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On Early Warning Models For The Identification of Problem Banks In Nigeria

By

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This paper proposes alternative early warning models which could be helpful in identifying problem banks in Nigeria. The models rely on the logit-analytic technique and the use of financial ratios derived from the monthly returns the licensed banks render to both the Central Bank of Nigeria (CBN) and Nigeria Deposit Insurance Corporation (NDIC). The two separate models, each developed for commercial and merchant bank, are more efficient in that they drastically reduced the mis-classification errors inherent in other failure prediction models developed in the past. To illustrate the applications of the models for policy, an appraisal of the financial condition of all the reporting commercial and merchant banks in the third quarter of 1995 was performed. Apart from identifying all banks that were already known to be distressed by the regulatory authorities, the results also revealed that some banks require urgent attention in order to prevent them from becoming problem banks.

I. INTRODUCTION

The increased risks assumed by the commercial and merchant banks, poor quality of loans and advances, mis-management, fraud and local and national economic trends, amongst other things, have led to an increase in the number of problem banks (weak or failed) in Nigeria since the early 1990's. During the 1970s and 1980s, when banks were relatively smaller in number, only very few banks were distressed. While the number of distressed banks increased to approximately 29 in 1993, the regulatory authorities reported over 30 distressed banks in 1994. Thus, the early 1990s can be regarded as a period of upheaval for the banking industry in Nigeria. Many causes of the problem of distress have been advanced in the CBN-NDIC (1995) study of distress in the Nigeria's financial system. These include operational ineffectiveness, political instability and overall macroeconomic instability. The willingness of banks to exceed the "normal" limits of risks, taken for the sake of enhanced profits, has contributed to a high degree of risk exposure which, in retrospect, proved to be unwise. Clearly, banks must be prepared to take risks if they are to serve the financial needs of the economy, but these risks must be tempered by the public's interest for a sound and stable banking system, since the potential costs of widespread instability in banking extend far beyond the banks directly concerned.

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The recent increase in the rate of distress of banks in Nigeria has refocused attention on efforts to identify problem banks and to predict failures with sufficient lead time for regulators and management to institute remedial action to prevent them from going into insolvency. Since September, 1992, the CBN has been using the performance ratings of banks as off-sight early warning system to assist in the identification of likely unhealthy banks. These ratings are based on a bank satisfying the prescribed requirements on six performance criteria variables, namely, capital adequacy ratio; loans-to-deposit ratio; liquidity ratio; liquid asset structure ratio; minimum paid-up capital and sectoral credit allocation, which is a residual criterion.

A number of factors make an effective statistical early warning system desirable, especially for aiding regulatory authorities respond efficiently to initial signs of distress. First, significant changes in a bank's management policies and financial conditions can occur between examinations. Second, an on-site examination is a lengthy and expensive process and not always the most cost-effective method of tracking small, but important changes in a bank's financial condition. Third, although examiners generally are sensitive to developing trends that indicate potential future management or financial problems and normally comment on such matters in their reports, they must necessarily emphasize their findings concerning the actual condition of the bank rather than the estimated impact of potential problem. Fourth, an examiner's findings are part of the official record and could provide the basis for the enforcement or other supervisory actions. In contract, statistical early warning measures can be informal, affording the opportunity for experiments with techniques to uncover financial weakness at its earliest stages. Moreover, an efficient early warning system can be a useful tool of analysis in the appraisal of a bank's financial condition.

The primary objective of this paper is to develop and test early warning models using the logit-analytic approach, that can assist both the CBN and NDIC in identifying potential problem banks based on the statutory monthly returns the banks render to them. As a secondary objective, the paper assesses the relative performance of the models with that of Nyong (1994) and Jimoh (1993) using the variant of the weighted efficiency measure of performance. The rest of the paper is structured into six sections. Section two discusses the methodological and conceptual framework of the logit model. The estimation of the model using 1993 data is carried out in section three. The hypothesis of stability of the model parameters is tested in section four. Section five evaluates the models developed in the paper and the competing alternatives. An appraisal of both the reporting commercial and merchant banks' financial conditions in 1995 is conducted in section six on the basis of our models. Finally, section seven summarizes and concludes the paper.

II. THE EARLY WARNING MODEL

The achievement of an appropriate balance between risk taking and the preservation of comfortable margins of safety with respect to earnings, capital and liquidity is a goal that bankers and regulatory authorities have a vital stake in pursuing. From this point of view, it is important to recognize what bank regulators have always known: that on-site examinations provide accurate insight into developing as well as actual financial problems at banks. The experience of bank regulators and the results of financial research indicate that financial deterioration typically does not occur overnight. A decline in earnings, capital, liquidity, asset quality and inadequate management (otherwise known as CAMEL components), as reflected in poor internal control and auditing procedures, usually develop over a period of time. Regular scheduled bank examinations would uncover these adverse developments.

The agencies that supervise and insure banks depend, in part on the results of on-site bank examinations to provide information about the condition of individual deposit institutions and the banking system as a whole. The CBN and NDIC try to examine the licensed banks, sometimes jointly, about once every two years, but more or less frequently, depending upon their condition. On-site examinations are expensive and scheduling is often difficult. If healthy (or sound) banks are examined too frequently, valuable resources are wasted. If problem banks are not examined often enough, the possibility of failure may increase. In particular, bank regulators need a method of identifying banks that are unsound or that show signs of weakness before examination teams are sent into the field.

There are varieties of multivariate statistical techniques that can be used to predict a binary dependent variable - a problem (vulnerable, weak or distress) or non-problem bank from a set of discriminatory independent variables. Multiple regression analysis and discriminant analysis are two related techniques in this regard. However, as noted by Altman et al (1991) and Eisenbeis (1977), these techniques pose difficulties when the dependent variable follows a binary choice model. These difficulties include:

(i) when the dependent variable can have only a binary choice, the assumptions necessary for hypothesis testing in regression analysis are necessarily violated. For example it is unreasonable to assume that the distribution of error terms is normal.

(ii) predicted values cannot be interpreted as probabilities, since they are not constrained to fall in the interval between 0 and 1.

(iii) linear discriminant analysis does allow direct prediction of group membership, but assumptions of multivariate normality of the independent variables as well as equal variance-covariance matrices in the two groups, are required for the prediction rule to be optimal.

