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THE CAPITAL MARKET AND EQUITY FAILURE IN NIGERIA

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The Capital Market is recognized in the literature as an important barometer for economic growth and development in a nation via its allocative efficiency properties. In investigating equity failure in Nigeria, the paper applied the predicitive models developed for discriminant and logistic analyses for selecting equity stocks to invest in. In the study relating to a sample of 47 Equity Issues from 45 Nigerian companies over the period 1988-92, two classification models were applied on a data set comprising macro and micro economic indicators, an industry variable and various accounting ratios. The models were the multiple discriminant and logistic regression models.

Both models performed well and were able to classify equity issues correctly as failed or successful to a high degree (over 70 per cent correct classification). Overall, it was clear that for both models, the major warning signals appear to be low profitability, low dividends and high price earnings ratio. However, the precise variable characteristics evaluated in the two models do differ in some interesting ways.

For instance, the discriminant model considers industry membership and returns as important factors, a position not shared by the logit model. However, the logit model considers income and liquidity as important, but not the discriminant model. These differences might be responsible for the better performance of the discriminant model over its logistic counterpart in the classification results. In addition, the superior performance of the discriminant model may be a sign that distributions in the Nigerian capital market approximate normal if we accept the findings of Lo (1986). Furthermore, using actual values of independent variables may enhance the efficiency of the discriminant model in contrast to the coded values used throughtout in the logit estimation. This indicates that coding the variable values may lead to loss of efficiency in classification between failed and successful Issues.

Several applications of the two models were suggested. A potential theoretical area of importance is the conceptualization of efficient portfolio selection. On the practical side, applications were suggested for investment guidelines, credit management as well as company internal controls.

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I. INTRODUCTION

In general, research on determinants and behavior of flows into the capital market is important especially for a fuller understanding of the general pattern of investment behaviour. This in turn will shed important light on the risk diversification benefits of the stock market and the cost of capital.

On a specific note, failures (and by implication successes) are important business phenomena. In a competitive economy, market forces usually operate to eliminate businesses that are inefficient. Several causes of business failures have been suggested (Altman, 1983) ranging from exogenous factors to endogenous ones. Exogenous factors are those outside the control of the firm and are usually the result of macroeconomic events such as government policies. These factors affect all firms in the economy although not to the same degree and are therefore, not very useful in assessing financial health of specific firms (Chye and Chong, 1988).

Endogenous factors are factors within the control of the firm and often relate to management inefficiencies. Such inefficiencies translate to poor company performance and are eventually reflected in (subject) company's financial statements. Therefore, it is logical to use endogenous factors to assess the financial health of companies and in doing this, financial ratios are the logical variables employed.

Following from the introduction, the paper is divided into five sections dealing with theoretical review, model development, empirical results, summary of findings as well as policy implications and recommendations.

II. THEORETICAL REVIEW

Empirical evidence shows that business failures are neither sudden nor unpredictable and that the probability of business failure can be predicted through financial ratio analysis. Financial ratios which are said to be good discriminators between failed and non-failed firms include the following:

a. **Liquidity Ratios**
b. **Profitability Ratios**
c. **Leverage Ratios**
d. **Activity Ratios**
e. **Returns and Market Ratios**

Although the number of financial ratios said to be good discriminators is large, in constructing a failure-predicting model, all that is needed is a set of dominant ratios derived from a larger set of related ratios (Chye and Chong, 1988). The selection of dominant variables can be accomplished either by stepwise procedures or by collapsing the number of ratios into a smaller set of un-correlated or orthogonal variables. A further survey of literature reveals that about six (6) different statistical classification models are employed in failure prediction studies. The models can predict with some degree of precision, the financial prospects of firms from annual report data. These models are as follows:

a. The Univariate Analysis Model
b. The Multiple Discriminant Analysis Model
c. The Linear Probability Model
d. Logit Analysis Model
e. Probit Analysis Model
f. Nonparametric Analysis Model

Empirical evidences using the different models are highlighted below.

II.1 Univariate Analysis Models

Beaver (1966) conducted one of the first and most extensive studies in failure prediction. His results concluded that financial ratios can predict failure at least 5 years in advance. Booth (1983) also employed univariate analysis to test four decomposition measures to ascertain the ability of the attributes, size and stability to discriminate between failed and non-failed companies. His results concluded that the attributes of most of the decomposition measures discriminate between failed and non-failed. However, other researchers have identified its lack of multi-variate analysis as a major shortcoming of such studies i.e they only consider the measurements used for group assignments one at a time.

II.2 Multiple Discriminant Analysis (MDA)

Discriminant analysis is one of the most widely used methods for identifying financial distress especially bankruptcy. (Altman 1968, Altman ***et al.*** 1977, Eisenbeis 1977, Pettway and Sinkey 1980, Lo 1986, Booth 1983, Zavgren 1985). The purpose of discriminant analysis is to classify an observation into one of several a priori groupings on the basis of a profile of its characteristics. It requires categorical dependent variables and continuous independent variables. The first step in MDA is to establish explicit group classifications (the groups could be two or more) after which data are collected for objects in the groups. The MDA then attempts to derive a linear combination of the characteristics which "best" discriminate between the groups. The MDA procedure maximizes the variance of the linear combinations between and within the two groups usually by applying the Fisher procedure.

Fisher's (1936) classical approach to discriminant analysis is based on choosing linear combinations which are denoted as scores. The scores for the non-failed (solvent) group 1 (of $\mathbf{n_1}$ observations) are denoted by $\mathbf{Z_{1i}}$, $\mathbf{i=1 .... n_1}$, and the scores for the failed (bankrupt) group, 2 (of $\mathbf{n_2}$ observations), by $\mathbf{Z_{2j}}$, $\mathbf{j=1...,n_2}$, ($\mathbf{n_1}$ and $\mathbf{n_2}$, do not have to be equal).

Where:

$$\mathbf{Z}_{1i} = \sum_{\varepsilon=1}^{p} \omega_{i*} X_{1i} = X'_{1i}\omega_p$$

$$\mathbf{Z}_{2j} = \sum^{p} \omega_{i*} X_{2j} = X'_{2j}\omega_p$$

ω_{i*} is the discriminant coefficient for variable X_i

It is equal to the i[th] weighted value applied to the i[th] independent variable. There are **p** variables.
Z is the discriminant score and
$\mathbf{X_i}$ is the i[th] independent variable.

Using a different notation, Fisher's procedure maximizes

$$\frac{\mathbf{S^2\ (between)}}{\mathbf{S^2 (within)}}$$

where $\mathbf{S^2}$ = variance of linear combinations.

