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An investigation on Nigerian banks' status using early-warning signal

Abstract

This study is a follow-up to two other studies carried out with other scholars in 2012 and 2014 respectively. While the two studies combined principal component analysis (PCA) with discriminant analysis (DA), this study extends its frontier by developing an integrated early warning signal which pools PCA with three standard statistical models including DA, logit and probit models to determine the health status of Nigerian banks. The results show that discriminant analysis, logit and probit models are credible predictors of a bank's financial status. The results indicate key variables that are significant to the performance of a bank including variables that measure profitability, liquidity, credit risk and capital adequacy because their coefficient estimates exhibit consistently statistical significance in the three models. It can thus be concluded that an early warning model predicated on a comprehensive analysis of a bank's financial operations concomitant with an adoption of discriminant and logit cum probit estimations could serve as a device for effective supervision to maintain a safe and sound banking system. Applying the research methodology employed in the study to a more all-inclusive data set that enables the estimation of these prediction models could reveal additional insights into the processes that engender financial distress of Nigerian banks.

Keywords: bank failure, discriminant, logit, probit, principal component analysis, banking reform.
JEL Classification: C25, C38, G21.

Introduction

The repercussions of the financial meltdown that started in 2007 with the crisis related to subprime-mortgage finance in the United States of America (USA) negatively affected the world economy and spread to other economies of the world including Nigeria. This crisis has led to the collapse of numerous banks and other financial institutions, and rendered (and is still rendering) a number of nations bankrupt.

Banks occupy a strategic position in promoting the growth and development of any economy. This role has been punctured by its vulnerability to systemic distress and macroeconomic volatility rendering regular policy changes inevitable. Thus there has been a substantial change in the Nigerian banking environment since structural renewals were introduced into the system in 1986. The reform yielded some positive results including permission of market forces to determine financial prices like interest rates and exchange rates; promotion of financial savings; reduction in the distortions in investment decisions; inducement of more effective intermediation between savers and investors; establishment of many banks and emergence of new financial institutions and increasing competition and innovation in the sector, just to mention a few.

However, according to Sobodu and Akiode (1994), as sighted in CBN (2006), the emerged banking environment from the reform became ineffective, riskier, illiquid and produced poorer return on assets compared to periods preceding the reform. Besides, banking institutions have been subjected to one squeeze or the other by the introduction of some measures to sanitize their operations which remarkably affected some of them adversely. For instance, the monetary authorities adopted some measures to mop up excess liquidity in the system; these included the use of stabilization securities, prudential guidelines, statement of accounting standards and the like. Consequently, some marginal banks which had earlier posted fat profits were forcefully pushed to illiquidity as they could not meet depositors' demand thus engendering near-panic in the system. Consequently, the banks embarked upon "distress borrowing" in the interbank market at exorbitant rates (Imala, 2005; CBN, 2006).

Furthermore, the deregulation brought about increased competition and innovations accompanied by noticeable traces of strains in the industry. Many banks faced intense competition from non-bank financial institutions (Iyoha and Udegbunam, 1999). Many of these non-bank competitors invaded "prime service areas" such as consumer loans and deposits, cash management services and investment advisory services that were traditionally dominated by licensed banks before the introduction of the structural adjustment program.

According to Adeyeye (2013), 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 restore public confidence in the financial system and ensure efficient payments system. Indeed, between 1991 and 2004, the banking system witnessed a series of systemic distress occasioned by the sudden proliferation of banks and the noticeable weakness in their operations as well as

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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 operating licenses of 31 banks were invalidated by the Central Bank of Nigeria (CBN) comprising of 4 in 1994, 1 in 1995 and 26 in 1996 respectively (CBN, 1998; NDIC, 1995; NDIC, 1999; Sanusi, 2004; Toby, 1999).

By 2004, the number of banks operating in Nigeria was 89 with 3310 branches. The CBN's surveillance report at the end of that year (CBN, 2004) showed that 62 banks out of the existing 89 were categorized as operating satisfactorily, 14 as doubtful, while those regarded as unsound banks had declined from 9 at end of December 2003 to 11. In addition, the report showed that 2 of the banks failed to make statutory returns all through the period (Nnanna, 2004; Imala, 2005; and CBN, 2006).

According to Adeyeye and Oloyede (2014), 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 attainment of strong, competitive and reliable financial markets that meet international best practices. To this end, the CBN took a number of decisive actions with a view to successfully consolidating the banking industry in Nigeria. The emerging consolidation initiative of the CBN with its attendant mergers and acquisitions unprecedented in the history of Nigerian banking system ended up reducing the number of banks from 89 to 24 banks (Adeyeye, 2013).