One maximum likelihood estimation technique (MLE) that is appropriate for binary choice problems, such as classifying banks into problem and non-problem groups, is the logit model. This model has been used extensively, for example, by Pastena and Ruland (1986), Odedokun (1995) and West (1985).

One objective of a logit model is to determine the conditional probability P_i, that the i^{th} bank will fail, given a set of k derived balance sheet ratios: $X_{i1}, X_{i2}, \dots, X_{ik}$ for that bank. The model could be expressed thus: let $Y_1, Y_2, \dots, Y_n$ be independent binary response variables whose probability functions $P_1, P_2, \dots, P_n$ satisfy the equation:

$$Log\left(\frac{P_i}{1-P_i}\right) = a_0 + \sum_{j=1}^{k} a_j X_{ij} \qquad (1)$$

where $i = 1,2, ...n$, and P_i is given by

$$P_i = \frac{1}{1 + \exp(-\beta_i)} \qquad (2)$$

with β_i defined as,

$$\beta_i = a_0 + \sum_{j=1}^{k} a_j X_{ij} \qquad (3)$$

The coefficient a_j ($j=1,2..,n$) measures the effects on the odds of failure of a unit change in the corresponding independent variable. Thus the logit model (2) tends to be more preferred to a set of competing alternatives by researchers, especially as a unique maximum always exists for the logit model, and almost any non-linear estimation routine will find the estimated parameters of the model. Specially, the parameters of equation (2) are estimated by maximizing over the a_j's the log-likelihood function:

$$L = \sum_{i=1}^{n} Y_i \log(P_i) + \sum_{i=1}^{n} (1-Y_i)\log(1-P_i) \qquad (4)$$

Espahbodi (1991) developed and tested logit models that could aid regulatory agencies, as well as bank examiners in identifying potential failures in the United States' banking industry. Recent studies in Nigeria, particularly by Jimoh (1993) and Nyong (1994), made use of the logit model to investigate the predictability of bank failure using publicly available data for commercial and merchant banks. This study differs from that of Jimoh (1993) and Nyong (1994) in that instead of using publicly available data (which in most cases are only available on annual basis) data from regulatory authorities (obtained from routine monthly returns the banks render to them) are used for estimating the parameters of the logit model. Furthermore, Nyong (1994) combined commercial and merchant banks data in the estimation of the model parameters. In view of the banks' operational uniqueness, such as, retail and wholesale banking and the fact that merchant banks are prohibited from carrying out certain functions performed by commercial banks, this study develops separate models for the two types of banks using 1993 data to capture these varying operational characteristics.

A bank may be classified as weak or sound based on its conditional probability, P_i of failure. A bank is classified as a problem bank if the conditional probability of failure for that bank is greater than an optimal cut-off point, CCP. Following past studies, this study chooses the usual cut off point:

$$CCP = 1/2 \qquad (5)$$

to report both the estimation and validation results. In general, for purposes of utilizing the models, individual decision makers should select a cut-off point that is consistent with their decision. However, it is important to note that the models developed are not intended to be used in classifying banks into two categories (banks which are expected to fail and which are not). Rather, the models are intended to aid the regulatory authorities in identifying potential problem banks. That is, the models may be used to assign a probability of failure to each bank and to rank banks in terms of their probabilities of failure. Banks with the highest probabilities of failure can then be accorded immediate attention or supervision by both the CBN and NDIC.

III. LOGIT REGRESSION APPROACH

3.1. Discriminatory Variables Used in the Study

The variables used in the study are derived from the financial statements in the form of monthly bank returns the licensed banks render to both CBN and NDIC. A list of these variables, their definitions and their expected signs are reported in Table 1. These variables are expressed in ratio form (percentages). Many of these variables are the same as those employed in various monitoring systems used by bank regulators or in studies elsewhere to predict problem and failed banks [see in particular Jimoh (1993), Nyong (1994) and Sinkey (1979)]. The variables in Table 1, reflect various banking characteristics. The first two variables CAR and CLR are capital adequacy measures. The variables LRWA, LQR, LCR, LTA and BDL are measures of the quality and risk of a bank's portfolio. Variables LAS, LR and LDR reflect in various ways, the liquidity position of the bank and its ability to respond to liquidity pressures. Variables SFR and TKA reflect the source of a bank's funds, while variable LSL measures the dependence of a given bank on a particular loan category. Lastly, variables ROA and ROC are measures of bank profitability. However, in the computation of ROA and ROC, retained profit (or loss) is used as proxy for earnings since the earning figures for 1993 to 1995 for most of the sampled banks were not readily available.

The set of factors derived by West (1985) from his analysis incorporates a larger number of observed banking variables very similar to the ones in Table 1. Of particular note is the close similarity between the factors produced by West's analysis and the CAMEL rating created by on-site examination in the United States. Considering the close similarity to the factor analytic approach, West suggested that the factors produced can be employed as inputs into the logit model to predict which banks might be showing signs of weakness and thus require more frequent attention.

3.2 Construction of the Dummy Dependent Vector

In addition to the a prior classification by the regulatory authorities of problem and non-problem banks in December, 1993 and 1994, another quasi-independent source using the performance ratings, was also used to support the a prior classifications. For example, a bank is classified as a 6-rated bank if it satisfies the prescribed requirements on the six performance criteria variables. In particular, banks with high performance criteria ratings of 6, 5 or 4 were considered sound and those with ratings of 3, 2, 1, or 0 were adjudged to be problem banks. Banks with a performance rating of 3 are not believed to be in imminent danger of failure, but do demonstrated a degree of weakness sufficient to mark them as 'problem'. This is important in a monitoring or early warning sense, because these are banks considered most likely to become 2, 1, or zero rated. Regarding 3 rated banks (i.e. banks satisfying only three of the six performance criteria) as problem, also has the advantage of providing a more stringent test of the model.