This approach is equivalent to maximizing the Pearson's correlation ratio denoted by eta^2 (Barniv and Raveh, 1989). From the above,

$$\eta^2 = \frac{S^2\ (*)}{S^2\ (total)} = \frac{(\bar{Z}_1 - \bar{Z}_2)^2}{S_1^2 + S^2_2 + (\bar{Z}_1 - \bar{Z}_2)^2}$$

where: $\mathbf{S^2}$ $(\bullet)$ = $\mathbf{S^2}$ between

$\bar{\mathbf{Z}}_1$ and $\bar{\mathbf{Z}}_2$ are the two arithmetic means of scores $\mathbf{Z_{1i}}$ and $\mathbf{Z_{2j}}$ while $\mathbf{S_1^2}$ and $\mathbf{S_2^2}$ denote the variances of the two distributions of scores respectively.

Theoretically, the Pearson's correlation ratio has a **0** minimum (if and only if there is no difference between the two means) and a **1** maximum (if and only if the variance within each population is zero i.e every member of a given population is at the mean of that population).

The goodness of the separation between the two groups of scores can be measured by the derivation of the Pearson's correlation ratio from 1, its theoretical maximum.

The standard MDA classification rules have been derived from minimizing loss functions of the form (for the two groups case)

$$M = P(1|2)\,\Pi_2 + P(2|1)\,\Pi_1.$$

$$L = C(1|2).\,P(1|2).\Pi_2 + C(2|1).\,P(2|1)\Pi_1.$$

which takes into account a priori probabilities (e.g π_is) and costs of misclassification (e.g **C(g/h)** where:

C(g/h)=cost of misclassifying an observation as a member of a group **g** given that it came from group **h**.

P(g/h) = conditional probability of misclassification.

For example, the linear form of the two group rules is Assign **X'** to group 1 if

$$X'B - 1/2(\overline{X}_1 + \overline{X}_2)'B \leq \ln \frac{C(1|2)\Pi_2}{C(2|1)\Pi_1}$$

OR

$$X'\omega_p \geq CP$$

Otherwise assign **X'** to group 2

CP = cut-off point usually chosen to minimize total number of misclassifications.

Shortcomings of MDA model identified in literature include the violation of the normality assumptions and lack of predictive ability 2 years prior to bankruptcy. However, in practice, deviations from, the normality assumption at least in economics and finance, appear more likely to be the rule rather than the exception. This is partly due to the fact that most available normality tests are for univariate and not multivariate normality (Kowalski 1970, Malkovich and Afifi 1973, D'Agostino 1973, Shapiro and Francia 1972). Moreover, recent empirical research suggest that either the normality assumption is inappropriate for accounting ratios in economics and finance (Deakin, 1976 and Foster, 1986) or departures from normality result from the occurrence of outlier observations (Frecka and Hopwood, 1983).

Another limitation of MDA is in determining the relative importance of individual variables. This is because unlike classical regression, the discriminant function coefficients are not unique; only their ratios are. There is therefore no meaningful test for the absolute value of a particular variable. This limitation may be of more importance in economics given the nature of the behavioral hypotheses generated; which require that the influence of specific variables be isolated and quantified in a cardinal sense.

However, other researchers have suggested testing whether the ratio of two coefficients is equal to some constant i.e whether addition of a given variable to a set significantly increases the overall discriminatory power of the set (Kshirsagar 1972, Eisenbeis and Avery 1972, Lachenbruch 1975). Other studies by Joy and Tollefson (1975), Richardson and Davidson (1984) also comment on and/or criticize possible misapplication and potential misinterpretation of MDA in the identification of failure.

II.3 The Linear Probability Model

When considering the occurrence or non-occurrence of an event such as business failure, it is convenient to define a dichotomous random variable $\mathbf{Y}_j$
where;

$\mathbf{Y}_j = \mathbf{0}$ if the jth firm is failed **(F)**

$\mathbf{Y}_j = \mathbf{I}$ if it is not **(Non-F)**

Varaible $\mathbf{Y}_j$ is dependent on a vector of independent variables $\mathbf{X}_j$ with vector of unknown parameters **b**.

Thus we can have a general model of the form

$\mathbf{Y}_j = \mathbf{G}\ (\mathbf{X}_j'\ \mathbf{b})$

where:

$\mathbf{X}'_j\mathbf{b}$ are column vectors

$\mathbf{X}_j'$ = transpose of $\mathbf{X}_j$

G = function for the given set of data

For the linear probability (LP) model, the function G is specified as

$\mathbf{G(Q) = Q}$ where: $\mathbf{Q = X_j'B}$

In regression form, the LP model is written as:

$\mathbf{Y}_j = \mathbf{X'jb} + \in_j$ **i. e.** $\mathbf{Y} = \propto + \beta\mathbf{X} + \in$

where: $\in_j$ random error term

$\mathbf{E}(\in_j) = \mathbf{0}$ = expected value of $\in_j$

$\mathbf{X}$ = attribute e.g income

B= coefficient; α = constant term.

The specification of the Linear Probability Model is $\propto$ = constant term as given below:

$$P_i = \beta_i + \beta_1 X_1 + \ldots \beta_n X_n + \in_i$$

Where: $\mathbf{P}_i$ = Probability of event **1** occurring.

The LP model was used by Parosh and Tamari (1978) to predict the failure of 34 firms that failed between 1967-68. This model was found not to be as efficient as MDA models. Observed flaws of the model included the presence of heteroscedasticity and the violation of the normality assumption for $\in_j$**'s**. Consequently, the necessary tests of hypotheses cannot be performed. Furthermore, of more serious limitation is the possibility of getting probabilities outside the 0-1 range which values cannot be interpreted (Falusi 1974, Pindyck and Rubinfeld 1985).

II.4 Logit Analysis Model

Logistic regression also known as logit technique estimates a non linear function that maximizes the probability of observing the sample of dichotomous events using log -odds transformation based on the predictor variables. The prediction is interpreted as the probability (likelihood) of failure conditioned on the attribute vector (i.e set of predictor variables). This model uses cumulative logistic functions which measure probability in terms of the base of natural logarithms. In the logit model, the **G** function in the linear probability equation is specified as:

$$G(Q) = L(Q) = \frac{\epsilon^{Q}}{(1 + \epsilon^{Q})} = \frac{1}{1 + \epsilon^{-Q}}$$

where: **L(.)** is the logistic function.

Consequently, the probability function for this model can be writtten as below:

$$P_i = \frac{1}{1 + \epsilon^{-Q}} = \frac{1}{1 + \epsilon^{-(\alpha + \beta X)}}$$

The difference from standard econometric problems is that we assume observations on the dependent variable (an Index) which theoretically exist are not available. Instead, we have data which distinguish whether individual observations are in one category (high values of index 1) or a second category (low values of index 1). What the model tries to solve is to estimate the coefficients for the constant and predictor variables and at the same time to obtain information on the unmeasured index. This information is then compared to a critical cut off value of the index to explain the choice made.