In addition to the foregoing, by October 2009, another set of 10 out of the surviving 24 banks had the services of their respective chief executives and executive directors terminated for what the CBN labelled undue exposure to toxic assets, pervading weakness in risk management and general poor corporate governance, which are signs of systemic failure of the banks concerned (CBN, 2009). While three of them were liquidated and their assets and liabilities taken over by the CBN and ultimately transferred to other new outfits, five others engaged in mergers and acquisitions whereby their identities were subsumed in their respective preferred investors (i.e. Intercontinental Bank Plc was taken over by Access Bank while Oceanic Bank Plc was taken over by Ecobank Plc, to mention just a few).

Moreover, by March 30, 2010, the CBN in a circular ordered the replacement of the existing universal banking system with other types of licences due to what Adekunle (2010) labelled "lack of expertise, exposure to high risk situation, mismanagement of depositors" funds and inefficient monitoring of subsidiaries'. In addition, the CBN set up an asset management company (AMCON) to assist in mopping up all the toxic assets built up by the banks on the stock market. The company was expected to play the all-important role of facilitating an improvement in liquidity position of the banking sector as well provide a much needed stimulus for the revival of the Nigerian capital market. To mitigate financial distress in the system, the CBN set up ₦1.5 trillion Financial Stability Fund in collaboration with the Bankers Committee, which would be funded over a ten-year period to cushion the effects of distress in the system (Adeyeye, 2013).

It is obvious that the impact of an unhealthy financial system, particularly the banking sector would leave no stakeholder untouched including the government, the supervisory authorities, the banks themselves and the banking public. Therefore, this study attempts to determine a criterion for measuring the health status of banks and use the framework to predict the probability of failure. Generally, a test of early warning models that is capable of predicting the probability of bank failure in Nigeria is our main focus in the study.

1. Objectives and hypotheses

The study seeks to examine, given an early warning model and publicly available financial data, the probability that a Nigerian bank would fail. Specifically, the study tries to: (1) examine the effect of bank-specific attributes and economic variables on the probability that a bank would fail or survive; (2) develop an integrated early warning signal that is capable of distinguishing failed from non-failed banks and (3) use the predictive ability of the models so developed to forecast the possibility of bank failure.

To enhance the achievement of the set objectives of this study, the hypotheses to be tested are based on the assumption that a bank is faced with two binary choices of survival or failure and that the various characteristics of behavior and performance of a particular bank of concern, which may be induced by such variables as economic uncertainty, management incompetence, characters and attitudes of employees of the bank, poor internal control system and weak loan recovery, can be measured and explained by the banks' financial statements and accounting ratios.

In view of this, it is hereby hypothesized that:

H_o: the probability that a bank would fail or survive is significantly dependent on some bank-specific characteristics and economic variables.

1.1. Justification for the study. Adequate knowledge of the health status of banks in an economy is important to financial regulators including the government, the CBN and National Deposit Insurance Corporation (NDIC). Bank failure could exert dire consequences on the banking system and an extensive repercussion on the whole economy at large. Time and again, bank failures rather than occur spontaneously are usually due to sustained periods of financial distress. Therefore, it is pertinent to generate an early warning signal that is capable of identifying potentially failing or "high-risk" banks that are going through a period of financial distress.

According to Adeyeye and Oloyede (2014), incessant systemic distress syndrome in the banking sector over the years is unwholesome and thus demands for a compelling need for gauging the banks' performance to enhance early identification of those that show signs of ill-health so that preventive measures could be undertaken to prevent ultimate failure. 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. Availability of such early warning system could enable the bankers themselves to make serious self-assessment with a view to taking pre-emptive action on time to forestall any emerging problem.

1.2. Scope of the study. The study attempts to show how, with an integrated early warning model and publicly available data, the health status of Nigeria banks can be predicted. The study focuses primarily on Nigerian banks that operated from 1986 to 2010. This period sufficiently spans through the SAP era to the era of deregulation, recapitalization, consolidation and various reforms that has engendered different scenarios in the banking sector. It is during this period that a number of banks had their licenses revoked and some others simply folded up or were subsumed in mergers and acquisition while strains of distress pervaded the landscape like a colossus thus impacting negatively on public confidence in the system (Adeyeye and Oloyede, 2014).

The early warning model applies to publicly quoted banks in Nigeria. This limitation in scope naturally arises because only 3 out of 24 banks operating in the country are not publicly quoted in the Nigerian Stock Exchange. In addition, the data of these three non-quoted banks may not be readily available because it is not statutory to have their financial records published. This will obviously make data gathering on them very daunting and uphill task. Hence, high reliance is placed on the various official accounts and other information from the target quoted banks which are readily available with the regulatory authorities like NDIC and the CBN as well as in the Nigerian Stock Exchange *Factbook*.