Table1: Independent variables that have Impact on Bank Condition.

j	Variable code	Definition of Variable	Measure of	Expected Sign \1
1.	CAR	Total Qualified Capital over Risk Weighted Assets	Capital Adequacy	-
2.	CLR	Equity Capital over Total Assets	Capital Adequacy	-
3.	LRWA	Risk Weighted Assets over Total Assets	Asset Quality	+
4.	LQR	Provision for Bad and Doubtful debt/Total Assets	Asset Quality	+
5.	LCR	Provision for bad and Doubtful Debt/Equity Capital	Asset Quality	+
6.	LTA	Total Loans/Total Assets	Assets Quality	+
7.	BDL	Provision for Bad and Doubtful debts/Total Loans	Asset Quality	+
8.	LAS	Treasury Bills & Certificates over Total Current Liabilities	Liquidity	-
9.	LR	Total Specified Liquid Assets over Total Current Liabilities	Liquidity	-

10.	LDR	Total Loans/Total Current Liabilities	Liquidity	+
11.	SFR	CBN Overdrafts/Equity Capital	Source of Funds	+
12.	TKA	Takings/Total deposits and Takings	Source of Funds	+
13.	LSL	Loans & Advances to States and Local Governments/Total Loans	Loan Quality	+
14.	ROA	Retained Prófit (or Loss) Over Total Assets	Profitability	-
15.	ROC	Retained Profit (or Loss) Over Equity Capital	Profitability	-

\1: A positive sign means that an increase in the given Variable increases the risk of failure, and a negative sign implies the opposite.

A number of discriminatory variables are selected for testing (see Table 2a). These are variables that past experience indicated were closely associated with financial strength or weakness. The objective is to find the smallest set of variables which could be used to detect early signs of financial deterioration. For each variable employed, its mean, lambda (λ) and standard deviation, σ are computed from the sample. The values of the variables are then compared with the means for all sampled banks in the study, and the differences are divided by the respective standard deviations of each of the variables. The resulting standardized deviations (or z-scores) are added algebraically to form an overall bank score, SF_i in which the component variables are weighted equally. That is:

$$SF_i = \sum_{j=1}^{k} C_j \left(\frac{X_{ij} - \lambda_j}{\sigma j} \right), \quad i = 1, 2 \ldots\ldots n \qquad (6)$$

where C_j takes the value of 1 or -1, as shown in Table 2a. A score is then obtained for each of the sample banks from the financial data for December, 1993 and December, 1994 for both commercial and merchant banks.

It is expected that the higher the overall bank score, the more vulnerable the bank would be to adverse economic or financial developments, while the lower the overall score, the greater its resistibility. As Korobow et al (1976) observed, this scoring approach provides a means of comparing and tracking bank financial performance over varying periods of time. However, one of the main problems in applying these procedures to the supervisory process is the need for a link between the overall bank scores and the conditional probabilities P_i given in equation (2). In other words, it is important to know the significance of a high overall score and the degree of vulnerability indicated by progressively higher standings in the list of these scores.

Following Korobow et al (1976), we construct an observed probability YPD_i, for each bank in the sample in order to obtain the dummy dependent variable vector YPD. The observed probabilities are obtained as a binary choice variable taking the value of 1 for vulnerability (problem bank), and 0 for resistibility (non-problem bank) as follows:

$$YPD_i = \begin{cases} & \text{if } SF_i \geq 0 \\ 0 & \text{otherwise} \end{cases} \qquad (7)$$

where $SF_i = 0$, is consistent with the cut-off point, CCP defined in equation (5). These YPD_i values are then compared with the regulatory authorities' a priori classification of sound and distressed banks in both 1993 and 1994. Table 2b presents the cross-tabulation of the scoring function and a priori classification of banks by the regulatory authorities as at December, 1993.

It is of interest to observe that apart from identifying the weak commercial and merchant banks as perceived by the regulatory authorities, the scoring function has also identified 7 commercial and 3 merchant banks that were marginally weak, but were hitherto given the bill of health by the regulatory agencies. Thus, the dependent variable vector YPD for the commercial banks in 1993 consisted of 24 weak banks, with values of 1, and 36 non-problem banks with values of zero. For merchant banks, the model used 15 distressed banks and 35 healthy banks to obtain the YPD vector for the non-linear estimation of the logit model.

Table 2 (a): Construction of the Scoring Function, SF Defined in Equation (6).

j	X_{ij} \1	Definition of Variable	Measure of	C_j
1.	CAR	Total Qualified Capital over Risk Weighted Assets	Capital Adequacy	-1
2.	LRWA	Risk Weighted Assets over Total Assets	Asset Quality	+1
3.	LCR	Provision for bad and Doubtful Doubtful Debt/Equity Capital	Asset Quality	+1
4.	LR	Total Specified Liquid Assest over Total Current Liabilities	Liquidity	-1

5.	LDR	Total Loans/Total Current Liabilities	Liquidity	+1
6.	SFR	CBN Overdrafts/Equity Capital	Source of Funds	+1
7.	LSL	Loans & Advances to States and Local Government/Total Loans	Loan Quality	+1
8.	ROA	Retained Profit (or Loss)/Total Assets	Profitability	-1

\1: These variables have been standardized through the transformation $z = (X.j - \lambda)/\sigma$, where λ and σ are the mean and standard deviation of the independent variable X.j, respectively.

Table 2(b): A Priori identification of Problem Banks and the Scoring Function SF, in December, 1993

A Priori	Commercial Banks			Merchant Banks		
	SF			SF		
	Weak	Sound	Total	Weak	Sound	Total
Weak	17	0	17	12	0	12
Sound	7	36	43	3	35	38
Total	24	36	60	15	35	50

3.3 Model Estimation

The predicted probabilities of failure (or weakness) are obtained by using the non-linear regression approach based on the model defined in equations (2) and (3), respectively. Our a priori expectation on the parameters of the model could easily be deduced from equations (2) and (3) that, as β_i moves towards infinity, the chances of bank i failing increases. Therefore, for β_i to attain its maximum value, the logit regression constants a_j ($j = 1, 2, \ldots, k$), in equation (3) are expected to behave as in Table 1. Equation (2) is a point estimate of the probability that bank i will fail, given the set of financial ratios for the bank. This probability estimate will always be between zero and one, regardless of the value of the optimum linear combination of the independent variables given in equation (3).

The purpose of the logit regression is to estimate the relationship between the bank financial variables (X_{ij}) and the observed probabilities YPD_i to obtain the predicted probabilities P_i. This relationship is assumed to be a continuous function, approaching zero for large negative scores (SF_i) and approaching one for large positive scores. The non-linear maximum likelihood estimation technique in MICROFIT software was employed to estimate the parameters (a_j, $j = 0, 1, 2, ...k$) of the logit model defined in equation (2); with the observed (constructed) probabilities YPD_i as the dummy dependent variable.

