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BANK SUPERVISION AND THE SAFETY-AND-SOUNDNESS OF THE BANKING SYSTEM: AN EARLY WARNING MODEL APPLIED TO NIGERIAN DATA.

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This study attempts to provide an early warning model to assist bank regulatory and supervisory authorities in Nigeria in scheduling bank examination so that potential insolvent (problem) banks would be examined more frequently and more intensely than solvent (non-problem) banks. A combination of factor analytic framework, multiple discriminant analysis and logit model were used. A host of critical factors that should enter the supervisory and regulatory authorities information set was identified. The framework provided some improved methodology for classifying banks into problem and non-problem banks. The results suggest that bank regulators and supervisors in Nigeria should give a weight of 0.0656 to Ownership 0.1297 to risk (BDDLON), 0.1846 to LONASS (asset quality), 0.862 to BDDASS (quality of management), –0.9589 to return on assets (ROA), -0.2366 to return on capital (ROC), –0.2146 to Liquidity (LQDEPO), –0.0245 to capital adequacy (KADLON) and 0.5886 to operating efficiency (EXPEARN). The sum of these weighted variables should be used to compute a bank's probability of failure. Overall, our results show that an early warning model, predicated on a comprehensive analysis of a bank operations coupled with an adoption of factor analysis-cum-logit model, could serve as a powerful discriminating device for effective supervision to maintain a safe and sound banking system.

The importance of banks in the economy is well established. Banks occupy a critical position in a complex financial system that supplies the money and credit needs of the economy. Empirical evidence exists which suggests a positive correlation between real economic growth and bank assets and between money supply, bank assets and economic development (Alashi, 1991).

The development of banking system is seen by both the financial liberalization and repressionist schools as a critical factor in economic development in developing countries (Mckinnon, 1973; Shaw 1973). This fact is evident in Roussakis's (1977) assertion that no other financial institution contributes more significantly to the successful functioning of a nation's economy than does its commercial banks.

Apart from promoting the payment mechanism, banks offer an efficient mechanism or channel for the mobilization of savings and their allocation to

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productive investment. This promotes economic growth and development (Ojo and Adewunmi, 1981; Nyong, 1989a; Nwankwo, 1991; Nyong, 1992).

However, the ability of banks to promote growth and development depends on the extent to which financial transactions are carried out with trust and confidence and least risk (Jimoh, 1993). This requires safe and sound banking practices. Where banks indulge in unsafe and unsound banking practices, the confidence which the public reposes in them may be threatened. In particular, public confidence and trust in the banking system may be shaken by bank failures, with adverse consequences on the development process. To minimize the risks and cost of bank failures, and ensure a safe and sound banking system, banks are regulated and supervised by the regulatory and supervisory agencies.

The objectives of this study are to: (i) develop an early warning model to predict the probability of bank failure, (ii) assess the severity of distress in the Nigerian banking industry, and (iii) proffer some policy suggestions to improve bank supervision in Nigeria. The developed early warning model is expected to assist the regulatory and supervisory authorities in Nigeria in scheduling bank examinations so that potential insolvent (problem) banks would be examined more frequently and more intensively than solvent (non-problem) banks.

The rest of this study is organized as follows. Section I has been the introduction. Section II examines bank supervision and early warning models. Section III provides the analytical framework and methodology. In section IV we provide the empirical results and the analysis. We conclude the study in section V with a summary of the main result and an articulation of policy prescriptions to improve bank supervision in Nigeria.

II Bank Supervision and Early Warning Models

In most countries the tasks of maintaining safe and sound banking system are carried out by the central banks and the deposit insurance corporations. The regulatory and supervisory agencies interpret their "safety-and-soundness" mandate as one of failure prevention or minimization. This interpretation is consistent with stabilization goal which suggests that given the institutional structure, failure of bank should be prevented lest it precipitates a run on other banks. A run on other banks may leads to significant reduction in the money stock and could lead to a depression (Maver, 1980). To see this notice that banks provide the bulk of our money supply. Large scale bank failures consequent on a run on banks limit the ability of banks to create money, jeopardize the payment mechanism and disrupt bank lending activities. The disruption of their lending activities may lead to decline in investment and hence to a depression.