1.3. Empirical literature. Various past efforts to measure bank performance and hence predict the probability of its failure are often affected by the absence of any coherent yardstick as a result of which various approaches have been adopted by various researchers as detailed in the following paragraphs. An assessment of bank performance as noted by Ojo (1992) posed some drawbacks because the bank objectives against which an assessment has to be made are often conflicting. 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. Examples include the study conducted by Beaver (1966 and 1968) Altman (1968) Wilcox, Benishay (1973), Dietrich and Kaplan (1982). Other examples are given in Smith (1974) Houget (1975) and Libby (1975). All these efforts affirm that bankers could make precise and consistent predictions of business failure with the use of accounting ratios. Thus it seems plausible that a model of bank failure incorporating ratios can be developed.

In Nigeria, regulatory authorities especially the CBN and NDIC have extensively employed the CAMEL rating system in evaluating the performance of Nigerian banks (Nnanna, 2004; Bello, 2005; and Omankhanlen, 2011). CAMEL is an acronym of financial ratios depicting capital, asset quality, management competence, earnings quality and liquidity level. In line with this, Osaze and Anao (1990) posited that corporate performance can be investigated in terms of profitability, liquidity, leverage (long-term solvency) and activity (efficiency of operations) ratios. Adekanye (1992) agreed with these variables but added potential and actual growth as a key measure of bank performance. He suggested that quality and quantity of service should be a further measure.

Another variant of the CAMEL rating system is that advanced by Wemambu (1994). He found that the banks' performance determinants are dependent on both endogenous and exogenous variables. These include, among others, the national economic variables, regulation, capital adequacy, capital structure, dividend policy, asset quality, liquidity, managerial efficiency, loan portfolio, revenue sources, revenue application, branch location, bank size, working capital, management, the number of banks and their pattern of distribution as well as liquidity management. The ownership structure of the bank and the gravity of competition in the banking sector also hold a place of prime importance in the performance of the banks. In 1996, in an attempt to focus more on risk in its rating system, the Federal Reserve System added a sixth element (sensitivity/market risk) to the CAMEL rating system, making it CAMELS (Sahajwala and Bergh, 2000).

Shumway (2001) used logit model to investigate industrial corporations over 31 years. His model was an improvement over the Altman's model in utilizing multi-year information for each company. Also, Iyoha and Udegbunam (1999) used logit regression analysis to predict bank failure in Nigeria. The model was estimated using both pooled and cross-sectional data. The result indicate overall correct predictions ranging from 62 per cent in 1991 to 88 per cent in 1993, an indication that the model's predictive power increases over time. That is, as the date of failure draws closer, the model's predictive power equally increases. Although the findings of the study are to an extent consistent with the findings of other similar studies for Nigeria, especially those of Jimoh (1993), Nyong (1994) and Doguwa (1996), the model suffered a major defect in that the sample used was small compared with that used in some other previous studies. The ratios used in the study were simply limited to published figures which were generally assumed to be subjective in its estimation and a number of the explanatory variables were inter-correlated.

Falkenstein, Boral and Carty (2000) used a probit model in their study. The study has an edge over other benchmark models as it shows an increased accuracy due to the large sample size, careful data transformation and normalization employed in the model. Blums (2003) attempted an improvement on earlier studies on bankruptcy prediction by evolving a D-score model using forward selection process in a relaxed Gambler's ruin and Merton model context. He uses current financial statistics for middle market of publicly traded companies over many years. But, he saw no justified reason for attempting to contrast the results of various previous researchers, as in doing so yields no meaningful result.

A combined early warning framework was proposed by Canbas, Cabuk and Kilic (2005), which comprised of four elements including discriminant analysis (DA), Logit model, Probit model and principal component analysis (PCA). The PCA determines the financial variables that explain observed variances in the financial condition of the banks under review while the remaining three components are used as the regression models. They combined all these together to create an integrated early warning system (IEWS). They also tested the system on 40 privately-owned commercial banks in Turkey and concluded that the predictive ability of the IEWS is more effective than several other models used in the literature.

The foregoing section has reviewed different quantitative and qualitative early warning models employed by different scholars in an attempt to determine the health status of banks in different studies. It is against this background that this study attempts to complement the above reviewed studies by the application of a methodological framework that can be used for constructing an early warning signal that could be used for detection of bank failure in Nigeria. Specifically, the study employs an integrated multivariate statistical technique to determine the fundamental features of the banks under study and equally use three econometric models comprising discriminant analysis, logit and probit models to construct an early warning model that will enable a prediction of the likelihood of bank failure and evaluate the severity of their financial positions in Nigeria.