The parameter estimates of the final logit models for commercial and merchant banks as well as the summary statistics comprising: the analog R^2-adjusted, the maximum of the log likelihood function, the residual sum of squares and the F-statistic are presented in Table 3. From the summary statistics presented, it is clear that the overall results appeared to be satisfactory at the1 per cent level; with the discriminatory variables explaining over 77 per cent of the variation in the dummy dependent vector, YPD.

From the logit model; it is seen that five of the discriminatory variables have correct signs consistent with a priori theoretical expectation in the case of both commercial and merchant banks. As shown in this table, five variables are important in distinguishing weak from sound commercial banks. These variables are CAR, LRWA, LAS, LSL and ROA. The capital adequacy ratio (CAR) is characterized as capital adequacy; risk weighted assets-to-total assets ratio (LRWA) as asset quality; the liquid assest structure ratio (LAS) as liquidity; loan and advances to state and local governments-to-total loans and advances ratio (LSL) as loan category; and retained profit (loss)-to-total assets ratio (ROA) as profitability. One interesting result is that four explanatory variables (discriminatory factors) in the analysis bear close resemblance to the CAMEL components: capital adequacy, asset quality, earnings and liquidity, while the loan category factor indicates that increased loans to states and local governments have contributed to the distress condition of commercial banks.

Like the commercial banks, five variables are also important in distinguishing weak merchant banks from sound ones. The variables are CAR, LCR, LTA, LDR and TKA. The capital adequacy ration (CAR) is an indicator of capital adequacy; both loans-to-total assets ratio (LTA) and provision for bad and doubtful debt-to-equity capital ratio (LCR) asset quality; loans-to-deposit ratio (LDR) liquidity; and takings-to-total deposits and takings ratio (TKA) is source of funds. It is noted that while four of the CAMEL components were significant variables in the case of commercial banks, only capital adequacy, asset quality and liquidity components of CAMEL were significant variables explaining distress in merchant banks. This conclusion suggests that only liquidity, capital adequacy and asset quality components of CAMEL seem to be important determinants of merchant banks financial conditions in Nigeria. One result from the analysis suggests that the merchant banks' sources of funds, characterized by takings (money at call takings, takings from discount houses and inter-bank takings)-to-total deposits and takings ratio (TKA), is a very important factor in determining the financial condition of a merchant bank. Thus, increased takings will increase the risk of vulnerability (or distress) of a merchant bank. It is noted also that other than the capital adequacy ratio, the commercial and merchant banks have different explanatory factors of distress unique to them.

Table 3: The Logit Regression Results of the Model defined in Equation (2) using the 1993 data \1.

	Commercial Bank			Merchant Bank		
Variable	**a-value**	**t-value**	**p-value**	**a-value**	**t-value**	**p-value**
Constant	-27.2230	-2.977	0.004	-11.0027	-2.688	0.010
CAR	-0.4721	-2.811	0.007	-0.1381	-1.962	0.056
LRWA	0.5439	3.135	0.003	-	-	-
LCR	-	-	-	0.0023	1.239	0.222
LTA	-	-	-	0.1346	2.588	0.013
LAS	-0.1590	-1.892	0.064	-	-	-
LDR	-	-	-	0:0547	2.581	0.013
TKA	-	-	-	0.1323	2.299	0.026
LSL	2.8029	2.337	0.023	-	-	
ROA	-0.5848	-1.720	0.091	-	-	-
Analog R^2-adjusted			79.5%			77.0%
Maximum of Log-Likelihood			7.824			6.6280
Residual Sum of Squares			2.7065			2.2457
F - Statistics F(5,54):			46.661	F(5,44):		33.8340

\1 The F-Statistics are significant at the 1 per cent level. The t-values reported are the asymptotic t-values, while the p-values give the approximate significance level, α. For example, the constant parameter is significant at the 1 per cent level for both commercial and merchant bank's logit model. Also, the analog R^2 adjusted proposed (by Pindyck and Rubinfeld, 1981: *Econometric models and economic forecasts,* New York, p 312) as a measure of goodness-of-fit for logit models suggests that the discriminatory variables have very high explanatory power. This measure is calculated in the same manner as the classic R^2-adjusted measure for the linear regression model.

Table 4: Test of Parameter Stability of the Logit Models (as in Equation 10).

	Logit Models	
Statistics \1	**Commercial**	**Merchant**
SSR_g	5.6847	2.8285
SSR_{g-1}	2.7065	2.2457
m_g	48	21
m_{g-1}	60	50
k	5	5
F_g	1.2609	0.5561
$F_{tabulated}$ $(m_g, m_{g-1}\text{-}k)$:	1.5500	1.8700
Null Hypothesis: H_0:	Accepted	Accepted
Are parameters stable ?	Yes	Yes

\1 See section 4 for the definition of the statistics. The test is conducted at the 5 per cent level.

IV. TEST OF COEFFICIENT STABILITY

To test the stability of the regression coefficient aj's defined in equation (2), Chow predictive test of coefficient stability (which presumes knowledge of the point of suspected instability), as proposed by Harvey (1976) was conducted. This test requires that at least two mutually exclusive time periods be specified. The fit of the model estimated in one time period is then compared to the fit over the entire time period. The model can be rewritten allowing for parameters to vary over time. Incorporating the time constraint. equation (2) becomes:

$$P_{i,t} = \frac{1}{1 + \exp(-\beta_{i,t})} \qquad (8)$$

where

$$\beta_{i,t} = a_{0,t} + \sum_{j=1}^{k} a_{j,t} X_{ij,}t \qquad (9)$$

and $P_{i,t}$, $a_{j,t}$ and $X_{ij,t}$, are as defined in equation (3) and t denotes dynamic time element.

Chow (1960) predictive test of the coefficient stability:

$$H_0 : a_{j,t} = a_{j,s} \text{ VS } H_a : a_{j,t} \neq a_{j,s}$$

where t and s are the two distinct time periods, uses the F statistic defined as:

$$F_g = \frac{(m_{g-1} - k)\ (SSR_g - SSR_{g-1})}{m_g\ .\ SSR_{g-1}} \qquad (10)$$

where

SSR_g	=	residual sum of squares based on all observations in the two distinct time periods (t and s).
SSR_{g-1}	=	residual sum of squares based on observations in the first time period.
m_g	=	number of observations in the second time period.
m_{g-1}	=	number of observations in the first time period.
k	=	number of independent variables in the model.

