ICESDA 2024 PROCEEDINGS
ISSN -3057-3912 PRINT
3057-3920 ONLINE

Modelling Financial Distress in the Nigerian Banking Sector

Adeyemi Aderin[2]

Executive Business Centre, Greenwich Business School, University of Greenwich

Track 1: ESG/ CSR and Sustainability of Africa Continental Free Trade Area

Abstract

The study seeks to develop a model for bank sustainability through the prediction of financial distress in the Nigerian banking sector, which could also find applicability for the entire Africa region. The banking sector in any economy is largely important due to its ability to redistribute funds from the surplus segment to the deficit segment of the economy, hence, developing a distress model to predict financial distress in the banking sector helps to enhance the sustainability of corporate financial institutions in Africa. The study utilises a total of 2,205 point-observations consisting of a balanced sample of distressed and non-distressed banks. The analysis involves the use of the multiple discriminant analysis in developing a model for the accurate prediction of financial distress among Nigerian listed banks, necessitated by the inherent shortcomings in extant prediction models. The study achieves its goal of accurate distress prediction by developing a concise model that adequately predicts financial distress among Nigerian banks with a success rate of 91.4% and has high predictive ability for long range distress forecasts extending beyond five years. It is recommended that relevant regulatory authorities should experiment this new model in testing the 'health' status of banks at the end of every financial year to ascertain their true state of affairs. This will assist in taking proactive measures to guide against any form of inherent anomalies which could snowball into disastrous outcomes.

Keywords : Modelling, Financial distress, Accounting ratios, Traditional models, Multiple discriminant analysis.

Aderin, A. (2024). Modelling Financial Distress in the Nigerian Banking Sector. In: Owusu-Manu, D., Adesi, M. and Acheampong, A. (Eds) Proceedings of the 1st International Conference on Environment, Social, Governance and Sustainable Development of Africa (ICESDA-2024), 26-29 March 2024, Kwame Nkrumah University of Science and Technology (KNUST)-Kumasi, Ghana, Green Communities International, 1-20.

Introduction

Every organisation is ordinarily expected to continue as a going concern into the foreseeable future. An organisation that cannot sustain its activities and operations would begin to encounter distress signals, which if not properly managed or promptly checked could lead to its eventual collapse. Financial distress has been referred to interchangeably in the literature with such terms as depressed firm, sick firm, unhealthy firm, firm default, financial failure, and firm bankruptcy (Altman 1968; Cao and Chen, 2012; Bauer and Agarwal, 2014; Mizdrakovic and Bokic, 2016; Sabela et al., 2018). The operational definition of financial distress entails the occurrence of events such as financial losses, default on bond redemption, non-payment of dividends on preferred stocks, and the risk of corporate insolvency (Beaver, 1966). The progress in literature has shown a paradigm shift from a purely legal

[1] adeyemi.aderin@greenwich.ac.uk

ISSN -3057-3912 PRINT
3057-3920 ONLINE

definition of financial distress to a more encompassing concept that incorporates not just accounting variables, but other non-financial and economic variables (Sabela et al., 2018).

Corporate financial distress entails a lack of soundness of the corporation both internally; in relation to the inner workings and make-up of the firm, and externally; in relation to its interactions with its communities and ecosystems (Monnaso, 2007). Boratynska and Grzegorzewka (2018) asserted that firm distress in itself is not an entirely negative phenomenon, as it helps to give warning signals of impending danger to unprofitable entities, but could nevertheless lead to significant long-run shift in economic equilibrium. This shift in economic equilibrium arises as a result of firms' inability to adjust appropriately to distress situations and eventually going bankrupt. The distress in this sense is technically distinct from failure and refers to the strains and pressures encountered by firms as forerunners to their eventual failure (Adekanmbi, 2017).

The incidence of corporate failures worldwide brought to the fore the need for a financial architecture embodying distress prediction and management (Lin et al., 2010). The continually growing literature on firm distress and failure are borne out of the increasing cases of distress scenarios in recent decades, as researchers try to identify factors that precipitate or contribute to these scenarios. Timely and accurate assessment and prediction of the distress probabilities become essential with major implications for business and investment decisions. This has led to increased level of interest in the development of more contemporary distress prediction models in order to overcome the flaws inherent in the traditional prediction models (Sensini, 2016).