The reasoning behind the model is that each firm has some un-observable index $\mathbf{I}_j$ which is linear in the explanatory variables.

i.e $\mathbf{I}_j = \mathbf{X}_j'\mathbf{B}$

The event of failure **(F)** and non-failure **(Non-F)** is determined by some threshold level $\mathbf{I}^*$ so that if $\mathbf{I}_j^* < \mathbf{I}^*$, then F occurs.

Researchers who used this model include Martin, 1977 and Ohlson 1980. Their results indicate that logit and MDA are related. In fact Maddala, 1983 and Amemiya, 1981 argue that MDA is a special case of logit. However, there are divergent views in comparing the efficiencies of the two models. While McFadden (1976) believes that logit is more robust than MDA, Lo (1986) is of the opinion that MDA is superior to logit if distributions approximate normal.

However, this model is sometimes criticized for resting on a very strong behavioral assumption, the independence of irrelevant alternatives. This sometimes imposes limitations on probabilities and imply that conditional logit analysis may not be appropriate in situations where several alternatives in the choice set are close substitutes (Judge ***et. al.*** 1980).

II.5 Probit Analysis Model

Probit analysis like Logit analysis, is one of the prediction methods that restrict the probability of failure to fall within unit interval. This method, unlike the LP method, avoids the problems of heteroscedasticity and non-normality of the error term. In Probit analysis, the **G** function of equation 2 above is specified as follows:

$$\mathbf{G(Q) = N(Q)}$$

where: **N(.)** is the standard cumulative normal function.

The intuition behind the Probit model is similar to that behind the Logit model. However, for Probit, it is argued that if failure is the result of many independent individually inconsequential additive factors, it is reasonable to assume the threshold level $\mathbf{I}^*$ to be normally distributed (Chye and Chong, 1988). This implies that probability is measured by the area under the standard normal curve which has means =0 and variance =1.

However, this flexibility (unlike logit) results in additional costs in computational burden. Researchers who used this model include Grablowsky and Tally (1981) who used the technique to classify credit applications of 200 companies using 11 explanatory variables. Their study employed both Probit and MDA analyses and concluded that probit analysis was a viable alternative to MDA as a classification model. Furthermore, Probit analysis was found to outperform MDA in efficiency principally, because, like the Logit model, Probit method does not require the normality assumption.

Empirical evidence also suggest that Probit and Logit have similar distributions, both being very close in mid range although the logistic distribution has slightly thicker tails. Given this similarity, their results are likely to be very similar as well unless an extremely larger number of observations is used (Chambers and Cox, 1967) in which case, the Probit model becomes more suitable. In fact, it has been suggested that Logit estimates can be multiplied by (0.55) to produce estimates comparable to Probit model (Chye and Chong, 1988).

However, a major problem of using both the Logit and Probit methods is the lack of readily available procedures in many of the existing statistical packages. Moreover, specifications for Probit analysis are rather complex computationally. Furthermore, Theil (1971) also noted that the theoretical background of Probit analysis is rather complicated and that the theoretical justification for employing the model is often limited. Comprehensive reviews of many of the models discussed so far and citation of empirical studies are presented by Altman ***et. al.*** (1981) , Zavgren (1983) and Altman (1984).

II.6 Nonparametric Analysis Model

Nonparametric models (NM) are a relatively new approach to classification problems. Their approach appears to overcome some of the shortcomings and problems of traditional MDA and LP models. Of note is that the Nonparametric Models is a modification of MDA which uses inequalities (instead of equalities) in its maximization procedures. Moreover, the number of misclassification errors identified and the expected costs of misclassification are often smaller than those obtained with MDA, Logit or Probit analyses. This latter propety and the fact that different coefficients are obtained for the same variables shed light on the relative significance and magnitude of the individual variables, as well as on the interpretation given to results. The NM usually uses forward stepwise analysis to obtain coefficients for selected variables.

Notable researchers who used NM include FAK (1985), Marais ***et. al.*** (1984) as well as Barniv and Raveh (1989). Both FAK and Marais ***et. al.*** employed a NM namely a recursive partitioning algorithm for classification of bankruptcy and commercial loans respectively. Their technique was found to outperform MDA for most empirical results.

However, a major shortcoming of the recursive partitioning method is that it cannot be used for scoring observations within the same group as it does not employ a ratio scale unlike the MDA which assigns a score to each observation on a continous scale.

Following the results of FAK and Marais ***et al.***, Barniv and Raveh (1989) developed a Nonparametric Discriminant Analysis (NDA) model based on Fisher's (1936) classical approach but using a different "separation" rule namely a different quantity to be maximized. The NDA uses linear combination of the observations, and chooses the coefficients so that the scores $\mathbf{Z_{1i}}$ given to group 1 are greater than (or less than) the scores $\mathbf{Z_{2j}}$ of group 2 i.e the measure to be maximized is based on the inequalities.

$$\mathbf{Z_{1i} \geq Z_{2j}}$$

where:

$\mathbf{Z_{1i}}$ are scores for group **1, i=1,.... $\mathbf{n_1}$**
$\mathbf{Z_{2j}}$ are scores for group **2, j=1,.... $\mathbf{n_2}$**
The inequalities for all i and j equivalent to $\mathbf{Z_{1i} - Z_{2j} \geq 0}$

$$\text{s. t. } (Z_{1i} - Z_{2j}) = |Z_{1i} - Z_{2j}|$$

Similarly, for k > 2 ordered groups (between k > 2 groups order always exist), the generalized rule is $\mathbf{Z_{1i} \geq Z_{2j} \geq Z_{3r}}$ for all I, j and r from the three groups respectively.

This generalization is similar to ordered Logit or Probit, the difference being that the former is non parametric while the latter techniques are parametric. The separation rule developed by this method is such that

$$|IS(\underline{Wp})| \geq \eta$$

where: **IS(<u>Wp</u>)** =Index of separation for NDA

$$\eta = \sqrt{\eta^2}$$

as defined in section II.4 above.

Herein lies the difference between NDA and Fisher's technique. While Fisher's technique maximizes Pearson's correlation of equation 1 and is optimal for two (overlapping) multinormal distributions, the NDA maximizes **IS(<u>Wp</u>)** which is based on monotonic relations between scores of two (or more) groups and is optimal for any two non-overlapping multivariate distributions. Although this method is yet to undergo rigorous testing in literature, it is possible that it may have the limitations of the inequality restricted estimator in that it depends on the availability of future values of explanatory variables (Judge ***et al.***, 1980).

II.7 Conclusions and Summary

Various classification models in literature use financial ratio in their construction. However, barring any selection bias, it would appear that one model could do as well as the other. This reasoning is supported by the results of the study done by Chye and Chong (1988) who found the predictive accuracies of most of the models (except NM) to be identical at 90 per cent. Their results further suggest that sophisticated models may not be significantly superior to computationally less complex models such as the LP model; at least one year prior to failure.