The statistic F_g follows the classical F-distribution with m_g and m_{g-1}-k degrees of freedom. We then reject the hypothesis of coefficient stability if F_g for the model exceeds the upper $100(1-\alpha)$ per cent of the critical tabulated F-value with m_g and m_{g-1}-k degrees of freedom. The results of the test of the coefficient stability of the logit models for both the commercial and merchant banks for the two distinct time periods December, 1993 and December, 1994 are presented in Table 4. The results suggest that the coefficient of the models are time invariant, and could therefore be used for predictive purposes.

V. ERROR ANALYSIS

Before turning to specific models and specific measures of performance (or error analysis), the question of what constitutes an accurate and efficient result needs elaboration. The objective of early warning analysis is to isolate, on the basis of prior information, a group of banks that consists largely of those that are likely to deteriorate significantly or fail in the future. A perfect model would identify those banks and only those banks, that subsequently develop serious problems (or fail). A very good model would identify a relatively small group of banks, among which a high percentage of those that would subsequently develop serious problems, is included. An inefficient model would tend to identify as weak or (failed), many banks that subsequently would not become weak (or fail) and not identify significant number of banks that either would fail or deteriorate severely.

The less efficient the model, the greater the dilemma of not classifying the banks correctly, especially when the number of weak or failed banks is very small in relation to the total number of banks being screened. For example, to ensure that a high percentage of weak or failed banks is captured in the 'vulnerable' segment of the sample, as determined by a particular model, this segment must be large if the model is not efficient. Also, Altman (1968:600) shows that when models developed are used to reclassify the original sample banks, the classification accuracies are normally biased upward. Thus, this study validated the models developed and appraised their performance in relation with earlier models of Nyong (1994) and Jimoh (1993), by ex-ante forecasting of probabilities of failure in 1994.

A measure of a model's accuracy denoted as CC and used by Collins and Green (1982), Bovenzi et al (1983), Nyong (1994) and others, is the fraction of banks classified correctly. This measure is defined as,

$$cc = \frac{n-(a+b-2c)}{n} \qquad (11)$$

Where

a	=	banks identified as weak (or failed) by the model.

b = total number of truly weak (or failed) banks in the sample.
c = weak (or failed) banks correctly identified by the model.
n = number of sampled banks.

Table 5: The Logit Regression Results of Jimoh and Nyong as Defined is Equation (2) \1

	Jimoh's Model:			Nyong's Model:		
Variable	a-value	t-value	p-value	a-value	t-value	p-value
Constant	-	-	-	0.4045	27.89	0.000
Ownership	0.136	1.811	0.006	0.0656	6.87	0.000
LRWA	0.123	3.152	0.003	-	-	-
CLR	-	-	-	0.0245	1.45	0.154
BDL	0.480	3.658	0.001	0.1297	3.06	0.004
LTA	-	-	-	0.1846	4.65	0.000
LQR	-	-	-	0.8620	3.50	0.001
LR	-0.002	-2.786	0.008	-0.2146	-17.12	0.000
ROA	-1.298	-1.753	0.086	-0.9506	-4.56	0.000
ROC	-	-	-	-0.2366	-18.04	0.000
ETE	-	-	-	0.5886	97.58	0.000
Analog R^2-adjusted			66.3%			79.5%
Maximum of Log-Likelihood			-			-
F - Statistics:			18.888	F(10,49):		1103.5

\1 a, t and p - values are as defined in table 3. Ownership is a dummy variable with 1 for government banks and 0 for others. ETE is the expenses-to-total earnings, while the other variables are as defined in table 1.

A perfectly accurate model classifies all the banks correctly. Thus for a perfect model, CC would be equal to unity, while for an inefficient model CC would tend to zero.

When the two groups of banks (problem and non-problem) to be classified are significantly different in size, as in the case of weak (or failed) banks compared to all banks in the sample, the CC value can be close to 1, while only a relatively low fraction of the small, but crucial target group (weak or failed) is identified correctly by the model. In this case the measure CC defined in equation (11) is not a reliable measure of a model's usefulness, because it fails to highlight the importance of correctly identifying the truly weak (or failed) banks in the sample.

Karobow and Stuhr (1985) suggest several factors that should go into the appraisal of a model's early warning performance, as a practical tool for bank analysis. These factors are incorporated in a modification of the standard measure of performance, to provide increased sensitivity to both the accuracy and efficient aspects of early warning analysis. The Karobow and Stuhr (1985) weighted efficiency measure of performance denoted by KS, is defined as:

$$KS = \frac{c^2}{ab}\left(1-\frac{a+b-2c}{n}\right) \qquad (12)$$

where a, b, c and n are as defined in equation (11). For a perfect model, KS will be equal to unity. If not, KS will be sensitive both to the fraction of those banks that actually weakened and the fraction of all weak banks correctly classified by the model. As these two components decline significantly below unity, weighted efficiency, KS tends to decline sharply.

Analogous to the classical mean square error (MSE) measure of model efficiency in parametric statistic, this paper introduces another measure known as the mis-classification error (MCE). This measure which is a variant of equation (12), could be used to evaluate a logit model's efficiency. It follows from (12) that the measure MCE could be defined as:

$$MCE = 1-\frac{c^2}{ab}\left(1-\frac{a+b-2c}{n}\right) \qquad (13)$$

Thus the model that has the minimum MCE amongst the other competing models is said to have the highest efficiency. We now evaluate the MCE of the models developed in this paper and those of Nyong (1994) and Jimoh (1993).

Since the MCE is a function of the critical cut-off point, CCP, defined in equation (5), we computed MCE for the models developed in the paper (Table 3) and those of Nyong and Jimoh (Table 5), for values of CCP ranging from 0.5 to 1.0 in steps of 0.025. Thus, for each model, 21 values of MCE were generated based on a sample of 35 commercial and 21 merchant banks whose actual financial conditions were truly known by the regulatory authorities as at end-December, 1994. The CCP and MCE values for the models are presented in Table 6 for both the commercial and merchant banks.

It is clear from Table 6 that the newly proposed models for the two types of banks have the smallest mis-classification errors compared with Nyong and Jimoh's models, and could, therefore, be said to have the highest efficiency. Thus, the proposed models tend to recommend themselves more than the failure prediction models developed for Nigerian banks previously. The performance analysis also has some interesting results. In particular, Nyong (1994:422) opined that the study by Jimoh (1993), though commendable, has certain important methodological and interpretational inconsistencies that may seriously diminish the usefulness of his proposed model for policy purposes. However, the error analysis, presented in Table 6 contradicted Nyong's view about Jimoh's model. In fact, for very large CCP values, Jimoh's model appears to be more efficient than the model developed by Nyong, in the case of commercial banks. Perhaps, one reason that could be adduced for the poor performance of Nyong's model is its very high sensitivity to the expenses to earnings ratio which is not so readily available on monthly basis.