Similarly, since banks serve as conduit through which stabilization policy is transmitted to the economy at large, generalized bank failures impair the continued usefulness of the banking system as a conduit for macroeconomic stabilization policies. By identifying banks with the highest probability of failure (i.e. problem banks), and intervening before much damage is done to the economy, the regulatory and supervisory authorities may achieve their goal of maintaining stability in the banking system and generating continued confidence by the public in the system.

In Nigeria, the Central Bank of Nigeria (CBN) and the Nigerian Deposit Insurance Corporation (NDIC) undertake both off-site and on-site (field) examinations of banks to determine the extent of their financial health. While off-site examinations of each bank is undertaken once every month, field examination of every bank is hardly conducted every year.

Part of the problem may be ascribable to inadequate manpower both in quality and in quantity. With the recent explosion in the number of banks operating in Nigeria since the adoption of Structural Adjustment Programme (SAP) in 1986[2], the available human resources of the supervisory agencies would be stretched beyond limit. Yet deregulation of the baking system expected to enhance competition will also lead to greater risk-taking by banks as recent experience indicates.[3] Therefore, there is need to develop a rigorous and scientific early warning model for identifying problem banks that need the attention of the regulatory and supervisory authorities most. By devoting the limited human resources to potential problem banks, bank supervisors could arrest or minimize bank failures and achieve their goal. This does not mean that only problem banks are to be examined. It implies that potential problem banks would be examined more frequently and more intensely than non-problem banks.

In this study problem banks are insolvent banks either closed or still operating. Insolvency means negative net-worth, a situation where the liabilities of a bank is in excess of its assets. Benston et al (1986) defines a failed bank as one where there is complete or partial loss to shareholders, combined with a cessation of independent operation or continuance only by virtue of financial support from a deposit insurance corporation.[4] Section 36 of Banks and Other Financial Institutions (BOFID) Decree No. 25 of 1991 provides the power of the CBN to revoke the license of a failed bank with the approval of the president. The CBN may appoint the NDIC as a receiver for the purpose of systematic restructuring and subsequently selling the failed bank or winding up the business of the bank.

At the core of a distressed bank are two fundamental problems. These are illiquidity and insolvency. Whereas an illiquid bank cannot meet its liabilities as they fall due for payment, an insolvent bank as previously defined presents far more serious problem and is viewed with the greatest seriousness by the regulatory and supervisory authorities. This follows because the monetary authorities are best able to perform their function of lender-of-last resort only to banks that are illiquid but solvent. However, inspite of the greater problem inherent in insolvency compared to liquidity, the latter cannot be ignored because it is an ominous sign of insolvency. For instance, if the problem of illiquidity continues for a long lime it

2 In 1986 there were 40 banks in Nigeria comprising 28 commercial banks and 12 merchant banks. By 1992 the number has jumped to 120 banks comprising 66 commercial banks and 54 merchant banks (CBN, 1992).

3 Alashi (1991) indicates that in 1989 there were 7 technically insolvent and under capitalized banks. By 1990, the number has increased to 9. See also Annual Report of NDIC (1989).

4 See also Alashi (1993).

may lead to insolvency (i.e. banks may forcefully sell their assets below market values).

There are four potential advantages of an efficient early warning model. First, an efficient early warning model assists 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 disruptions to the payment mechanism. Second, it leads to more efficient allocation of regulatory and supervisory agencies' resources among problem and non-problem banks. Third, it provides a more objective separation of problem and non-problem banks than any ad-hoc or heuristic method. Lastly, an early warning model constitutes a basis for critical self-assessment by banks so that they could take remedial action in good time to arrest the problem.

Desirable as an early warning model is for Nigeria, a systematic search of the literature could only find one for the country: Jimoh (1993). Jimoh developed two early warning models, the cluster and logit models to identify the critical factors that adequately predict bank's solvency. This study complements the study by Jimoh in three significant areas. First, it provides a rigorous analysis of methodological and interpretational problems in classificatory 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.

Although the study by Jimoh is commendable as seen by its pioneering contributions, there are certain important methodological and interpretational inconsistencies inherent in the study that may seriously diminish the usefulness of the results for policy purposes. For instance, from his regression results he concluded that 'banks supervisors and bank management should give a weight of 0.123 to RISK, –.002 to LIQUIDITY, 0.480 to ASSET QUALITY, 0.136 to OWNERSHIP and –1.298 to RETURNS to TOTAL ASSETS variables'' (p. 38). This means that if the bank supervisors and bank management use the coefficients of the model, they would be able to predict a bank's solvency status. In other words, since the model was able to identify banks classified by the regulatory authorities as insolvent, the proposed model has a ''high predictive power''.