III. MODEL DEVELOPMENT

III. 1 Sample Selection

A sample size of 47 Equity Issues from 45 quoted companies (with attempts at pairing them mostly in terms of relative size of Issue and industrial sector) was selected after considering such matters as the financial base for the study, industrial concentration and the presumed efficiency[2] of the stock market. However, we note that the concept of industry is not precise enough to get a fixed unquestionable assignment of corporations to industry. Particular problems are presented by conglomerates. Therefore, perceived industry may be relevant than any other grouping when investigating corporations. Although not strictly randomized, the selection was stratified across various categories to give some random effects.

III.2 Data Collection

Sources of data for the study included the following:

a. Structured Questionnaire
b. Annual Reports and Accounts of Selected Companies
c. Security and Exchange Commision (SEC) Reports and Publications
d. Nigerian Stock Exchange (NSE) Reports and Publications
e. Central Bank Nigeria Reports (CBN) and Publications

III. 3 Analytical Framework and Models

The analytical tools employed were **Statistical Classification Models** which were used to predict the failure of Equity Issues. Based on the relative merits and demerits of about six relevant models found in the literature (univariate, multiple discriminant, linear probability, logit, probit and nonparametric analyses), the study employed the discriminant and logit methods of analysis.

II.3.I Measurement of the Variables.

a. The Dependent Variable (S)

The level of subscription of Equity Stocks (S) was chosen as the appropriate dependent variable for this study. This is because it simultaneously represents the demand for Equity Stocks and the supply of Equity Capital. However, the level of subscription was measured as a rate in conformity with the belief in the literature that a lack of normalization of the dependent variable leads to bias as well as loss of efficiency (Schultz, 1982b).

b. Explanatory Variables

i **Liquidity (LH)** - was represented by the Quick Ratio[3] (QR). The Issuing Company's liquidity position reflects its solvency and was hypothesized to have a positive estimated coefficient.

ii. **Profitability (R)** - was represented by the return on owners' equity[4] (ROE) which was hypothesized to have a positive estimated coefficient.

iii. **Returns (E)** - This was represented by earnings per share (EPS).[5] The expected sign of the coefficient.

iv. **Pay-outs (D)-** This was represented by dividend per share (DPS)[6] and the coefficient was expected to be positive.

v. **Offer Price (OP)** - This is the price at which the stock was offered to the investing public. The expected relationship is negative if (S) is taken as demand for equity stock and positive if (S) represents supply of equity capital.

vi. **Industrial Sector (IS)** - This was represented by the weights of risk attached to the industry by investors. The behavior of this variable was left for empirical test since there is no consensus in the literature about it.

vii. **Available Capital (Y)** - Capital available for investment was represented by savings rate in the year of Issue. This was expected to have a positive relationship.

viii. **Leverage (L)**[7]- The expected sign of the coefficient is negative.

ix. **Timing (T)** - This was a binary variable representing the depth (capacity) of the Stock market and indicated ability to absorb large Issues. The expected relationship is positive.

x. **Issuing Coy. Size (Z)** - This was represented by the equity base of the Issuing Company. A positive relationship is hypothesized for this variable.

xi. **Working Capital Ratio (W)**[8] - It indicates efficiency of asset use and was hypothesized to have a positive relationship.

xii. **Price Earning Ratio (PER)**[9] - It is a means of anticipating future performance in terms of earnings and growth. It indicates the number of years earning (based on current information) which will be paid for if stock are bought at the quoted price. A negative correlation was expected from the coeffificient.

xiii. **Retention Rate (RR)** - Refers to the percentage of profit not distributed but retained. It was expected to have a negative coefficient.

III.3.2 Stastitical Classification Models.

III.3.2.1 Choice of Models

Based on the relative merits and demerits of the six applicable models found in literature, the logistic and discriminant functions were selected as the more appealing models for the study. More recent models like the nonparametric models were not selected due to lack of adequate testing of their theoretical basis. The logit and discriminant analysis models are binary choice models.

III.3.2.2 Specification of the Logistic Functions.

The logit model is based on the cumulative logistic probability function. To specify this model, let us assume that there exists a theoretical (but not actually measured) index **I**. This index is assumed to be a continous variable which is random and normally distributed for the usual econometric reasons; that is,

$$\mathbf{1_j = X_j\text{'}B = \alpha + \beta X_j}. \qquad \ldots\ldots\ldots\ldots\ldots\ldots\mathbf{1}$$

Observations on **I** are not available although we have data which distinguish whether individual observations are in one category (high values of index $\mathbf{1_j}$) or a second category (low values of $\mathbf{1_j}$). It is assumed that the larger the values of index **1**, the greater the probability that event **F** in question will occur. Each individual makes a choice between not investing **(F)** and investing **(non-F)**, by comparing $\mathbf{I_j}$ to some critical value of the random index **1*** which reflects individual tastes. Hence, an individual chooses to invest (non-F) only if $\mathbf{1_j \geq 1^*}$. **If** $\mathbf{1_j < 1^*}$, then **F** occurs.

If **S** as defined above represent a dummy variable which equals **1** when **non-F (Success)** occurs and **0** when **F (Failure)** occurs, then for each explanatory variable, $\mathbf{1^*}$ represents the critical cutoff value which translates the underlying index into an investment decision. The conditional probability of event **F's** occuring given $\mathbf{1_j}$ is therefore,

Probability of Failure: prob $\mathbf{[F:1_j]}$

$$\mathbf{=P_j \;=Prob\;[1^* > 1_j] \;= G(1_j) = G(X_j\text{'}B)} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\mathbf{2}$$

where **G()** is the normal cumulative distribution function (CDF)

Let $\mathbf{Q = X_j\text{'}B}$**,** then for the logistic CDF

$G(\mathbf{X_j}\text{'}B) = \mathbf{G(Q) = L(Q)}$

and

$$L(Q) = \frac{1}{1 + \exp(-Q)} = \frac{\epsilon^{Q}}{(1 + \epsilon^{Q})} \quad ,-\infty < Q < \infty, \;\ldots\ldots\ldots\ldots 3$$

This function closely approximates the normal CDF (Cox, 1970) and is numerically simple. If $\mathbf{P_j}$ **in (2)** is related to the index $\mathbf{1_j = Q}$ above by the logistic CDF, then

$$P_j = \frac{1}{1 + \exp(-I_j)} = \frac{\epsilon^{Ij}}{(1 + \epsilon^{Ij})} \qquad \ldots\ldots\ldots\ldots 4$$

Where ϵ represents the base of natural logarithms and is approximately equal to 2.718.

