios, and the important factors in explaining changes in financial conditions were calculated for each of the bank, and these scores were used as independent variables in estimating the parsimonious early warning model. Also, the predictability of the estimated parameters of the models was tested.

Some diagnostic tests were carried out including the means and standard deviations of the financial ratios for the two groups (failed and non-failed) and significance tests for the equality of group means for each ratio as well as the *F* statistics and their observed significance levels estimated. The significant level was found to be small (< 5%) for 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). Hence, the null hypothesis that two group means are equal is rejected at 5% significant level for these ratios.

The other test statistics calculated in *Table* 1 (see Appendix) is Wilk's Lamda (λ) which is the ratio of the within-groups sum of squares to the total sum of squares. Wilk's Lamda is the multivariate analogue to the K-samples test. Generally, the measure is the determinant of the pooled within-groups sum-of-squares and cross products matrix (SSCP) divided by the determinant of the total sample SSCP matrix (see Schmidt and Hollensen, 2006).

Wilks' Lamda indicates how well the categories are separated. The smaller the statistics, the better the separation. It teaks 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 from our analysis 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 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 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 were used in the study; then each ratio's standardized variance is 1 and the total variance is 11. 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.

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):

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

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:

$$F_{ik} = \sum_{k=1}^{m} w_{jk} Z_{ij}, \quad k = 1, 2, 3 \qquad \cdots(4)$$

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*.

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

To make for easy interpretation of the financial factors, the Orthogonal Varimax factor rotation method with Kaiser Standardization was adopted in the PCA (see Cambas et al, 2005). Convergence was achieved after 15 iterations. This method minimizes the number of variables that have high loadings on a factor. *Table* 4 presents the factor loadings.

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) have 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 has less than average negative loading on the second factor. This result supports the theoretical expectation of the study. Increase in the value of this 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 and R_6) 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.

F_4 represents the profitability structure of a bank. An increase in the score of the profitability factors (R_3 and R_4) 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 consists of three ratios, the first two representing capital adequacy while the third representing earnings structure. Since the factor loading of R_{11} is relatively small and below our specified benchmark, we simply ignore it, though positive more so 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.

4.2 The D-score 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* 4.7 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:

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

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.

Table 4.7 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, 2005). 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* 4.7 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, 2006). 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 highly significant result (low *p*-value) may in practical terms be a too-sensitive indicator of inequality. *Table* 4.8 shows the results of Box's M statistic.

The obvious inequality within group covariances is appropriately appreciated by the size of the Box's M value and the corresponding significance value of less than 1%. In order to evaluate effectiveness of the ratio of between-groups to within-groups the model statistics were calculated in *Table* 4.9. 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 estimated discriminant model, sum of squares of D-scores is as large as possible. Any other linear combination of the predictor variables will have smaller ratio.

The *Eigenvalue* statistic presented in *Table* 4.9 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 0 for failed banks and 1 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* 4.10 shows the calculated D-scores for each of the banks under study.

From the summary results of our three models in *Table* 4.11, it is observed that overall classification accuracy is relatively high with discriminant model recording 78.1 per cent correct classification. In other words, D-score model can correctly identify approximately 16 out of the 21 sampled banks respectively. This is very impressive. The implication of this is that employing these models will enable an early detection of problems that could engender remedial actions to prevent a bank from failing.

4.3 Discussion on Findings

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 (healthy) and failed banks.

As net income to total assets ratio decreases over time, the more likely a bank is to fail. On the other hand, a healthy bank is found to be generating relatively higher returns on assets which keep the bank afloat by absorbing losses when they occur. But a higher return can come from different sources including higher net operating income, low provision for loan losses and lease losses, and low operating costs. It is therefore not surprising that loan total expense-to-total assets ratios are found to have insignificant and sometimes counter-productive effects on bank probability of failure. Their effects on bank performance may likely have been subsumed and overshadowed in the key predictive ratios.

The consistent impressive performance of ratios measuring capital adequacy in this study is noteworthy as this was noted to have exhibited a very poor performance in some past studies. The reason for this may not be far-fetched. First, the ratio used to proxy capital adequacy has risk-weighted capital measure embedded in it. Secondly, unlike in the past, it is increasingly difficult for banks to carry on in their books substantial amounts of sub-standard and bad loans as performing assets instead of writing them off against the capital accounts. This is made possible due to the necessity for the banks to strictly comply with the CBN's Prudential Guidelines which has been in operation over the past decade. This means that capital significantly responds positively and effectively to changes in bank conditions.

Inability to measure credit policy in the study and hence determine its performance in predicting bank failure is noteworthy. Loan loss provisions were intended to be used to proxy credit policy instead of actual loan losses as there no published figures for loan losses during the period of study. Unfortunately, available data on loan loss provisions are scattered and very inconsistent in the published books of virtually all the banks under study.