However, a careful analysis of his methodology and interpretations indicate that these conclusions are unwarranted and premature. Since his results were based on the original sample banks and no effort was made to apply the model to out-of-sample banks (banks not originally included in the sample or hold-out sample), it is difficult to adduce predictive power to the proposed model. The study provides example of inconsistency between purpose and analysis. Surprisingly many other studies are guilty of this interpretational abnormality as seen in Altman (1968) and Edminster (1972).

The intention of Jimoh (1993) was to assess the usefulness of financial ratio analysis in predicting bank's failure or insolvency. But he succeeded only in demonstrating ex post discriminatory success! Ex post discrimination is the necessary first step before ascribing any explanatory importance to the independent variables. Prediction means to foretell the future. Ex post discrimination may provide a useful foundation for explanation of the past, but it does not provide sufficient evidence for concluding that the future can be predicted. Of course if the assumption is made that the population of banks is stationary over time ex post discrimination is equivalent to prediction. But the researcher must establish that stationarity does exist.

In the Nigerian case the number of banks operating in the country exceeds his sample size of 53 banks. In the context of Jimoh's study what needed to be done was to adopt inter-temporal validation by applying the model to banks not previously included in sample. This is *ex ante* prediction. The predictive power of the model will be predicated on the success of the model to properly classify the out-of-sample banks into problem and non- problem banks. Additionally, there may be need to test for the stability of the parameter estimates since the weights are to be applied to all banks, whether they are included in the sample or not.

Seen against the background of the issues raised above, this study complements other studies which attempt to develop early warning models to predict the probability of bank failure and assess the severity of their financial distress. The models are applied to a cross section of 60 banks (commercial and merchant banks) operating in Nigeria in 1990.

III Analytical Framework and Methodology

Discriminant analysis is a multivariate statistical technique suitable for use in classification of observations into two or more groups based on specified predictor variables. These groups may be problem or non-problem banks, insolvent or solvent banks, bankrupt or non-bankrupt firms etc. A linear discriminant function maps a set of entities in two different groups, from an m - dimensional attribute space into a one-dimensional space in such a way that the distributions of the points are optimally separated.

Although the application of discriminant analysis to dichotomous classification problems has increased over the years little attention appeared to have been given to design and interpretational difficulties associated with discriminant analysis. Consequently, the conclusions and generalization that can be drawn from such studies are frequently tenuous and questionable. The use of linear multiple discriminant analysis (LMDA) in two category classification provides optimal solution if the categories have identical variance-covariance matrices (Tellefson, 1975; Sinkey, 1975; Morrison, 1976; Sinkey, 1977, 1980; Juncker, 1980; Bovenzi et al, 1983; West, 1985; Johnson and Wichern, 1988; MINITAB Manual, 1991). But when the variance- covariance matrix are not identical, it is well known that quadratic rather than linear multiple discriminant analysis yields optimal solution to the dichotomous classification problem (Minitab Manual, 1991).

The application of linear multiple discriminant analysis into two a priori groups yield two linear discriminant functions (LDF) each of the form:

$$Z = b0 + b1X1 + b2X2 + b3X3 + \ldots + bmXm + e1 \qquad \ldots \ldots \ldots \ldots 1$$

where Z = discriminant score;

Xj = the jth discriminating variable (independent variable);

bj = the discriminant function coefficient of the jth variable;

e = stochastic error term with the usual properties.

Whereas a discriminant function is effective as a classificatory device, a logit model complements discriminant analysis by predicting the conditional probability of an attribute or entity belonging to one group or the other based on a set of explanatory variables (Martin, 1977; Espanhbodi, 1991). The general logit models is of the form:

$$\text{Log } Pi/(1-Pi) = a0 + a1X1 + a2X2 + 13X3 + \ldots + amXm + u \qquad \ldots\ldots 2$$

where Pi = probability that the ith bank fails;

Xj =jth explanatory variable;

aj = regression coefficients or weights of the jth regressor and u the stochastic error term

The pi's are obtained from:

$$Pi = Exp\,(Vi)/\{1 + Exp\,(Vi)\}$$

where $Vi = a0 + a1X1 + a2X2 + a3X3 + \ldots + amXm$
for the ith bank

The initial estimates of the coefficients are obtained from the regression:

$$\text{Dummy } 1 = b0 + b1X1 + b2X2 + b3X3 + \ldots + bmXm + e2 \qquad \ldots\ \ldots 3$$

where Dummy 1 = 1 for banks that are classified as insolvent and

Dummy 1 = 0 for banks that are classified as solvent. The Xjs are the discriminatory variables.