This formulation has the property that the odds ratio is a log-linear function of $\mathbf{X_j\text{'}B}$ and is given by

$$\exp(I_j) = \frac{P_j}{1 - P_j}$$

$$\therefore I_j = \log \frac{P_j}{1-P_j} = \alpha + \beta Xj \ldots\ldots\ldots\ldots\ldots\ldots 5$$

log $P_j/1-P_j$ is simply the logarithm of the odds that a particular event will occur and can be generalized as follows:

$$\log \frac{P_j}{1 - P_j} = I_j = \alpha + \beta_1 X_1 + \beta_2 X_2, + \ldots +, \beta_n X_n \ldots\ldots 6$$

where α = constant

$\beta_1 \ldots \beta_n$ = unknown parameters to be estimated

Equation **(6)** is the specification of the standard Logit model to be estimated.

III.3.2.2.1 Measurement of the Defined Variable

The goal of the logit model is to predict the odds of an Equity Issue failing, conditional upon information about investor attributes and attributes of particular companies. Five variants of the Logit model were specified as below. This model was estimated using Logistic Regression procedures of the Statistical Package For Social Sciences (SPSS/PC+)

$$\log \frac{P}{1 - P} = \alpha + \beta_1 L_h + \beta_2 R_h + \beta_3 E_h + \beta_4 D_h + \beta_5 OP + \beta_6 IS + \beta_7 Y + \beta_8 Z + \beta_9 T + \beta_{10} L + \beta_{11} PER + \beta_{12} E_p + \beta_{13} D_p + \in \ldots\ldots\ldots 7$$

$$\log \frac{P}{1 - P} = \alpha + \beta_1 L_h + \beta_2 R_h + \beta_3 E_h + \beta_4 D_h + \beta_5 OP + \beta_6 IS + \beta_7 Y + \beta_8 Z + \beta_9 T + \beta_{10} L + \beta_{11} PER + \in \ldots\ldots 8$$

$$\log \frac{P}{1 - P} = \alpha + \beta_1 Y + \beta_2 IS + \beta_3 E_h + \beta_4 D_h + \beta_5 OP + \beta_6 PER + \in \ldots\ldots 9$$

$$\log \frac{P}{1 - P} = \alpha + \beta_1 L_h + \beta_2 R + \beta_3 Z + \beta_4 OP + \beta_5 L + \beta_6 PER + \in \ldots\ldots 10$$

$$\log\frac{P}{1-P} = \alpha + \beta_1 E_h + \beta_2 D_h + \beta_3 OP + \beta_4 Y + \beta_5 E_p + \beta_6 D_p + \in \text{.....} 11$$

Note: The subscripts **h** and **p** represent historical and projected values respectively.

III.3.2.2.1.1 Model 1 (equation 7)

This model sought to capture the combined effects of historical and projected financial performance on ivestment patterns. Moreover, the model serves as the full model.

III.3.2.2.1.2 Model 2 (equation 8)

This model served as a semi-full model and contained cost and benefit variables, industry investment in theory.

III.3.2.2.1.3 Model 3 (equation 9)

This is a selective model which was used to test the hypothesis that industrial and market variables (in addition to the most important cost and benefit variables) significantly influence the probability of Issue failure.

III.3.2.2.1.4 Model 4 (equation 10)

This model sought to test the effects of variables within the control of the company only. It tested the "Management Effect".

III.3.2.2.1.5 Model 5 (equation 11)

This model is another selective model and had to do with costs and benefit of equity investment. It tested the selectivity of investors in making equity investments. The investment attributes and their definitions are listed in Table 1 below.

III.3.2.2.2. Logit Estimation Technique.

Following reports from the literature on suitable techniques for estimating Logit specifications (Schultz 1982 a&b, Judge et. al. 1980, Pindyck and Rubinfeld, 1985), the study employed maximum likelihood estimation (MLE) technique for the Logit model.

Desirable properties of MLE are that parameter estimators are consistent, asymptotically efficient and normal especially for large samples.

The computational method used is the iterative linearization method in which nonlinear equations are linearized (using a Taylor series expansion) around some inital set of coefficient values. Thereafter, successive ordinary least squares (OLS) are performed on successive linear equations, generating new sets of coefficient values with the succeeding equations being relinearized around these values until convergence is attained, i.e., until the coefficient values do not change substantially after each new ordinary least squares regression.

Advantages of this method include computational efficiency and the provision of clear guidelines for applying statistical tests (e.g $\mathbf{R^2}$ & t statistics). Sometimes, convergence is dependent on the particular initial guesses chosen. The danger here is that the iterative process may not converge at all and might even diverge i.e. successive estimates of the coefficients may differ with the difference growing larger with each new iteration. Should divergence occur either a new set of initial guesses is chosen and the process started afresh or a different estimation method is employed.

III.3.2.2.3 Expected Information from the Logistic Model.

The results of our estimation were expected to shed light on why Equity Issues fail or succeed and why investors invest or refrain from investing. The results were also to clarify whether investors respond to economic factors only or they respond to both economic and non-economic factors. Relative impacts of changes in the specified variables were also to be ascertained.

III. 3.2.2.4. Interpretation of and Predicting with Estimated Parameters.

Since the left hand side of the logit model is the logarithm of the odds of choice and not the actual probability, the interpretation of individual estimated parameter need to be done with care. For example, to interpret the effect of a change in $\mathbf{D_h}$ on the probability of Issue failure, we need to solve for the change in probability $\Delta\mathbf{P}$ as follows.

$$\Delta\log \frac{P}{1 - P} = \beta_d \Delta D \text{ ....12}$$

To predict the odds of an Issue failing, we simply evaluate the right hand side of the estimated equation. Taking antilogarithms of the calculated logarithm (**base $\in$**) of the odds and solving will yield the predicting probability.

III.3.2.3 Discriminant Analysis Procedure

The computational method of the MDA procedure forms linear combinations of the independent (predictor) variables which serve as the basis for classifying cases into one of the groups.

The data used was the actual values of the variables for cases whose group membership were known. In addition, the actual data of the dependent variable was coded for the known groups (e. g. 1 for the failed and 2 for the successful group). Thus, the information contained in the actual values of the predictor variables is summarized in a single index (Z values). To distinguish between the groups, thc computed Z values for the groups must differ.

Furthermore, the computation of the discriminant function compares the known group membership to the predicted group membership and determines the most likely group for a case based on discriminant analysis (the group with the largest posterior probability). Misclassified cases can therefore be identified using the discriminant function and the rates of misclassification determined. These rates serve as important indices of the effectiveness of the discriminant function.

The danger here is that when one of the groups is much smaller than the other, a highly correct classification rate can occur even when most of the "minority" group cases are misclassified.

The desired result is therefore not to minimize overall misclassification rate but to identify most cases of the smaller group. In this respect, observed misclassification rates should always be viewed in the light of results expected by chance. The model was also estimated using the SPSS/PC+.

III.3.2.3.1 Specification of the Discriminant Functions.