2. Model specification

Following recent studies by Shumway (2001), Bernhardsen (2001), Blum (2003) and Adeyeye and Oloyede (2014), a dependent binary variable is hereby specified signifying that an event "insolvency and failure" will or will not occur has a functional relationship with a vector of bank-specific attributes and economic factors as follows,

where:

$$Z_i = \beta_0 + \sum_{j=i}^{k} \beta_j X_{ij} + \varepsilon. \qquad (1)$$

Z_i = the dependent variable for bank i (the chance of bank i becoming 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, $j = 1, 2, 3, ..., k$. ε = error term.

Now, we have assumed that there is a critical unobservable level of Z_i*, such that if $Z_i > Z_i$*, bank i will fail, otherwise it will not become bankrupt. Therefore, the equation to be estimated in real terms becomes.

$$Z_i^* = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} +, \cdots, + \beta_k x_{ik} + \varepsilon_i. \qquad (2)$$

Applying the specification of *Equation* (2) to the insolvency prediction model, the independent variables x_{i1}, x_{i2},...x_{ik} are the computed ratios generated from the financial statements of individual banks under review, and the specification $\beta_1 x_{i1} + \beta_1 x_{i1} + ... \beta x_{ik} = Z_i$*, measures the financial viability of the bank of interest. Should this quantity go beyond a benchmark, the bank is presumed to be distressed. The stochastic term ε_i is thus introduced because the critical value is assumed to fluctuate among individual banks. According to Bernhardsen (2001), this structure will simply imply a constant rate of compensation between variables by any choice of a monotonic distribution function for ε.

The relevant financial ratios used in the study measure the various characteristics of behavior and performance peculiar to individual banks under study. These are capital adequacy, liquidity sufficiency, asset quality and profitability, management quality, operating efficiency, credit policy, public confidence, staff productivity and economic conditions under which each of the banks operate.

2.1. Expected signs of variables. On *a priori* theoretical expectation about the expected behavior of the regression estimates of the above listed variables, the probability that a bank will be insolvent and therefore fail is assumed to be inversely associated with variables that measure liquidity, capital adequacy, profitability, economic conditions, public confidence and staff productivity. The reason for this position stems from: (1) a bank with high level of liquidity and highly capitalized is not likely to fail; (2) a bank with sustained high level of profitability is not likely to fail; (3) a bank's capital adequacy is its capacity to withstand losses arising from risk exposures in the bank's capital; (4) a bank's increased market stock prices is an indication of public confidence in its future performance and (5) conducive economic conditions lessen the cost of production, increase ease of doing business and increase productivity.

On the other hand, the probability of a bank failing is likely to rise with variables that measure high credit risk, weak credit policy and poor management quality. The reason being that: (1) the depth of management quality determines loan portfolio quality and hence, the soundness of credit policy; (2) weak credit policy equally manifests in loan problems usually measured by high degree of non-performing loans or loan loss reserves; (3) a significant increase in any of these ratios will obviously decrease profitability and thus increase probability of failure; (4) banks facing decreasing profitability tend to take excessive credit risk (i.e. a high and rising loan/assets or loan/deposit ratio) in order to bolster their profits.

2.2. Estimation technique. Both *Equation* (1) and (2) are computed from the cumulative probability function and because these functions are non-linear, ordinary least square (OLS) method cannot generally be applied. Therefore, the parameters were estimated using a maximum likelihood, non-linear estimation method (Gujarati and Porter, 2009). The study equally relied on *SPSS 17* to generate the discriminant analysis 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. The study equally relied on *Stata 10* and *E-views7* econometric software for PCs to carry out all other necessary analysis and estimations because of their respective high degree of consistency, reliability and dependability.

2.3. Data sources. The sample statistics for the study covers 23 year-period from 1993 to 2010 and comprises of ratios of 21 banks out of the total 24 presently operating as Money Deposit Banks (MDBs) in Nigeria. All the 21 banks under review are quoted on the Nigerian Stock Exchange (NSE). 11 financial ratios for both the banks that are known to have failed and surviving ones 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*.

3. Empirical results

3.1. Principal component analysis. According to Cambas et al. (2005) and Adeyeye and Oloyede (2014), PCA seeks to establish the critical factors that are capable of explaining observed variations in the financial state of the banks under review. In the study, we applied PCA to the earlier specified 11 early warning ratios and calculated the critical factors that describe the variations in financial situations of each of the banks under review, and also used the scores generated as explanatory "variables in estimating parsimonious early warning models" for the three models respectively. In addition, we tested the predictability of the parameter estimates of each of the models.