VI. APPRAISAL OF REPORTING BANKS' FINANCIAL CONDITIONS

From the results of the estimated model in Section 5, bank weakness and/or failure is attributed mainly to poor management, which manifests in excessive credit and liquidity risk, poor loan quality and sluggish internal generation of capital. These types of weaknesses are reflected over time in the various financial ratios reported by banks. In particular, CAR, LRWA, LAS, LSL and ROA are important discriminatory factors in distinguishing weak from sound commercial banks. In contrast, CAR, LCR, LTA, LDR and TKA are the important discriminatory factors that can distinguish weak from sound merchant banks in Nigeria. Given these facts, the two models that have been proposed, validated and found to have the highest efficiency are used in appraising the financial condition of all the reporting commercial and merchant banks in 1995. However, in order to maintain confidentiality, the study has adopted a new and unique coding system for all the banks.

Using the statutory monthly returns which the reporting banks rendered to the Central Bank of Nigeria for the months of July, August and September, 1995, we computed the discriminatory factors for each of these banks. The two models are then applied to these factors to obtain
the failure probabilities of the banks for each of the months in the third quarter of 1995. These failure probabilities and their averages for the commercial and merchant banks, during the quarter are presented in Tables 8 and 9, respectively. These average failure probabilities are then used to classify the banks as weak or sound using the following decision rule:- A bank is considered terminally distressed TD, if its average probability of failure is unity. If this average probability is greater than or equals 0.85, but less than unity, then the bank is classified as highly distressed, HD. An average probability greater than or equal to 0.5, but less than 0.85 is an indicator of distress, D. A bank is likely to be mildy distress MD, if its average probability is less than 0.5, but greater than or equals 0.25. However, a bank is considered sound, if its average probability of failure for the quarter falls below 0.25.

Using the above decision rule, the overall financial condition of both commercial and merchant banks in the third quarter of 1995 is presented in Table 7. From this table, it appears that 21 commercial and 8 merchant banks are terminally distressed, while 10 commercial and 10 merchant banks are highly distressed. Of the 115 licensed banks that reported on their activities in the third quarter of 1995, 59 or 51.3 per cent are non-problem banks, comprising 47 that are truly sound and 12 that appear to be mildly distressed.

The breakdown of the commercial banks' financial condition which is reflected by the average probabilities of failure is given in Table 8. From this table, it is clear that 21 banks are terminally distressed. This number includes the 17 banks that were already identified by the regulatory authorities as at December, 1994. However, the remaining 4 terminally distressed banks that were not identified include CB23, CB26, CB51, and CB52. Ten more commercial banks have been identified by the model as being highly distressed. These are: CB12, CB59, CB01, CB45, CB66, CB56, CB35, CB13 and CB42. Thus, attention should be focused on these banks by the bank examiners before they become terminally distressed. Similarly two additional banks: CB16 and CB54, in that order, are also distressed. The bank examiners should target these banks for further examination in order to prevent them from deteriorating further. This means that the examiner's resources could be geared towards highly distressed or just distressed banks for indepth examination. The bank examiners should, however, continue to monitor the remaining 7 mildy distress and 24 sound commercial banks based on the monthly returns they submit to the regulatory authorities.

Table 9 presents the breakdown of the 51 reporting merchant banks' financial condition in the third quarter of 1995. Of the 12 merchant banks that were classified as distressed by the regulatory authorities in December, 1994, 11 have been identified by this model as either terminally distressed, highly distressed or distressed, while the remaining one (MB51) has been identified by the model as sound. The bank MB27, which was not identified as distressed by December, 1994, has been found to be terminally distressed in the third quarter of 1995 by the model. Ten more merchant banks have been classified as highly distressed by this appraisal. These are MB02, MB54, MB50, MB43, MB19, MB06, MB40, MB16 and MB04 in that order.

Table 6: The Mis-classification error (MCE) of the Models as a Function of the critical Cut-off Point, CCP

	Mis-classification Errors of the Models:					
	Commercial Bank			Merchant Bank		
CCP	**Jimoh**	**Nyong**	**Proposed**	**Jimoh**	**Nyong**	**Proposed**
0.500	0.736	0.736	0.080	0.726	0.593	0.000
0.525	0.736	0.736	0.080	0.726	0.593	0.000

0.550	0.736	0.736	0.080	0.726	0.593	0.000
0.575	0.736	0.736	0.080	0.726	0.593	0.000
0.600	0.736	0.736	0.080	0.726	0.593	0.000
0.625	0.736	0.736	0.080	0.726	0.593	0.000
0.650	0.736	0.736	0.080	0.726	0.593	0.000
0.675	0.736	0.736	0.080	0.726	0.593	0.000
0.700	0.736	0.736	0.080	0.726	0.593	0.000
0.725	0.736	0.736	0.080	0.726	0.593	0.000
0.750	0.736	0.736	0.080	0.726	0.593	0.000
0.775	0.736	0.736	0.080	0.726	0.593	0.000
0.800	0.736	0.736	0.080	0.726	0.593	0.000
0.825	0.736	0.736	0.080	0.726	0.593	0.000
0.850	0.736	0.736	0.080	0.726	0.593	0.000
0.875	0.736	0.736	0.080	0.726	0.593	0.000
0.900	0.736	0.736	0.080	0.726	0.593	0.000
0.925	0.736	0.736	0.080	0.726	0.593	0.000
0.950	0.736	0.736	0.080	0.726	0.593	0.134
0.975	0.736	0.736	0.080	0.686	0.593	0.134
0.995	0.713	0.736	0.000	0.686	0.593	0.134
0.999	0.713	0.736	0.000	0.538	0.593	0.377

Another five merchant banks have been identified as distressed. These are MB47, MB48, MB45, MB31, and MB24. Thus, the bank examiners should target these 15 distressed merchant banks for detailed examination before they become terminally distressed. In addition the 28 non-problem banks could be monitored more closely based on the returns they normally submit to the regulatory authorities for any unhealthy development before they are scheduled for detailed examination.

Table 7: Financial Condition of Reporting Commercial and Merchant Banks in the Third Quarter of 1995.