Five variants of the Multiple Discriminant model were specified as follows.

$$Z = \omega_0 + \omega_1 L_h + \omega_2 R + \omega_3 E + \omega_4 D + \omega_5 OP$$

$$+ \omega_6 IS + \omega_7 Y + \omega_8 Z + \omega_9 T + \omega_{10} L$$

$$+ \omega_{11} PER = \omega_{12} W + \omega_{13} RR \quad \ldots\ldots\ldots\ldots 13$$

$$Z = \omega_0 + \omega_1 L_h + \omega_2 R + \omega_3 E + \omega_4 D$$

$$+ \omega_5 OP + \omega_6 IS + \omega_7 Y + \omega_8 Z$$

$$+ \omega_9 T + \omega_{10} L + \omega_{11} PER \quad \ldots\ldots\ldots\ldots 14$$

$$Z = \omega_0 + \omega_1 E + \omega_2 D + \omega_3 OP$$
$$+ \omega_4 IS + \omega_5 Y + \omega_6 PER \quad \ldots\ldots 15$$

$$Z = \omega_0 + \omega_1 L + \omega_2 Z + \omega_3 OP$$
$$+ \omega_4 L_h + \omega_5 R + \omega_6 PER \quad \ldots\ldots 16$$

$$Z = \omega_0 + \omega_1 E + \omega_2 D + \omega_3 OP + \omega_4 Y \quad \ldots\ldots 17$$

Model 1 (equation 13) serves as the full discriminant model while model 2 (equation 14) is a semi-full model, Models 3-5 (equations 15-17) are variants similar to the logistic regression models 2-5 section 3.3.2.2 above.

III. 3.2.3.2. Expected Information From MDA Model

i. The magnitudes of the standardized (to a mean of 0 and standard deviation of 1) discriminant function coefficients indicate relative importance (contribution) of the variables. The standardization is to adjust for unequal means and standard deviations give the different units of measurement. The actual signs of the coefficients are considered arbitrary.

ii. The canonical correlation was obtained as a measure of the degree of association between the discriminant scores and the groups. This is equivalent to eta from one way analysis of variance, in which the discriminant score is the dependent variable and group is the independent variable. In our 2 group situation, this is the Pearson correlation coefficient between the discriminant score and the group variance which is coded 0 and 1 (i.e. the dependent variable).

iii. Wilks' lambda was obtained as the ratio of the within-group sum of squares to the total sum of squares. It is the proportion of total variance in the discriminant scores not explained by differences among groups (Lambda + eta^2 = 1). Small values of lambda could imply much variability between groups and little within groups. A lambda of 1 imply equal mean for the discriminant scores in all groups and no between-group variability.

iv. Eigenvalues were obtained as a meausre of "goodness of fit". Large eigen values are associated with "good" functions.

III.3.3 Hypotheses Testing

III.3.3.1 Logistic Analysis

In addition to employing t-ratio tests, model chi-square tests were to assess the statistical significance of differences between failed and successful Issues. This is comparable to the overall F test for regression analysis. a second method, the likelihood ratio test was also employed for logistic analysis to test the significance of the entire model.

III.3.3.2 Discriminant Analysis

Wilks' lambda was transformed to a chi-square value to determine the level of statistical significance of the model. This was to test the null hypothesis that in the populations from which the samples were drawn, there is no difference between the group means i.e the population means are equal.

However, it is important to note that significance in this test does not neccessary indicate effective classification by the discriminant function. This is because, small differences may be statistically significant but still not allow good discrimination among the groups. Moreover, if the means and covariance matrices are equal, then discrimination is not possible at all.

IV. EMPIRICAL RESULTS

IV.1 Logistic Regression Analysis

The probability of failure or success of an Equity Issue was estimated directlly using logistic regression and the most important results are presented below.

Model 1: Equation 7

This model employed variables depicting the combined effects of historical and projected financial, industrial and market conduct factors on investment. It served as the full logistic model. The results indicated that only the coefficients for dividend and profitability appeared to be significantly different from zero using a significant level of 10 per cent. Furthermore, the values of the R statistic indicated that as the values of price earnings ratio and liquidity decrease, the likelihood of Equity Issue success increases and vice versa.

On the other hand, as the values of profitability, dividend and income increase, so does the likelihood of Issue success and vice versa. The variables leverage, size, offer price, industrial sector, timing, earnings (historical and projected) as well as projected dividend were found to have no partial contribution to the model although their not having negative values may indicate a positive relationship with Issue success.

The result also showed that 29 out of 32 (90.63 per cent) "Failed Issues" were correctly predicted by the model while 9 out of 15 (60 per cent) "Successful Issue" were also correctly predicted. Of the 47 cases studied, the model found 9 cases (19.15 per cent) of misclassification leaving overall correct classification at 80.85 per cent). This indicated that the model can predict to a very high level (80.85 per cent) the probability of Issue failure or Success.

The significant level of the model chi-square (.0820) indicated that the over all model was sufficiently significant although the relatively small observed significant level for the -2LL (.2414) and goodness-of-fit statistics (.0175) suggested that the model differed "significantly" from the perfect model (which has a *likelihood* of 1) although it fitted the data reasonably well.

Model 2: Equation 8

This is the semi-full model which excluded the variables for projections and the results are presented below. This specification increased the number of significant variables from 2 in the full model to 3 and even imporved on the previous level of significance of the significant variables. The coefficient for profitability was found to be significant at 5 per cent level while those for dividend and liquidity were both significant at 10per cent. The values of the *R statistic* imply that in this specification, offer price and liquidity had negative relationship with the likelihood of Issue success whereas profitability, dividend and income showed a positive relationship.

The variables leverage, price earnings ratio, size, industrial sector, timing and earnings indicated no partial contribution to the model. Also of note is the fact that this specification had a positive sign for the B coefficient for earnings instead of the negative sign obtained in the full model. Furthermore, in terms of signs, only the variables for liquidity and timing had signs contrary to eoconomic expectations.

The results indicate that the removal of the projection variables (DP and EP) only affected the correct prediction of successful Issues but no failed Issues. Only 7 out of 15 (46.67 per cent) successful Issues were correctly predicted, thereby reducing correct prediction by 13.33 per cent. This translates to a 4.24 increase in mis-classification rate and a corresponding decrease in overall correct classification. This was a clear indication that projected earnings play a significant role in Issue success and supported findings on preferences of investors. Nevertheless, the model still predicted to a high level (76.60 per cent) the probabilty of Issue failure or success.

These results did not differ significantly from those of the full model. They indicated that the model fitted the data reasonably well.

Variables in model 2 were further subjected to a stepwise selection procedure to identify subsets that are good predictors of the dependent variable. The results of the subset show the B coefficient for income being significant at the 10 per cent level in addition to an improvement in the significant level of the dividend coefficient to 5 per cent level. Furthermore, the resulting classification table shows that although the overall predictive power was not better than the substantive model (at 76.60 per cent), it was not worse off. Nevertheless, the subset succeeds in improving the percent correct prediction of successful Issues without increasing the overall mis-classification rate.