Several diagnostic tests were carried out including the following: (1) the means and standard deviations of the financial ratios for both failed and non-failed banks (the two groups); (2) significance tests for the equality of group means for each ratio; (3) estimates of F statistics and their respective levels of significance and (4) Wilk's Lamda (λ) which is the multivariate analogue to the K-samples test. Detailed analysis of how all these tests were carried out, their reports and the criteria for arriving at the choice of the five key factors that show common characteristics of the observed variables are contained in Adeyeye et al. (2012) and Adeyeye and Oloyede (2014).

The five key factors include the following: F_1 symbolizes economic conditions and staff productivity (ratios R_1 and R_2). F_2 contains two ratios (R_3 and R_4) signifying credit risk and liquidity structure of a bank respectively. F_3 includes two ratios (R_5 and R_6)

representing management and asset quality of a bank respectively. F_4 signifies the profitability structure of a bank and F_5 consists of three ratios, the first two representing capital adequacy while the third representing earnings structure.

3.2. Discriminant model. The results of the discriminant analysis as contained in the two studies mentioned above are with permission replicated here. Note that the *D*-model seeks to generate a linear combination of the categorical covariates that optimizes the changes between the populations in relation to within-group variance. The estimated factor scores of the linear combination allow a discriminant score (*D*-score) for each bank in accordance with the canonical discriminant estimates shown in the following equation:

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

Equation (3) represents each bank's *D*-score and F_1 to F_5 are factors that denote 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.

From the results of the covariance matrix and correlation matrix for the pooled-within groups matrices, it is clearly observed 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 other words, all the elements across the principal diagonal of the corresponding matrix are equal to 1 while the remaining components are equal to 0 as there is no existing correlation between the ratios. The results show 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 theoretically expected to be very sensitive meaning that a high *p*-value will be a good and acceptable indicator of equality, while a low *p*-value, which is regarded as a highly significant result, may be regarded as too sensitive indicator of inequality. 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%.

The model statistics were calculated to allow for a critical assessment of the efficiency of the estimated discriminant model. A discriminating model is said to be effective when the *D*-scores variability of between-groups are greater than *D*-scores variability of within-groups. The chosen discriminant coefficients of the model allow the ratio of the sum of squares of *D*-scores between-groups and within-groups to be large enough, as different linear combinations of the explanatory variables will generate reduced ratio value.

The estimated Eigenvalues shown is the quotient of the sum of squares of *D*-scores between groups to within-groups. Eigenvalue of 0.835 is an indication of a reasonably high discriminating ability for the parameter estimates of the discriminant model. Canonical correlation measures the functional relationship between these scores and each group variable (failed bank is coded 0 and non-failed is coded 1), which is moderately low at 0.539. Furthermore, the Wilk's Lambda of 0.710 shows that differences between the *D*-score means of the groups caused most of the total variations.

3.3. Logit and probit models. Maximum likelihood technique is employed for both logit and probit models in order to carry out their respective estimations using the quadratic hill climbing optimization algorithm. The sample period ranges between 1993 and 2010 and of the included observations totalling 246. 138 observations were categorized as 0 while 108 were categorized as 1 and convergence was achieved after 10 iterations. Moreover, the covariance matrix was computed and standard errors were obtained in each case from Newton's analytic second derivatives. For comparative analysis, we estimated both logit and probit models with two econometric packages: *Stata 10* and *EViews 7* for Windows.

The over-parameterized estimates of the logit and probit models, using all the variables earlier specified and with a pooled time-series and cross-sectional (panel) data were considered but not reported here while the more parsimonious estimates are reported in Tables 1 below.

The logit model is based on a cumulative logistic function and it provides the likelihood that, assuming its financial peculiarities, a firm (a bank in our study) belongs to one of the given groups. In the model, we calculate the likelihood that a firm (bank *i*) is going to fail (P_{Li}) by using the following cumulative logistic function:

$$Z_{Li} = \beta_1 F_{1i} + \beta_2 F_{2i} + \cdots + \beta_5 F_{5i}. \quad (4)$$

Similarly, the probit model is given by:

$$Z_{Pi} = \beta_1 F_{1i} + \beta_2 F_{2i} + \cdots + \beta_5 F. \quad (5)$$

The resultant probability values from *Equations 4* and *5* allows a bank to be categorized as failed or non-failed. This is also based on a success probability cut-off point of five per cent in each case in an attempt to minimize *Type I* (failed banks erroneously categorised as strong banks) and *Type II* (strong banks erroneously categorised as failed banks) errors respectively. Moreover, maximization of the log-likelihood function provides the over-parameterized estimates in the logit (Z_{Li}) and probit (Z_{Pi}) models (not reported here).