The banking sector in any economy is the singular most important sector in that economy due to its ability to redistribute funds from the surplus segment to the deficit segment of the economy (Adekanmbi, 2017). This highlights the crucial role of the sector in engendering economic growth (Wanke et al., 2015). This importance has prompted continuous regulations and interventions in the sector by government; especially in the case of Nigeria. Majority of the previously developed prediction models (Altman, 1968; Ohlson, 1980; Cao and Chen, 2012; Altman, 2013; Bauer and Agarwal, 2014; Shah, 2014; Jones, 2017) did not take cognisance of bank specific variables in their estimation which may have partly accounted for their low predictive ability in determining the likelihood of distress scenarios in banks. Country specificity should also be considered in the development of such models as extant literature (Ugurlu and Aksoy, 2006; Boritz et al., 2007; Wang and Campbell, 2010; Gupta, 2014; Singh and Mishra, 2016) have shown that models do not have universal applicability; given their predictive powers decrease as they are 'shipped' to foreign climes. Altman et al. (2014:1) supported this position when they asserted that: "...the classification accuracy may be considerably improved with country-specific estimation. In some country models, the information provided by additional variables helps boost the classification accuracy to a higher level."

In developing a concise distress prediction model, the adoption of an appropriate proxy for financial distress is of utmost importance. Prior studies such as Sabela et al. (2018) and Wang and Campbell (2010) utilised the delisting of firms from the stock exchange as a proxy for capturing distress. This is deemed to be a faulty measure as delisting can be a conscious strategy by firms to buy back their shares, and completely healthy firms could also be delisted by the regulatory authorities due to

Aderin, A. (2024). Modelling Financial Distress in the Nigerian Banking Sector. In: Owusu-Manu, D., Adesi, M. and Acheampong, A. (Eds) Proceedings of the 1st International Conference on Environment, Social, Governance and Sustainable Development of Africa (ICESDA-2024), 26-29 March 2024, Kwame Nkrumah University of Science and Technology (KNUST)-Kumasi, Ghana, Green Communities International, 1-20.

ICESDA 2024 PROCEEDINGS
ISSN -3057-3912 PRINT
3057-3920 ONLINE

violation of listing legislations. Cao and Chen (2012) used the direction of net cash flows (with major focus on negative cash flows from operations) as their indicator for financial distress. This proxy is also perceived to be faulty in the sense that the outcome of the direction of net cash flows could be temporary coping mechanisms by organisations to balance off such conditions as the need to take advantage of major investments or pay off some major debts that are hampering the efficiency of the organisations' operations. This study utilised an improved proxy backed by the Nigerian apex banking authority and classify the sample of the study as distressed or non-distressed based on the Central Bank of Nigeria (CBN) classification and subsequent intervention of the listed banks.

Literature Review

The foundational/traditional models of financial distress prediction (Altman, 1968; Ohlson, 1980; Taffler, 1983; Zmijewski, 1984) were developed mostly with accounting ratios contained in the annual reports of firms, and these ratios have gained general acceptability as important determinants of firm survival as well as significant indicators of financial distress. Despite this position, extant literature (Chava and Jarrow, 2004; Hillegeist et al., 2004; Bauer and Agarwal, 2014) opine that forecasting accuracy can be improved by adding market-based variables to accounting based variables. Hillegeist et al. (2004) utilised an option pricing model embed with market-based data. Their model was analysed vis-à-vis the prediction variables of Altman (1968) and Ohlson (1980). For the Altman (1968) model, they found only two of the variables (leverage and profitability) to be significant. For the Ohlson (1980) model, they found that five out of the eight variables have contradicting signs. Hillegeist et al. (2004) further revealed that distress probability was higher for larger, more profitable, cash flow rich firms with higher working capital. These results contradict casual empiricism and average expectations in real world scenario where it would ordinarily be expected that larger, more profitable firms would have lower probability of distress as opposed to smaller, less profitable firms. Nevertheless, the evidence showed the inability of 'old' models to cater for distress prediction in 'modern' settings which propelled the authors to develop their option based prediction model. They found that their model was more distress relevant than both the Z-score and logistic models. Charitou and Trigeorgis (2004) built on the flaws of the model of Hillegeist et al. (2004) and developed an improved model based on the option pricing model. Charitou and Trigeorgis (2004) asserted that their model is superior to that of Hillegeist et al. (2004), as the latter does not provide for time series prediction rates in the periods leading up to the distress. Charitou and Trigeorgis (2004) corrected for this shortcoming through the provision of a time series monitoring mechanism which allows a firm's progress to be tracked over time. They posited that the addition of a proxy for capturing intermediate defaults (such as cash flow coverage) helps to improve the overall prediction power up to four years before the distress situation occurs. Bauer and Agarwal (2014) utilised a hazard model consisting of both accounting and market-based variables. They did a comparison between the hazard model and traditional distress models and found that the hazard model embedded with market-based variables was superior to all the traditional model variants considered.