Model 3: Equation 9

This is a selective model which sought to test the influence of industrial and market variables on Issue success or failure. From the results of this specification, none of the coefficients appeared to be significantly different from zero although the overall predictive power was still good at 68.09 per cent. Nevertheless, the rate of mis-classification was " significant" at 31.91per cent and it mostly occurred with the successful Issues.

Using the parameters of this model, 11 out of 15 (73.33 per cent) successful Issues were mis-classified (i.e. correctly predicted as failed Issues) while 4 out of 32 (12.50 per cent) Issues classified as failed were predicted to be successful Issues.

Model 4: Equation 10

This specification was used to test the "management effect" and the results are presented in tables below. From the tables, a rate of misclassification (29.79 per cent) similar to model 3 was observed in this model although the overall correct classification was higher at 70.21 per cent. Although the results indicated that management effect could be significant (Profitability coefficient is significant at 5 per cent), like in model 3, this specification could not sufficiently explain why Issues "succeed" although it excellently explained why Issues fail.

Model 5: Equation 11

This selective model sought to analyze the effects of costs and benefits (historical and projected) on investment decisions. The results showed that this select model was as powerful in prediction as the full model. Although it had almost 100 per cent (96.88 per cent) predictive accuracy for failed Issues, it could not sufficiently explain successful Issue, thus suggesting the presence of other factors not captured here that influence success. This implied that while failure can be accurately predicted using the factors identified in this study, prediction of success requires some other factors not captured here.

IV.2 Discriminant Analysis

This classification technique was applied to the raw data in order to assess whether an Issue was a failure or success. The models for this analysis are as specified in section II (equations 13 to 17) and the most important results are presented below.

IV.2.1 Descriptive Statistics

The table of univariate group means (Table 2) below indicate that Issues which failed were from companies with lower probability, lower returns, lower dividend, lower retention rate and lower working capital ratio than successful Issues. Furthermore, failed Issues took longer to pay back investment and were in the less preferred industrial sectors than successful Issues.

Model 1: Equation 13

This was the full discriminant model which combined important financial,industrial and market conduct variables in the discriminant analysis procedure to classify Issues as failed or successful.

From the estimated results, offer price, earnings, dividend and income were the variables whose means were most different for failed and successful Issues. Also, from the standardized discriminant function coefficient results, offer price ranked the highest in terms of relative importance followed by income, size, industrial sector and leverage. The actual sign of these coefficients is arbitrary.

Secondly, the value of lambda imply that about 62 per cent of the total variance in the discriminant scores was not explained by differences among groups. In addition, the significant level for the transformed lambda (not significant) indicate that it was likely that Issues which failed and those which succeeded had the same means on the discriminant function i.e. we should accept the null hypothesis that the population means are equal. However, we note here that the level of significance of lambda only provides a test of the null hypothesis but not much information on the effectiveness of the discriminant function in classification.

The results also gave the eigenvalue as .6131 implying that the function fitted the data about 61per cent which can be considered a good fit. This fit was further supported by the high degree of association between the discriminant scores and the groups as recorded by the value of the Pearson correlation which is .6165. Furthermore, the classification table indicated a high level (76.6 per cent) of overall correct classification and low (23.4 per cent) level of incorrect classification by the model.

When we compared this result to that from the full logit model, we observed that even though the predictive power was slightly less 4.25 per cent, the specified discriminant function appeared to be a more effective classification function. This is because the proportion of mis-classified cases was almost evenly distributed and not unduly tilted towards the "minority" (successful) group as happened with the logit model. Given that our successful group was much smaller (15) than the failed group (32), this was a more desirable result.

Model 2: Equation 14

This semi-full model was specified without some of the variables considered insignificant from the analysis of the full model and the results are presented below. This specification also ranked offer price highest in terms of contribution to overall discriminant function followed by income and size like in the full model. The fourth and fifth ranks were occupied by leverage and earnings respectively.

The value of lambda here imply that the percentage of total variance in the discriminant scores not explained by differences among groups was increased with this specification. However, the level of significance indicated that the population means were not equal and that we should reject the null hypothesis. In addition, the eigenvalue statistic indicate that the function fitted the data reasonably well and supported by the substantial degree of association between the discriminant scores and the groups.

The results also indicated that the predictive power of the semi-full model was the same as that of the full model in all respects. This implied that the dropped variables did not affect the predictive power of the model. When we compared this model to its logit counterpart, we observe that the model had the same overall correct predictive power although it was more effective in classification.

Model 2 was further analyzed using stepwise variable selection rule that minimized residual variance (i.e the sum of unexplained variations) and the results are given below. From the summary table below, the procedure selects offer price, income, size and earning as the variables which contributed most to the overall discriminant function when residual variance was minimized. Even though the selected function marginally fitted the data (eigenvalue = .4611), the chi-square value of lambda was significant implying that it was unlikely for failed and successful Issue to have the same means on the discriminant function i. e. the population means were not the same.

Furthermore, the classification results showed that this was a more effective selection with overall correct classification at 78.72 per cent which imply lower misclassification rate especially for the minority group. This classification result also indicated the presence of poor predictors in the general model since percent correct classification was lower. This stepwise selection also out-performed its counterpart in the logit estimation technique both in terms of effectiveness and overall correct classsification.

Model 3: Equation 15

This specification ranked income, dividend, earnings and industrial sector in descending order of importance. The results indicated that the model did not fit the data well although its predictive power was high (72.34 per cent). Nevertheless, when compared to its logit counterpart, it also appeared to be a more desirable selection.

Model 4: Equation 16

Model 4 ranked offer price, profitability, size and leverage in descending order of importance. The goodness of fit was very low (eigenvalue = .2885) although lambda was marginally significant implying that the population means were not equal. evertheless, the predictive power was almost as high as the full model (74.47 per cent) although there was less effectiveness in classification. The model also compared more favorably with its logit counterpart.

Model 5: Equation 17

Although the goodness of fit for this model was not as good as model 1, the Wilk's lambda was highly significant. The model indicated that when it comes to purely cost and benefit factors of investment, income ranks the highest (over offer price) in terms of relative contribution to overall discriminant function.

Furthermore, the model showed high predictive power (72.34 per cent) and was quite effective in classification. A comparison with the logit counterpart also indicated greater effectiveness of the discriminant model.

V. SUMMARY OF FINDINGS

Results of the estimated equations are further summarized below:

1 Logit Model

The results of the full logit model indicated that as profitabilty, dividend and income increases, so does the likelihood of Issue success and vice versa. Similarly, as price earnings ratio and liquidity decreases, the likelihood of Issue success increases and vice versa. These results are generally in line with economic thinking.