From our estimated results, four explanatory variables were found in both models to be significant statistically at five per cent level with the exact *a priori* signs. They are: net-income/total assets (NITA), capital/total assets (CATAS), CARAS, and earnings per-share (EPS). The remaining six explanatory variables are not statistically significant except LOTAS which is only significant at ten per cent level.

Notably, the number of coefficients in our result that are significant statistically as shown by their pair-wise correlation coefficient are less impressive because high inter-correlation were exhibited by some of the explanatory variables. Nonetheless, the results exhibit consistency with outcomes of earlier studies that also used large number of financial ratios (Iyoha and Udegbunam, 1999; Canbas et al., 2005).

After testing all the explanatory variables considered sufficient to cover various aspects of bank performance, we reduced the magnitude of each model to only seven variables. These variables were chosen based on the performance of the initially over-parameterized model as noted above, and the purpose is to try to achieve a more robust goodness-of-fit result with minimum number of variables.

The results of the more parsimonious estimates records a significant improvement in both models, as the ratio of total loans/total assets (LOTAS) become significant at 5 per cent level, though with the wrong sign. This brings the number of explanatory variables that have statistically significant coefficients to five out of seven preferred variables.

Table 1. Parsimonious model

	Logit model				Probit model			
	Coefficients	Std. error	*z*-statistic	*p*-value	Coefficients	Std. error	*z*-statistic	*p*-value
CARAS	13.80789	2.769789	4.985177	0.0000	4.876439	0.866595	5.627125	0.0000
CATAS	-16.49290	4.188937	-3.937253	0.0001	-5.090051	1.267969	-4.014334	0.0001
LOTAS	-4.627606	1.947665	-2.375976	0.0175	-2.967164	1.047339	-2.833052	0.0046
EPS	0.866375	0.229156	3.780718	0.0002	0.570108	0.127679	4.465180	0.0000
NIECAP	-0.365855	0.360396	-1.015150	0.3100	-0.246245	0.221588	-1.111271	0.2665
NITA	32.99206	9.528590	3.462429	0.0005	21.22444	5.177621	4.099266	0.0000
SPRO	1.41E-06	1.93E-06	0.733046	0.4635	7.44E-07	1.13E-06	0.655762	0.5120
C	-1.071259	0.673452	-1.590698	0.1117	-0.492883	0.386193	-1.276260	0.2019

Source: authors' computation.

From the re-estimated result above, it is noted that the relative significance of the explanatory variables are almost the same in proportion as in the previous result, although the degree of their significance vary slightly. For example, in the *logit* model, capital/total risk-weighted assets ratio, capital/assets ratio, earnings per share, net-income/total assets ratio and total loan/total assets ratio, in that order, are the most significant predictors of a bank's failure, citeris paribus; while in the *probit* estimation, CARAS, EPS, NITA, CATAS and LOTAS, in that order, become much more important as predictors of a bank failure.

3.4. Expectation-prediction evaluation of discriminant, logit and probit models. The expectation/prediction evaluation capability of the three models under study for binary specification is as shown in Table 2. From the summary results of our three models, it is observed that overall classification accuracy is relatively high in each case with discriminant model recording 95.2 per cent correct classification, probit model recording 89.02 per cent correct classification and logit model recording 90.24 per cent correct classification respectively. In other words, discriminant analysis can correctly identify approximately 20, while both *logit* and *probit* models can both correctly identify about 19 of the 21 sampled banks respectively. This is very impressive.

Table 2. Overall correct prediction of the discriminant, logit & probit models

Models	Status	Total No. of Sample	Classified status		Classification achievement	
			FB	NFB	Correct prediction	Incorrect prediction
Discriminant	FB	21	1	20	95.2	4.8
	NFB	21	20	1		
Logit	FB	21	3	19	90.24	9.76
	NFB	21	19	3		
Probit	FB	21	3	19	89.02	10.98
	NFB	21	19	3		

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

Misclassification rates equally range from 4.8 per cent, 9.76 per cent and 10.98 per cent for *discriminant*, *logit* and *probit models* in that order. This means that the model *discriminant* has an edge over the *logit* and *probit* models having the lowest misclassification of just 1 (4.8%) out of sampled 21 banks.

From the foregoing, each model under study, in terms of overall goodness-of-fit, as evidenced especially by the percentage of correct predictions, is capable of predicting at least 89.02 per cent accurately that a bank will become distressed or fail a year before it actually fails. By implication, employing these models will enable an early detection of problems that could engender remedial actions to preclude a bank from failing.