Aderin, A. (2024). Modelling Financial Distress in the Nigerian Banking Sector. In: Owusu-Manu, D., Adesi, M. and Acheampong, A. (Eds) Proceedings of the 1st International Conference on Environment, Social, Governance and Sustainable Development of Africa (ICESDA-2024), 26-29 March 2024, Kwame Nkrumah University of Science and Technology (KNUST)-Kumasi, Ghana, Green Communities International, 1-20.

Other literature (Chen and Du, 2009; Lin et al., 2010; Kouki and Elkhaldi, 2011; Eriki and Udegbunam, 2013; Boratynska and Grzegorzewka, 2018) provided support for the superiority of the artificial intelligence models over the traditional statistical models. Chen and Du (2009) asserted that traditional methods cannot cater for the radical and revolutionary dynamism of the financial and global economic sphere, hence, the necessity to develop evolutionary measures to cope with the environmental dynamism. They proposed ideal models to cater for this dynamism based on artificial intelligence models (an integration of the artificial neural network and data mining techniques).

Lin et al. (2010) utilised the support vector machine model (an artificial intelligence model) and found that it gave better prediction accuracy than the traditional Z-score model. Kouki and Elkhaldi (2011) executed a three year comparative analysis of the multiple discriminant analysis models, logit models and the neural network models to determine the predictive powers of the models. Their results indicate that the neural network model exhibited the highest predictive powers for the short term horizon.

Eriki and Udegbunam (2013) utilised three classification sets (training, validation and test) and found overall superiority in the prediction accuracy of the neural network over the multiple discriminant analysis. Shah (2014) analysed the predictive effectiveness of distress models developed with diverse techniques such as the artificial neural networks, decision trees, discriminant analysis, logistic regression, recursive partitioning and hybrid methods. Though one of the hybrid methods (combination of the artificial neutral networks and the logistic regression) ranked first among all the techniques utilised, the artificial neural network ranked highest among the individual techniques utilised. The study of Stanisic et al. (2013) also highlights support for the superiority of the artificial neural networks over the Altman's Z-score model and other formulated models based on the logistic regression and decision tree methodologies. They used two sets of samples; a training set consisting of one hundred and thirty firms in Serbia (made up of sixty five healthy and sixty five distressed firms) and a hold-out sample of one hundred and two distinct firms for the period between 2009 and 2011.

The resultant superiority of the artificial neural networks over the Altman's Z-score model in these aforementioned studies is however believed to be flawed because the artificial neural network was developed with data representing the specific market conditions of those economies, while the Z-score model was developed with US data. A more appropriate comparison would be fostered by the development of multivariate scores using data from the specific economic context of interest.Monasso (2007) also gave credence to artificial intelligence default prediction models such as recursive partitioning and neural networks as being better measures of firm survival in terms of prediction accuracy, but asserted that their ingenuity is hampered by lack of concise and clear interpretations and generalisations. We also notice a seeming inconsistency from the previously highlighted studies (Lin et al., 2010; Kouki and Elkhaldi, 2011; Eriki and Udegbunam, 2013; Shah, 2014) that gave support for the artificial intelligence techniques; as those studies reported that the prediction accuracy of the analysed artificial intelligence methods was basically strong one year before the distress period with relatively weaker prediction capabilities in prior years forecast.