The overall model was sufficiently significant and fitted the data reasonably well. Furthermore, the predictive power of the model and its variants was found to be generally quite high suggesting that there are significant differences in the weights investors attach to factors influencing their investment decisions.

The stepwise selection of variables indicated that economic factors have significant influence on investment patterns.

The results indicated that "management effect" could be significant in determining Issue failure or success.

From the results of the various specifications, it would appear in general that while the selected variables in the study could excellently explain why Issues fail,they could not sufficiently explain why Issues succeed. This empirical evidence further supports our hypothesis that investment patterns in Nigeria are relatively less characterized.

The results showed that projected earnings and dividend play a significant role in Issue success.

2. Discriminant Analysis

The results of the discriminant analysis procedure indicated that Issues which fail are from companies with lower profitability, returns, dividend, retention rate and working capital ratio. Furthermore, such Issues took longer to pay back investment and were from less preferred industrial sectors.

The results indicated that offer price, earnings, dividend and income are the variables whose means are most different for failed and successful Issues. Furthermore, the results rank offer price and income higher in terms of relative importance (i.e. contribution to overall discriminant function).

The overall discriminant function also fitted the data reasonably well. Furthermore, the predictive power of the model and its variants like the logit model were found to be generally quite high also suggesting that there are significant differences in the weights investors attach to factors influencing their investment decisions.

The stepwise selection of variables indicated that offer price, income, size and earnings are the variables which contribute most to overall discriminant function when residual variance is minimized.

From the results of the various specifications, the high values (above 60 per cent) of lambda indicated that a high proportion of total variance in the discriminant scores was not explained by differences among groups. These findings also confirm the hypothesis that equity investment in Nigeria (a developing country) are relatively complex and hence relatively less characterized.

A comparison of the logit and discriminant results showed that the discriminant procedure produces more desirable results in terms of effectiveness and overall correct classification.

VI. POLICY IMPLICATIONS AND RECOMMENDATIONS

Policy implications and recommendations derivable from the results of the study are as follows:

Although investors, investment advisers, portfolio managers, company executives and credit managers will typically not have access to computer procedures such as the discriminant and logistic regression programs, the potential presents itself for utilization in their business dealings. The significant point is that the models developed in the study contain many of the variables common to their business evaluations.

For instance, corporate management needs to periodically assess the company's strengths and weaknesses and effect necessary changes in policies and actions. The implication here is that these models if used correctly, have the ability to predict corporate investment problems early enough to afford management time to avoid failure.

Similarly, these models could also be valuable techniques for screening out undesirable investments or for recommending appropriate investment policies. The potential implications should therefore be of interest to investors, investment advisers as well as portfolio managers. Furthermore, these models could be extended to provide a fast and efficient device for detecting unfavorable credit risks to enable credit managers avoid potentially disastrous decisions. This is in view of the very important role of financial statement analysis in credit management.

VII. CONCLUSIONS

In the study relating to a sample of 47 Equity Issues from 45 Nigerian companies over the period 1988-92, two classification models were derived from a data sct comprising macro and micro economic indicators, an industry variable and various accounting ratios. The models were the multiple discriminant and logistic regression models.

Both models performed well and were able to classify equity issues correctly as failed or successful to a high degree (over 70 per cent correct classification). Overall, it was clear that for both models, the major warning signals appear to be low profitability, low dividends and high price earnings ratio. However, the precise variable characteristics evaluated in the two models do differ in some interesting ways.

For instance, the discriminant model considers industry membership and returns as important factors, a position not shared by the logit model. On the other hand, the logit model considers income and liquidity as important but not the discriminant model. These differences might be responsible for the better performance of the discriminant model over its logistic counterpart in the classification results. In addition, the superior performance of the discriminant model may be a sign that distributions in the Nigerian capital market approximate normal. Furthermore, using actual values of independent variables may enhance the efficiency of the discriminant model in contrast to the coded values used throughtout in the logit estimation. This indicates that coding the variable values may lead to loss of efficiency in classification bewteen failed and successful Issues.

A potential theoretical area of importance is the conceptualization of efficient portfolio selection. On the practical side, recommendations were made for investment guidelines, credit management as well as company internal controls.

TABLE 1

Definition of Logistic Variables

Variable	0 (Failure)	1 (Success)
Liquidity (L)	If QR <1	Otherwise
Profitabilty (R)	If ROE <20%	Otherwise
Returns (E)	If EPS<20k for Issues before 1991 and <30k thereafter	Otherwise
Pay-outs (D)	If DPS<10k for Issues before 1991 and <20k thereafter	Otherwise
Office Price (OP)	If > economic value	Otherwise
Industrial Sector (IS)	If not in the first 11 preferred	Otherwise
Timing (T)	If other Issues also offered one month before or within offer period	Otherwise
Coy. Size (Z)	If Issued Capital <=N=10 Million	Otherwise
Available Capital (Y)	If Savings Rate<20% Per Capita Income	Otherwise
Leverage (L)	If>5 for large companies and >3 for small companies	Otherwise
Price Earning Ratio (PER)	If PER Negaive or >5	Otherwise

NOTE: 1. **QR, ROE, EPS, DPS, PER and L** are as defined above.

2. The Economic Value of a company was obtained by averaging the share values using the 3 popular share valuation methods i. e.
   - Average Maintainable Earnings Method
   - Net Tangible Assets Methods and
   - Weighted Average Net Profit Method.

Table 2: Group Means

Var	Failed Grp	Successful Grp
L	8.4147	9.7127
W	110.5944	112.8307
R	-9.4063	34.5333
PER	6.5441	3.7007
RR	46.125	53.000
Z	21.6492	19.3533
OP	85.500	124.33
IS	.176	.252
T	.844	.933
LH	1.67	1.13
E	16.481	44.833
D	7.397	17.863
Y	20.894	27.884

NOTES

1. Dr. Ako obtained her doctorate from the University of Lagos.

2. According to Avadi (1984), Samuels and Yacout (1981), the Nigerian stock market is price efficient.

3. Quick ratio is a measure of current assets of the company relative to current liabilities. For a liquid company, this ratio must not be less than 1 (one)

4. This variable is represented by the ratio of profit after tax to shareholder's funds.

5. To obtain this ratio, net earnings after interest and tax is divided by the total number of shares outstanding. It is a measure of the true productivity of a firm and can represent the level of insolvency.

6. This ratio is calculated by dividing total number of shares outstanding into earnings not retained (distributed). The measure shows how much income goes to owners of the firm (shareholders).

7. This is represented by the ratio of total liabilities to tangible net worth. It measures long term solvency of the company.

8. This is represented by the ratio of sales to working capital.

9. It is represented by the ratio of market price of shares to earnings per share or the ratio of market capitalization of shares to profit after tax.

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