3.5. Integrating the three early warning models. As suggested by Canbas et al. (2005) and corroborated by Adeyeye (2013), the three parametric models including discriminant analysis, logit model and probit models respectively can be systematically pooled with the principal component analysis to create an integrated early warning system (IEWS) as a veritable analytical support instrument for bank examination and supervision. Here is how the system is expected to work:

The system integrates the estimated models with their parameters including:

- the means (μ_i) plus the standard deviations (σ_i) for each financial ratio;
- the coefficients of the five factor scores generated by PCA (w_{jk});
- the coefficient estimates of the three models.

In assessing a particular bank of interest given the IEWS, while allowing the ratio of the evaluated bank in question (g_{ij}) to vary, all the other system parameter estimates are allowed to remain constant. These are the 11 ratios proxied as early warning indicators in the study. After standardizing the ratios, the five factor scores are then estimated with the use of factor score coefficient matrix. These estimates are then used in generating the probability scores of the three models for each bank. Figure 1 shown in the appendix demonstrates a flow chart showing the workings of the system.

All variables identified in the IEWS have the expected signs. Twenty per cent of the significant predictive variables measure the credit risk of the banks under study. This is reasonable as credit risk is more or less the most significant risk source in the banking industry. About forty per cent of the variables measure bank profitability. This may not be unconnected with the fact that banks that are less profitable possess higher propensity of running into financial problems. Furthermore, twenty per cent of the important explanatory variables measure bank characteristics related to capital adequacy. Notably, variables that measure quality of management and other bank features like economic conditions and staff productivity are potentially not significant predictors of financial difficulties for all banks but not impossible to make a difference for such group of banks that are facing difficulties. Banks with effective and efficient management quality possess a higher propensity to survive during times of financial crisis.

4. Discussion of findings

The analysis of the three regression models 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/total assets ratio decreases over time, the greater the probability that a bank will 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 total loan 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 (i.e. Iyoha and Udegbunam, 1999). 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 results of this study may be partially consistent with the outcomes of other similar studies in Nigeria and elsewhere (e.g. Iyoha and Udegbunam, 1999; Canbas et al., 2005); however, there are some important differences, which may be due to differences in procedure, number of banks used as sample, study period and financial ratios used. This study is the first of its kind in Nigeria in which multivariate statistical technique (PCA) is coupled with discriminant, logit and probit models to examine the key financial peculiarities of Nigerian banks and the parameter estimates so generated based on these peculiarities used to create integrated early warning signal using publicly available financial data to predict the probability of bank failure.

Implications

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

- Discriminant, logit and probit models are good predictors of a bank's failure.
- Both logit and probit formulations produce results that are similar in magnitude and proportion and thus can be used as substitutes in assessing bank performance.
- 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.
- The coefficients on the variables CARAS, CATAS, NITA and EPS have consistently received their expected signs for all data periods in all the three models used in the study including the over-parameterized and more parsimonious models.
- The coefficient estimates of the variables CARAS, CATAS, NITA and EPS are consistently statistically significant.
- LOTAS became statistically significant in the more parsimonious model.
- The result shows that an early warning model predicated on a comprehensive analysis of bank's financial operations coupled with an adoption of a discriminant and logit cum probit estimations could serve as a veritable device for effective supervision to maintain a safe and sound banking system.
- The results provide consistently impressive overall predictions.

Summary and conclusion

This study developed an integrated earning warning signal that distinguishes failed from non-failed banks. The principal component analysis is coupled with three standard statistical models (i.e. discriminant analysis, logit and probit models) to predict the probability of bank failure in Nigeria. The empirical analysis reveals that the IEWS produces a robust result with high prediction accuracy. This is a favorable result as it shows its invaluable usefulness for regulators in assessing the health status of banks of interest.

The integrated early warning signal constructed in this study could be employed as a support tool for analytical decision for both on-site and off-site bank examinations to distinguish banks which are undergoing severe financial difficulties. The capacity to identify early traces of financial strains in a bank from published data could also decrease bank monitoring cost by reducing the necessity for on-site examinations, and equally offer invaluable statistics to the monetary authorities and other stakeholders whose responsibility it is to prevent or forestall failure of banks. The IEWS could also be a veritable decision support tool for individual banks the results of which will provide the basis for proactive measures that can preclude any emerging distress conditions.