	Financial Condition \1					
Bank	**TD**	**HD**	**D**	**MD**	**S**	**Total**
Commercial	21	10	2	7	24	64
Merchant	8	10	5	5	23	51
Total	29	20	7	12	47	115

\1 TD = Terminally Distressed
HD = Highly Distressed
D = Distressed
MD = Mildly Distressed
S = Sound

From the appraisal of the financial condition of reporting banks in the third quarter of 1995, it was obvious that the information set on examinable banks has been narrowed to exclude those non-problem banks, for detailed examination. The 29 identified terminally distressed banks in the study should also be subjected to further action by the regulatory authorities in order to minimize the potential costs of widespread instability in the banking sector.

VII SUMMARY AND CONCLUSION

In view of the recent increase in the distress rate of banks in Nigeria, attention has been focused on efforts to identify problem banks and to predict failures with sufficient lead time for regulators and management to institute remedial action. This paper used the logit-analytic approach to explore ways of providing early warning on distress situations for commercial and merchant banks in Nigeria. The logit regression was used to measure the condition of individual financial institution and to assign each of them a probability of failure. For the models to be operational and useful for predicting potential problem banks, the paper employed widely used financial ratios derived from the reporting banks monthly returns rendered to both the CBN and NDIC.

From the logit regression analysis, five discriminatory variables are important in distinguishing weak from non-problem commercial banks. These variables are capital adequacy, CAR; asset quality LRWA; liquidity LAS; loan category LSL; and profitability ROA. In adequate management as reflected in poor internal controls and auditing procedures was expected to have direct impact on the five discriminatory variables. The model developed has given weights of -0.4721 to CAR, 0.5439 to LRWA, -0.1590 to LAS, 2.8029 to LSL and -0.5848 to ROA. The totality of these weighted variables should then be added to the constant value of -27.223 to computed the monthly commercial bank's probability of failure.

As with the commercial banks, five variables are also important in distinguishing weak from sound merchant banks. These variables are capital adequacy, CAR; asset quality, represented by both LCR and LTA; liquidity, LDR; and sources of funds, TKA. These variables bear correct signs consistent with theoretical expectation. The model developed for merchant banks has assigned weights of -0.13806 to CAR, 0.1346 to LTA, 0.0547 to LDR, 0.1323 to TKA and 0.0023 to LCR. The totality of these weighted variables should be added to the constant value of -11.0027 to predict the monthly probability of failure of a merchant bank. Note that these discriminatory variables are expressed in percentages.

Chow's predictive test of coefficient stability as proposed by Harvey (1976) was applied to the coefficients of the models, using both the 1993 and 1994 data. The results of the stability tests suggest that the coefficients (weights) of the models are time invariant and could therefore be used for predictive purposes. Furthermore, the two models developed were validated and evaluated, using the variant of the weighted efficiency measure of performance. It was found that these two models have drastically reduced the mis-classification errors inherent in other failure prediction models developed in the past and are, therefore, more efficient.

In order to illustrate the application of the models for policy, an appraisal of the financial condition of all the reporting commercial and merchant banks in the third quarter of 1995 was performed. Apart from identifying banks that were already known to be weak or distressed by the regulatory agencies, the results also revealed additional weak banks which require urgent attention in order to prevent them from becoming problem banks. The weak commercial banks that are in this category include: CB12, CB59, CB01, CB45, CB02, CB66, CB56, CB35, CB13, CB42, CB16, and CB54. The weak merchant banks fall in the same category as the commercial banks are listed in order of severity of distress as follows: MB02, MB54, MB50, MB43, MB26, MB19, MB06, MB40, MB16, MB47, MB48, MB45, MB31 and MB24.

Since on-site examinations are expensive and scheduling is often difficult, we propose that: (1) the identified weak banks should be urgently examined in order to minimize the risk of failure and (ii) the reporting non-problem banks should continue to be monitored monthly (based on these models), and as long as their failure probabilities remain below 0.5, they should only be subjected to periodic on-site examinations - thus minimizing valuable resources for the regulatory authorities. In conclusion, bank regulators now have an additional tool (models) for early identification of banks that are unsound or that show signs of weakness, before examination teams are sent into the field. Moreover, the proposed models have an inbuilt scheduling procedure: just ranking the problem banks from the severest to the least severe, based on their failure probabilities, with the former category being scheduled first for examination and the latter afterwards.

Table 8: Appraisal of Commercial Banks' Financial Condition In Third Quarter, 1995.

	Probability of Failure				Financial Condition	
New Code	July	August	September	Average	Condition	Severity
CB01	0.9999	0.9999	0.9999	0.99990	HD	3
CB02	0.9622	0.9998	0.9974	0.98647	HD	5
CB03	0.0000	0.0000	0.9269	0.30897	MD	5
CB04	1.0000	1.0000	1.0000	1.00000	TD	
CB05	0.5049	0.3762	0.4708	0.45063	MD	1
CB06	0.0093	0.0111	0.0010	0.00713	S	
CB07	0.5539	0.2398	0.0290	0.27423	MD	7
CB08	0.0787	0.8055	0.0787	0.32097	MD	4
CB09	1.0000	1.0000	1.0000	1.00000	TD	
CB10	0.0099	0.9962	0.0607	0.35560	MD	2
CB11	1.0000	1.0000	1.0000	1.00000	TD	
CB12	1.0000	0.9999	0.9999	0.99993	HD	1
CB13	0.9848	0.8205	0.9974	0.93423	HD	9
CB14	1.0000	1.0000	1.0000	1.00000	TD	
CB15	1.0000	1.0000	1.0000	1.00000	TD	
CB16	0.9476	0.3226	0.8865	0.71890	D	1
CB17	0.0000	0.0000	0.0000	0.00000	S	
CB18	0.0001	0.0001	0.0625	0.02090	S	
CB19	0.0000	0.0000	0.0000	0.00000	S	
CB20	0.0111	0.0235	0.3476	0.12740	S	
CB21	1.0000	1.0000	1.0000	1.00000	TD	
CB22	1.0000	1.0000	1.0000	1.00000	TD	
CB23	1.0000	1.0000	1.0000	1.00000	TD	
CB24	0.0000	0.0000	0.0000	0.00000	S	
CB26	1.0000	1.0000	1.0000	1.00000	TD	
CB27	0.0125	0.0024	0.0006	0.00517	S	
CB28	0.0007	0.0000	0.0002	0.00030	S	