Various financial variables pertaining to various characteristics of behaviour and performance were considered. These financial variables include total assets, total loans, ownership category, total liquid assets, total deposits, bad and doubtful debts, net profit, shareholders funds, operating expense, total earnings, bad debts/loan ratio, loans/total asset, bad debt/total assets, return on asset (ROA), return on capital (ROC). Others include measures of capital adequacy such as capital-loan ratio, capital- deposit ratio, capital-total asset ratio, measure of liquidity such as liquid assets/deposit ratio, measures of operating efficiency such as total operating expense/total earnings and total operating expense/total assets. In all about 22 variables were considered all of which have been identified by theories of efficient bank management or have been used in other studies such as Altman (1968), Edminster (1972), Joy and Tollefson (1975), Horvitz (1975), Sinkey (1975, 1977, 1980), Juncker (1980), (NDIC, 1992) and Jimoh (1993).

Because of the high multicollinearity among these variables, a factor analysis was used to collapse the variables into fewer number of variables. The factor analysis reduced the number of variables to 9 principal factors based on Kaiser's criterion. These factors were found to be related to:

i. Liquidity ratio (LQDEPO),
ii. asset quality (BDDASS),
iii. quality of management[5] (BDDLON),
iv. capital adequacy (KADLON),
v. return on capital (ROC)
vi. return on asset (ROA)
vii. operating efficiency (expense-earnings ratio or /EXPEARN),
viii. ownership category
ix. loan/asset ratio (LONASS).

The ownership category was simplified to a dummy variable which takes the value of 1 for Federal government owned banks, takes the value of O for private owned banks and state government owned banks. It is remarkable to note that the discriminating variables identified by the factor analysis is broadly consistent with CAMEL[6] rating and the views expressed in NDIC (1991) that "ownership structure and type of banks are important factors in explaining the financial condition of a bank" (p. 20). It is hypothesized that the condition or status of bank such as problem or non-problem bank, failed or healthy bank, which may be induced by dishonest bank managers, embezzlement or manipulations, frauds and forgeries, management incompletence, increased economic uncertainty, poor internal control system and weak loan recovery can easily be detected in bank balance-sheets and accounting ratios.

Thus the basic model in the analysis is of the form:

$$\text{Dummy 1} = bo + b1*Owner + b2*BDDLON + b3*LONASS + b4*BDDASS + b5*ROA + b6*ROC + b7*KADLON + b8*LQDEPO + b9*EXPEARN + u \quad \ldots\ldots 4$$

$b1 > O$ or $< O$, $b2, b3, b4, b9 > 0$; $b5, b6, b7, b8 < 0$

Some of these factors require emphasizing. Adequate capital is very important to any bank. It gives recognition to the role that capital plays as the foundation supporting business risk within the bank. The greater the risks faced by a bank, the greater is the need for a strong capital base. The asset quality based on the overall quality of the assets held by a bank relies heavily upon the classification of the bank's credits into loss, doubtful, and substandard categories. These categorizations are based on the likelihood of the bank's actually absorbing a loss on a credit.

The quality of management includes also the board of directors. It involves management's technical competence, leadership and administrative ability. This is

5 A more rigorous measure of quality of management in banking that incorporates both academic qualification and experience (number of years effectively spent on the job i.e banking related job) has been developed in Nyong (1989a, 1989b, 1989c)

6 CAMEL is an acronyn for Capital Adequacy, Asset Quality, Management-administrative quality, Earning Power and liquidity.

proxied by ratio of non- performing loans to total loans. The operating efficiency is the bottom line measure of bank's financial strength and capacity in the industry. Liquidity indicates the ability of a bank to manage its liability in such a way as to ensure that it meets the demand of its depositors and borrowers without undue strain (see Nyong, 1989c). The critical feature of our early warning model is that it permits simultaneous consideration of several factors that reflect the status of problem banks.