The findings of this study may be partially consistent with the findings of other similar studies in Nigeria and elsewhere however, there are some significant differences which may largely reflect differences in methodology, sample of banks used, period of study and financial ratios used. This study is the first of its kind in Nigeria in which multivariate statistical technique (principal component analysis) coupled with D-score model is used to explore the basic financial characteristics of banks to construct an early warning signal using publicly open financial data to predict the probability of bank failure.

Specifically, the following results could be deduced from our estimates earlier reported:

(i) D-score model is a good predictor of bank's failure.

(ii) Our results indicated important variables that are significant to the performance of a bank. Such variables include among others, ratios that measure capital adequacy/sustenance, profitability, liquidity and credit risk (asset quality) of a bank.

(iii) The coefficient estimates of the variables CARAS, CATAS, NITA and EPS are consistently statistically significant.

(iv) The result shows that an early warning model predicated on a comprehensive analysis of bank's financial operations coupled with an adoption of discriminant estimations could serve as a veritable device for effective supervision to maintain a safe and sound banking system.

(v) The results provide an overall 78.1 per cent prediction.

5. Conclusion

The early warning signal constructed in this study can be used as analytical decision support tool in both on-site and off-site bank monitoring system to detect the banks that are experiencing serious problems. The ability to detect any problem in bank condition from publicly available data will also reduce the cost of monitoring banks by lessening the need for on-site examinations, and equally provide very valuable information to the decision makers as well as to other interested parties and persons who are responsible from prevention of bank failure. The early warning signal could also be a veritable decision support tool for individual banks the results of which will provide the basis for proactive measures that can forestall any emerging distress conditions.

The results of the study show that PCA is a useful tool for explicitly exploring the financial characteristics of the banking system and comparing the banks with respect to these characteristics, thus determining the differences in the financial structures of the banks. Thus, PCA could be used as an alternative or supplementary decision support tool to the CAMELS rating system commonly employed by the CBN in bank examination process.

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Table 1: **Wilks' Lambda**

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

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

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

Ratios	F1	F2	F3	F4	F5
ASGR	0.985334	0.136481	-0.000275	0.009257	-0.025963
CARAS	0.048015	-0.011135	-0.108229	-0.049520	0.305769
CATAS	-0.095707	-0.017523	0.127798	0.004916	0.367290
EPS	0.028285	0.080362	-0.036637	-0.024409	0.099143
EXAS	0.131092	0.152933	0.371951	-0.182711	-0.039063
LNDEP	-0.119654	-0.078130	0.078158	0.119790	0.055601
LOTAS	-0.048094	-0.020088	0.386496	0.033054	0.018213
NIECAP	0.059617	0.411331	0.048599	-0.008138	-0.026524
NITA	0.128164	0.325675	0.041777	0.058795	0.006104
SPRO	0.022675	0.040501	-0.084194	0.837670	-0.040429
LADEP	0.053796	0.067335	-0.086248	-0.047328	0.088755

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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

Table 4.8: **Box's M Test of Equality of Covariance Matrices**

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

Table 4.7: **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.

Table 4.9: **The Statistics of the Estimated Discriminant Model**

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

Table 4.10: **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
B1	1	.012	1	.332	1	-1.023	1
B2	1	-2.939	0*	-.151	1	-1.158	1
B3	0	-.174	1*	-3.544	0	-2.072	0
B4	1	1.006	1	-.071	1	-1.222	1
B5	1	1.218	1	.252	1	.199	1
B6	0	-.145	1*	-.412	1*	-.120	1*
B7	1	-.194	1	1.464	1	1.529	1
B8	1	-.701	0*	.115	1	1.181	1
B9	1	-1.900	0*	.559	1	.039	1
B10	1	.422	1	.521	1	.792	1
B11	0	1.307	1*	-.586	1*	-.197	1*
B12	1	1.194	1	1.709	1	.925	1
B13	0	-.796	0	-.479	1*	.492	1*
B14	1	2.725	1	2.067	1	.326	1
B15	1	-1.660	0*	.269	1	1.185	1
B16	0	.234	1*	-2.751	0	-1.060	1*
B17	1	2.523	1	1.503	1	-2.813	0*
B18	1	-.180	1	1.310	1	3.240	1
B19	0	-.819	0	-1.273	0	-.289	1*
B20	0	-1.951	0	-2.945	0	-.058	1*
B21	1	.818	1	2.112	1	.104	1

Table 4.11: **Overall Correct Prediction of the Discriminant Model**

Models	Status	Total No. of Sample	Classified Status		Classification Achievement	
			FB	NFB	Correct Prediction	Incorrect Prediction
Discriminant	FB	21	5	16	78.1	21.9
	NFB	21	16	5		

Note: FB = failed banks and NFB = Non-failed banks