Other studies (such as those of Yang et al., 1999; Aziz and Dar, 2006; Abdullah et al., 2008) compared the effectiveness of different prediction models and found discriminant analysis to be superior to other prediction models with better overall distress prediction results. Abdullah et al. (2008)

Aderin, A. (2024). Modelling Financial Distress in the Nigerian Banking Sector. In: Owusu-Manu, D., Adesi, M. and Acheampong, A. (Eds) Proceedings of the 1st International Conference on Environment, Social, Governance and Sustainable Development of Africa (ICESDA-2024), 26-29 March 2024, Kwame Nkrumah University of Science and Technology (KNUST)-Kumasi, Ghana, Green Communities International, 1-20.

analysed three methodologies of distress prediction (multi discriminant analysis, logistic regression and hazard model). Their findings revealed a preference for the multiple discriminant analysis when the totality of the sample is considered. The multiple discriminant analysis produced higher accuracy in prediction rate than the logistic regression and hazard models. The results of Eriki and Udegbunam (2013) also indicated superiority of the multiple discriminant analysis over the neural network in one of the classification sets (training set) utilised. Furthermore, the results of Lin et al. (2010) unwittingly gave support for the multiple discriminant models when their results further indicated that though the support vector model gave better prediction accuracy in the one year forecast, the Z-score model gave better prediction accuracy for longer term forecast (precisely the two years and three years forecast).

The findings of Aziz and Dar (2006) indicate that statistical methods were the most widely used models of distress prediction, accounting for about 64% of all prediction methods. The discriminant analysis was the most popular of the statistical methods accounting for 30% popularity and usage followed closely by the logistic (regression) analysis accounting for about 21% usage, with the neural networks and decision trees accounting for 9% and 6% usage respectively. Smaranda (2014) attests to the fact that institutions and majority of distress prediction studies employ mostly the multiple discriminant analysis, and sometimes the logistic regression technique due to their ease of computation and interpretation in relation to other methods as well as their openness to the formulation of rules of classification. Based on the findings, he however asserted that there is need for the re-estimation of classical models. Jones (2017) also supported the position of Smaranda (2014) and advocated for continual refinement to prediction models given global dynamism especially in relation to significant technical intensification and increasing degree of technological progress.

Also, several studies (Ugurlu and Aksoy, 2006; Boritz et al., 2007; Wang and Campbell, 2010; Mizdrakovic and Bokic, 2016) have shown that previously formulated models which produced impressive prediction results during their formulation experienced continual reduction in their predictive ability as they are 'shipped' to foreign climes. Several reasons adjudged for this discrepancy includes the variations in the economic situations of the countries, as well as differentiations in business cycles. This motivates the position that improvements in financial distress prediction in the Nigerian banking sector would require the utilisation of prediction models developed using Nigerian specific data. As Monasso (2007:5) asserted: "Despite extensive literature, no unanimous set of firm viability indicators has been defined. It is unlikely that a first-best solution of firm soundness indicators can be achieved given the heterogeneity of characteristics at firm, industry and country level". This assertion is supported by the position of Lin et al. (2010) whom despite the improved predictive accuracy of their study asserted that their study was limited on the basis of industry and country specificity.

Methodology

The study adopts the stratified sampling approach in selecting the sample. The justification for this approach is the enhancement of the sample's representativeness of the entire population and the collation and appropriate segregation of information among the groupings of interest in an efficient

Aderin, A. (2024). Modelling Financial Distress in the Nigerian Banking Sector. In: Owusu-Manu, D., Adesi, M. and Acheampong, A. (Eds) Proceedings of the 1st International Conference on Environment, Social, Governance and Sustainable Development of Africa (ICESDA-2024), 26-29 March 2024, Kwame Nkrumah University of Science and Technology (KNUST)-Kumasi, Ghana, Green Communities International, 1-20.

ICESDA 2024 **PROCEEDINGS**
ISSN -3057-3912 PRINT
3057-3920 ONLINE

manner. The listed banks under review are partitioned into two strata based on their financial distress status as classified by the Central Bank of Nigeria (see Alford, 2010) during the period under consideration. The purposive sampling methodology is subsequently utilised to extract a balanced sample set from each stratum. This method mostly augured for the distressed banks because some of the banks were not listed on the Nigerian Exchange Group (NGX) and therefore do not come under the purview of the study. This brought our total sample to a balanced set of 70 firm-year observations.