CB29	1.0000	1.0000	1.0000	1.00000	TD	
CB30	0.0003	0.0020	0.2364	0.07957	S	
CB31	0.0005	0.0001	0.0001	0.00023	S	
CB32	1.0000	1.0000	1.0000	1.00000	TD	
CB33	0.0000	0.0000	0.0000	0.00000	S	
CB34	0.0001	0.0000	0.0000	0.00003	S	
CB35	0.9991	0.8156	0.9991	0.93793	HD	8
CB36	0.0026	0.0001	0.0018	0.00150	S	
CB37	1.0000	1.0000	1.0000	1.00000	TD	
CB38	0.0246	0.0002	0.0048	0.00987	S	
CB39	0.0000	0.0000	0.0000	0.00000	S	
CB40	0.0000	0.0000	0.0000	0.00000	S	
CB41	0.0000	0.0000	0.0000	0.00000	S	
CB42	0.9953	0.9144	0.7146	0.87477	HD	10
CB43	1.0000	1.0000	1.0000	1.00000	TD	
CB44	0.0027	0.0000	0.0008	0.00117	S	
CB45	0.9989	0.9999	1.0000	0.99960	HD	4
CB46	0.9999	0.0000	0.0000	0.33330	MD	3
CB47	0.0000	0.0000	0.0009	0.00003	S	
CB48	1.0000	1.0000	1.0000	1.00000	TD	
CB49	0.0005	0.0012	0.0013	0.00100	S	
CB51	1.0000	1.0000	1.0000	1.00000	TD	
CB52	1.0000	1.0000	1.0000	1.00000	TD	
CB53	0.0000	0.0000	0.0000	0.00000	S	
CB54	0.9317	0.7439	0.1674	0.61433	D	2
CB55	1.0000	1.0000	1.0000	1.00000	TD	
CB56	0.9782	0.8666	0.9782	0.94100	HD	7
CB57	1.0000	1.0000	1.0000	1.00000	TD	
CB58	0.1252	0.0442	0.0000	0.05647	S	
CB59	1.0000	0.9999	0.9999	0.9993	HD	2
CB60	0.0621	0.4088	0.3197	0.29430	MD	6

CB61	1.0000	1.0000	1.0000	1.00000	TD	
CB62	1.0000	1.0000	1.0000	1.00000	TD	
CB63	0.0000	0.0000	0.0000	0.00000	S	
CB64	1.0000	1.0000	1.0000	1.00000	TD	
CB65	0.1060	0.1448	0.0174	0.08940	S	
CB66	0.9577	0.9995	0.9999	0.98570	HD	6

Table 9: Appraisal of Merchant Banks' Financial Condition In third Quarter, 1995.

	Probability of Failure				Financial Condition	
New Code	**July**	**August**	**September**	**Average**	**Condition**	**Severity**
MB01	0.2912	0.0040	0.0487	0.11463	S	
MB02	0.9998	0.9998	0.9996	0.99973	HD	1
MB03	1.0000	1.0000	1.0000	1.00000	TD	
MB04	0.9134	0.9533	0.9545	0.94040	HD	10
MB05	0.0034	0.0002	0.0047	0.00277	S	
MB06	0.9912	0.9976	0.9795	0.98943	HD	7
MB07	0.0493	0.0441	0.2902	0.12787	S	
MB08	0.0000	0.0000	0.0000	0.00000	S	
MB09	0.0215	0.2354	0.0783	0.11173	S	
MB10	1.0000	1.0000	1.0000	1.00000	TD	
MB11	0.2692	0.5887	0.0045	0.28747	MD	5
MB12	0.0051	0.0002	0.0001	0.00180	S	
MB13	1.0000	1.0000	1.0000	1.00000	TD	
MB14	0.0149	0.0567	0.0219	0.03117	S	
MB15	0.0000	0.0000	0.2186	0.07287	S	
MB16	0.9851	0.9099	0.9894	0.96147	HD	9
MB17	1.0000	1.0000	1.0000	1.00000	TD	
MB18	0.0000	0.0000	0.0025	0.00083	S	
MB19	0.9961	0.9980	0.9819	0.99200	HD	6

MB21	0.0663	0.0331	0.1312	0.07687	S	
MB22	0.0219	0.1804	0.0122	0.07150	S	
MB23	0.1329	0.0077	0.0507	0.06477	S	
MB24	1.0000	0.3684	0.3506	0.57300	D	5
MB25	0.0328	0.1364	0.0723	0.08050	S	
MB26	0.9815	0.9986	0.9981	0.99273	HD	5
MB27	1.0000	1.0000	1.0000	1.00000	TD	
MB28	0.0625	0.6734	0.7281	0.48800	MD	1
MB29	0.0309	0.0011	0.0003	0.01077	S	
MB30	0.0048	0.0019	0.0001	0.00227	S	
MB31	0.1167	0.7421	0.9145	0.59110	D	4
MB33	0.0007	0.0002	0.0008	0.00057	S	
MB34	0.0012	0.0223	0.0019	0.00847	S	
MB35	1.0000	1.0000	1.0000	1.00000	TD	
MB36	1.0000	1.0000	1.0000	1.00000	TD	
MB38	0.9998	0.0025	0.0035	0.33527	MD	2
MB39	0.0002	0.0006	0.9993	0.33337	MD	3
MB40	0.9996	0.9513	0.9523	0.96773	HD	8
MB41	0.0001	0.0000	0.0000	0.00023	S	
MB42	0.0581	0.0674	0.7914	0.30563	MD	4
MB43	0.9983	0.9992	0.9849	0.99413	HD	4
MB44	0.0009	0.0002	0.0006	0.00057	S	
MB45	0.5432	0.6362	0.8059	0.66177	D	3
MB46	0.0054	0.0010	0.0358	0.01407	S	
MB47	0.5817	0.7480	1.0000	0.77657	D	1
MB48	0.9915	0.0375	0.9896	0.67287	D	2
MB49	1.0000	1.0000	1.0000	1.00000	TD	
MB50	1.0000	0.9999	0.9924	0.99743	HD	3
MB51	0.0882	0.0752	0.0209	0.06143	S	
MB52	0.0000	0.0016	0.0000	0.00053	S	
MB53	0.0200	0.0050	0.0849	0.03663	S	
MB54	0.9999	0.9995	0.9998	0.99973	HD	2

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