The data were collected from the Annual Reports of a cross section of 60 banks operating in the country in 1990/91. The banks were categorized into two groups: group 1 and group 0. Group 1 includes the 8 banks officially identified by the supervisory and regulatory authorities as insolvent and the two merchant banks whose license have recently been revoked (i.e in 1994). Thus, our group 1 is a sample of 10 banks. The remaining 50 banks constitute group 0. We first started from the general by fitting a quadratic multiple discriminant function (QMDF) to the data to determine whether the two groups do not have identical variance-covariance matrices. We find that, contrary to expectations the groups have identical variance-covariance matrices. This suggests the use of linear multiple discriminant model. We then fitted a linear discriminant function to the data using the nine explanatory variables.

IV Empirical Results and Analysis

A comparison of the total classificatory efficiency of the two models based on the confusion matrices in Tables 1A and 1B indicates that whereas quadratic discriminant model was 93 percent efficient, linear discriminant model was 95 percent efficient, indicating a 2 percent point superiority in efficiency classification.

Table 1A Classificatory Efficiency: Quadratic Multiple Discriminant Function

Group		0	1
	0	46	0
	1	4	10
Total		50	10
Number correct		46	10
Total Efficiency[7]:		0.93	

7 Computed from (46 + 10)/60.

Table 1B Classificatory Efficiency: Linear Multiple Discriminant Function

Group		0	1
	0	49	2
	1	1	8
Total		50	10
Number correct		49	8
Total Efficiency:		0.95	

Because of the superiority of the linear discriminant model, we report only the parameter estimates of the linear discriminant model which are shown in Table 2. We [illegible] the logit model using maximum likelihood estimation method to complement the results obtained from the discriminant analysis. The results of the logit model are presented in Table 3. An examination of the results of the fitted linear multiple discriminant function in Table 2 shows that they were respectable in terms of the a priori expectations of the signs of the parameter estimates.

Table 2: Parameter Estimates of the Linear Multiple Discriminant Analysis.

Group	0		1		Group 0	Means	Differ
Constant	3.207		–0 3130				
Ownership	0 399	(0.223)	–1.244	(0.697)	0 060	–0.50	0.56
BDDLON	6.752	(–0 560)	6 063	(–0 503)	0 240	0 39	–0.08
LONASS	9.783	(–0 342)	8 570	(–0.300)	0 275	0 31	–0 04
BDDASS	–41 887	(1 173)	–19 693	(–0 533)	0 053	0 08	–0 03
ROA	–5.469	(–0 210)	–13 427	(–0 842)	0 041	0 001	0 04
ROC	1 723	(1 489)	–0 975	(0.048)	0 560	–0.30	0.86
LADLON	0 0393	(0 012)	0 151	(0.885)	0 378	0 08	0 30
LODEPO	3.608	(1 040)	1 590	(0.453)	0.885	0 60	0.29
EXPEARN	–0 682	(0.729)	1 549	(–1 656)	–0.189	0 88	–1 07

Notes: The values in brackets are the associated relative discriminatory power of the variable. The group means are the means of each explanatory variable for group 0 an 1. Differ is the difference between group means for each explanatory variable.

We find that the relative discriminatory power of the variables (computed as bj(Xj0 - Xj1) where the bjs are the parameter estimates of the discriminatory variables and Xjk is the mean of the jth variable) for insolvent banks in order of importance of the discriminatory factors are: EXPEARN, ROC, OWNER, BDDASS, BDDLON, LQDEPO, LONASS, KADLON in that order. For solvent banks the order of importance of the discriminating factors are: ROC, BDDASS, LQDEPO, EXPEARN, BDDLON, LONASS, OWNER, ROA, and KADLON in that order. The model was again applied to enlarged sample of seventy banks, ten more banks than the original sample. The results show similar good performance. All the ten additional banks were correctly classified by the discriminant function indicating a high predictive power.

Table 3 presents the parameter estimates of the logit model together with the associated t-values and p-values. Convergence using maximum likelihood estimation procedure was achieved in ten iterations.[8] From the Table 3 it is clear that the results are respectable. The explanatory power of the model given by the adjusted R^2 is high, about 79.5%. This shows that about 79.5 percent of the total variation in a bank's status is accounted for by changes in the nine discriminatory factors. The standard error of the regression (SER) is low at 0.0453.