The results from the study clearly demonstrate that principal component analysis is a valuable instrument that can clearly explore the financial peculiarities of the Nigerian banks and relating each of them to such peculiarities, which may enhance determination of structural dissimilarities in the financial positions of the banks. Thus, the CBN can use the

IEWS as a substitute or complementary support tool as against CAMELS rating system commonly employed in its bank examination procedure.

It is noted that this study was predicated on data generated from few banks in Nigeria, applying the research methodology employed in the study to a more all-inclusive data set that enables the estimation of these prediction models could reveal additional insights into the processes that engender financial distress not only of Nigerian banks but also of other countries with similar characteristics. Also, the research methodology may equally apply to other financial and non-financial sectors of the economy.

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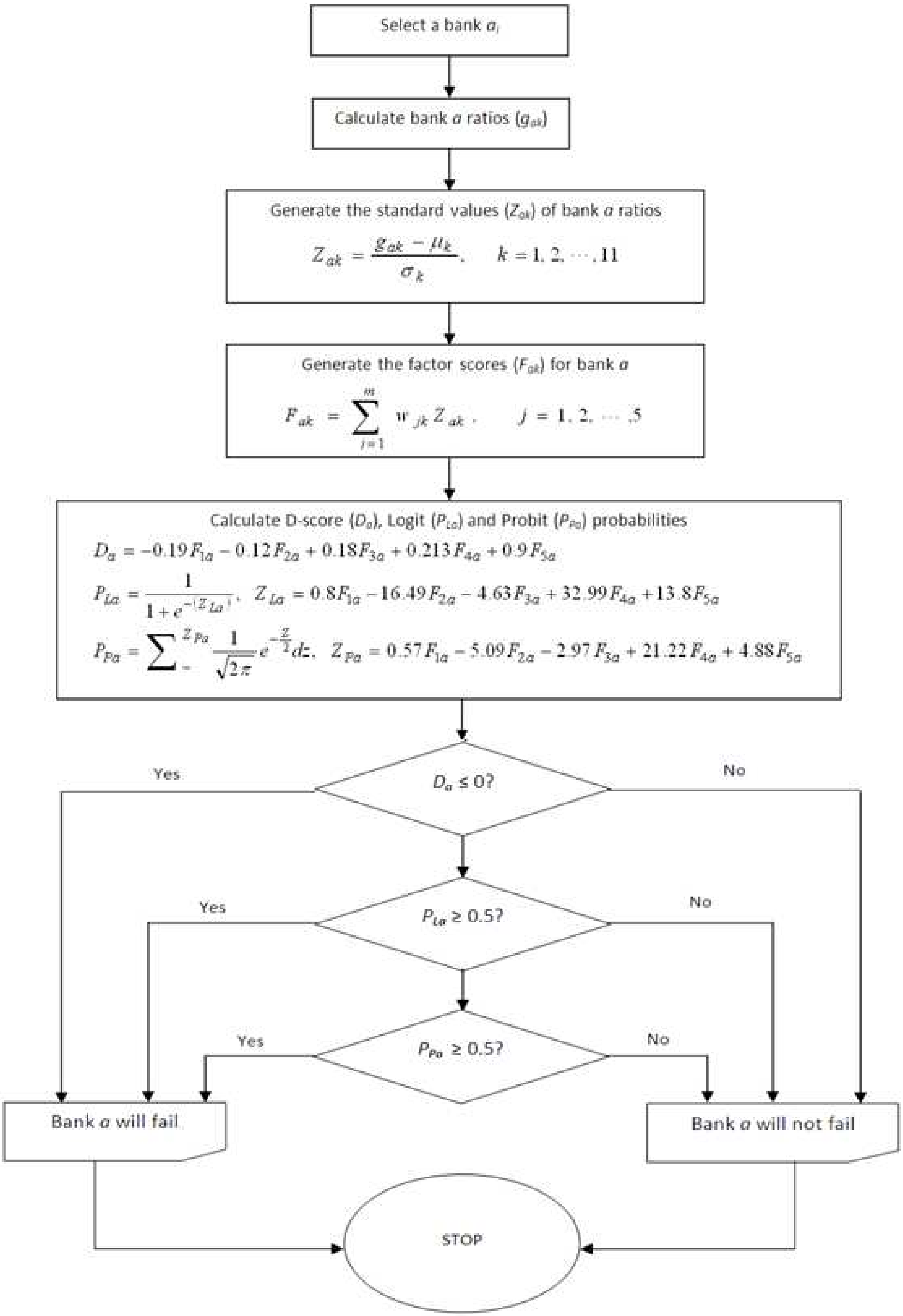
Appendix



Soure: author's conjecture adapted from Canbas et al., 2015.

Fig. 1. Flow chart showing integrated earning warning signal