Table 3: Regression Results (Logit Model)
Estimated Coefficients t-values p-values

Variable		Estimated Coefficients	t-values	p-values
Constant		0.4045	27.89	0.00
Owner		0.0656	6.87	0.00
BDDLON		0.1297	3.06	0.004
LONASS		0.1846	4.65	0.000
BDDASS		0.8620	3.50	0.001
ROA		-0.9506	-4.56	0.000
ROC		-0.2366	-18.04	0.000
KADLON		0..0245	1.45	0.154
LQDEPO		0.2146	-17.12	0.000
EXPEARN		O.5886	97.58	0.000
Adjusted R^2	79.5%	SER = 0.0453	F(10,49) = 1103.5	

8 In the estimation of parameters using logit model, an iterative procedure such as Cochrane-Orcutt or maximum likelihood is to be preferred. Use of ordinary least squares may yield results for probabilities far in excess of unity (or negative) which is meaningless (see Intriligator, 1978).

Table 4: Probability of Failure and Severity of Financial Distress

Bank	Class	Predicted Probability of Failure	Severity of Financial Distress (ranking)
001	0	0.59520	12
002	0	0.54820	16
003	0	0.53023	19
004	0	0.22961	57
005	1	0.97890	4
006	1	0.98619	1
007	0	0.49544	27
008	0	0.47594	31
009	1	0.97550	6
010	1	0.97207	8
011	0	0.39423	53
012	0	0.52909	20
013	0	0.43608	43
014	1	0.98452	2
015	0	0.53593	18
016	0	0.47778	30
017	0	0.51761	22
018	0	0.56751	14
019	0	0.57953	13
020	1	0.97141	9
021	1	0.97838	5
022	0	0.62426	11
023	0	0.46190	33
024	0	0.45570	36
025	0	0.49241	28
026	1	0.96800	10
027	1	0.98155	3
028	0	0.44603	40
029	0	0.45990	34
030	0	0.40175	52
031	0	0.40865	50
032	1	0.97418	7
033	0	0.36336	55
034	0	0.20234	59

035	0	0.41884	46
036	0	0.21688	58
037	0	0.26877	56
038	0	0.43180	44
039	0	0.41859	47
040	0	0.50425	25
041	0	0.06004	60
042	0	0.41623	48
043	0	0.46732	32
044	[illegible]	0.56298	15
045	[illegible]	0.52678	21
046	[illegible]	0.54143	17
047	[illegible]	0.36183	54
048	[illegible]	0.40688	51
049	[illegible]	0.45676	37
050	0	0.50819	26
051	[illegible]	0.49311	29
052	0	0.44296	41
053	0	0.42476	45
054	0	0.51136	23
055	0	0.43923	42
056	0	0.44916	39
057	0	0.45832	38
058	0	0.50886	24
059	0	0.45937	35
060	0	0.41275	49

From the logit model we find that seven of the discriminatory factors bear signs which are consistent with a priori theoretical expectations. Moreover, they are statistically significant at better than 0.1 percent level. Of the two remaining variables, KADLON has the wrong sign but it is not statistically significant even at the 10 per cent level. The other variable, liquidity related factor (LQDEPO) bears the wrong sign. It is, however, statistically significant.

To assess the predictive power of the model we apply the logit model to an enlarged sample of seventy banks, ten more banks classified by the supervisory authorities as healthy. In other words, we used the parameter estimates for the sixty banks to classify the ten additional banks. From the post sample results we find that the probability of failure of the ten additional banks are very low as to be expected. Thus, our model shows a high predictive power.

To impart greater confidence to our results we decided to test for the stability of our parameter estimates. We used Chow's test as reported in Doherty (1992). We ran the regression for the seventy banks and obtained the residual sum of squares of RSS2 = 4.6614. We compared this with the residual sum of squares obtained in the regression of the original sixty banks of RSS1 = 4.139. The computed F - ratio yields: F - ratio = {(4.6614 - 4.139)/10}/{4.139/50) = 0.05224/0.08278 = 0.631. The results show stability in the weights associated with the discriminatory factors. Given the high predictive power of the model as well as the stability in the regression parameters we next examined the probability of bank failure for the sample of sixty banks.

The probability of bank failure and severity of financial distress afflicting the banks are presented in Table 4. From the results in Table 4 it is clear that banks ranked 1 to 10 are technically insolvent, whereas the remaining fifty banks indicated varying degrees of soundness with the bank having code number 041 being the healthiest (most sound) of all the banks. The severity of their distress as indicated in column 3 shows that fifteen banks in our sample are average banks but need closer attention to prevent their "crossing the bar" into insolvency. These banks include those with code numbers 001, 002, 003, 012, 015, 017, 018, 019, 022, 040, 044, 045, 046, 050, 054, and 058.

From the results, four important findings emerged. First, bank regulators and supervisors in Nigeria should give a weight of 0.0656 to Ownership, 0.1297 to risk (BDDLON), 0.1846 to LONASS (asset quality), 0.862 to BDDASS (quality of management), - 0.9589 to return on assets (ROA), -0.2366 to return on capital (ROC), -0.2146 to Liquidity (LQDEPO), -0.0245 to capital adequacy (KADLON) and 0.5886 to operating efficiency (EXPEARN). The sum of these weighted variables should be used to compute a banks's probability of failure. Second, the model was able to predict the failure of the two merchant banks (Kapital Merchant Bank and Financial Merchant Bank) 3 years before they failed. Third, the logit model and the linear multiple discriminant analysis provided high predictive powers in discriminating between problem and non-problem banks (insolvent and solvent banks) although they give different weights to the discriminating factors. A possible reason is the fact that logit model presents one set of regression results for the entire sample while discriminant model presents two sets of results, one for each group (i.e group 0 and group 1). Another reason is that the two models are based on different assumptions.

Fourth, our results not only identified all the variables indicated in Jimoh's study, it also goes further to identify other important discriminating variables which should enter into the supervisory authorities' information set.[9]

Overall, our results provide a more objective separation of problem and non-problem banks than any ad-hoc or heuristic method. The results show that an early warning model, predicated on a comprehensive analysis of bank financial operations coupled with an adoption of factor analysis-cum-logit model, could serve as a powerful discriminating device for effective supervision to maintain safety and soundness in the banking system.

9 We may say that our model encompasses Jimoh's model.

V Concluding Remarks

Given some of the difficulties encountered with prediction models and the limited studies in failure prediction in banking this study undertook to re-examine the failure prediction question. The objectives have been to address some of the methodological and interpretational problems associated with prediction models. A host of critical factors that should enter the supervisory and regulatory authorities information set in the Nigerian banking environment were identified. The framework provided some improved methodology for classifying banks into problem and non-problem banks.

The three techniques used were: (i) factor analysis to collapse the twenty variables into nine variables; (ii) a linear multiple discriminant analysis, and (iii) the logit model to develop early warning models for identifying insolvent (or problem) banks and solvent (or non-problem) banks. Given the policy orientation of the study the models were subjected to rigorous testing that went beyond the conventional adjusted R^2 and t-tests or standard error tests. We subjected the models to inter-temporal validation to assess its predictive ability. This involved applying the results to out-of sample banks, called the hold-out sample, consisting of ten banks. The forecasting performance of the models was impressive. Additionally, we tested for the stability of the regression parameters of the logit model as means of evaluating the degree of confidence we may place in the results for future identification of problem and non-problem banks. Our Chow test indicated that the hypothesis of stability in the regression parameters can not be rejected at the conventional level (5%).

Our results suggest that bank regulators and supervisors in Nigeria should give a weight of 0.0656 to Ownership, 0.1297 to risk (BDDLON), 0.1846 to LONASS (asset quality), 0.862 to BDDASS (quality of management), -0.9589 to return on assets (ROA), - 0.2366 to return on capital (ROC), -0.2146 to Liquidity (LQDEPO), -0.245 to capital adequacy (KADLON) and 0.5886 to operating efficiency (EXPEARN). The sum of these weighted variables should be used to compute a banks's probability of failure.

Overall, our results show that an early warning model, predicated on a comprehensive analysis of a bank operations coupled with an adoption of factor analysis-cum-logit model, could serve as a powerful discriminating device for effective supervision to maintain a safe and sound banking system.

The proposed early warning model is not designed to be a replacement of the existing bank examination practices and personnel. It is also not intended to be a substitute for the human skills and judgement in dealing with problems of bank supervision. The realistic but limited objective of our model is to act as an aid in scheduling bank examination by the supervisory and regulatory authorities so that potential insolvent (problem) banks would be examined more frequently and more intensely than solvent (non-problem) banks.

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