The analysis involves the construction of a multiple discriminant model for the prediction of financial distress. Our choice of the multiple discriminant analysis is based on its proven ability to effectively predict financial distress for longer term periods before the eventuality of the distress situation. Also motivating our choice is the inherent ability of the multiple discriminant model to produce values that can be used as variables when testing causal relationships between several phenomena. This gives it an edge over other forms of prediction methods, most of which basically show the degree of prediction as opposed to representing the degrees in absolute values.

The multiple discriminant analysis classifies prediction issues with qualitative dependent variables into two or more exclusive groups. The first step is therefore to identify and establish explicit and mutually exclusive groupings based on defined criteria. Multiple discriminant analysis aims to formulate a linear model of the variable characteristics which best discriminates the established groupings. This is actualised by the formulation of coefficients for the variables which serves as the basis for classification into any of the groups (Rodriguez, 2007). The delineation into each of these groups is made possible by the computation of a score (Yscore in this case) which is computed as follows:

xi represents the explanatory variables, wi represents the discriminant weights, and c is a constant. We begin our data selection with a large number of accounting ratios, market-based ratios, corporate governance indices and macroeconomic factors. The formulation of a multiple discriminant model with a large number of variables helps to curb the possible existence of collinearity that might exist among the variables as a result of the probability of high correlation among the variables. The multiple discriminant methodology addresses this issue of collinearity by reducing the model to a small number of variables with high predictive powers, while at the same time improving the significance of the difference between the mutually exclusive groups. This variable selection process is however an iterative process done through factor analysis. The magnitude of the significance of the difference between the groups along with the combined prediction powers of the variables is what enhances the predictive accuracy of the discriminant model (Rodriguez, 2007). The variables utilised in the study are made up of accounting ratios, market-based ratios, corporate governance mechanisms and macroeconomic factors. A list of all variables utilised in the study is presented in table 1 (see Appendix 1).

Result and Discussions

The analysis encompasses a phase of procedures with the aim of ultimately arriving at the most predictive ratios (combination of ratios with the highest possible predictive powers) among all the

Aderin, A. (2024). Modelling Financial Distress in the Nigerian Banking Sector. In: Owusu-Manu, D., Adesi, M. and Acheampong, A. (Eds) Proceedings of the 1st International Conference on Environment, Social, Governance and Sustainable Development of Africa (ICESDA-2024), 26-29 March 2024, Kwame Nkrumah University of Science and Technology (KNUST)-Kumasi, Ghana, Green Communities International, 1-20.

forty-five (45) ratios and factors utilised in the study. The results of the scaled vectors (standardized for analytical purposes) are presented in table 2. The table shows the weights allotted to each of the ratios and variables in terms of their ability to predict banks' financial distress. The list of the variables is presented in descending order of the size of their weights. From the original list of variables, five variables are selected as having the best overall combined powers in predicting financial distress among Nigerian banks. From the first five ratios, four of the ratios namely: ratio of net income to total liabilities (NITL), ratio of primary capital to loan liabilities (PCLL), ratio of net income to total assets (NITA), and ratio of loan liabilities to total assets (LLTA) were automatically selected by the Multiple Discriminant Analysis (MDA) procedure as effective predictors. Surprisingly, the ratio of net income to gross earnings (NIGE) which had the second highest weight was not included in the predictive model as a discriminant factor. Rather, CSTA, which had the 16th largest absolute weight size (although positive) was included as a discriminant factor. This justifies the inclusion criteria of the MDA in considering the combined profile contribution of the variables as opposed to being an agglomeration of the most significant independent variables (Altman, 2013), implying that a variable low in significance (CSTA in this case) can rank highly in terms of overall contribution to the model's predictive ability. From table 2, it can also be seen that corporate governance indices and market-based ratios performed poorly in the discriminant function, with most of the ratios exhibiting negative weights.

Table 2: Relative Capacities of Ratios in Predicting Financial Distress

Variable	Scaled Vector	Variable	Scaled Vector	Variable	Scaled Vector
NITL	0.473	CSTA	0.171	MSYRa	-0.067
NIGEa	0.434	IITAa	-0.17	BD_COMa	-0.065
PCLL	0.433	BD_TOTALa	0.12	MVEBVEa	0.065
NITA	0.432	CEO_BDa	-0.119	NCFTAa	-0.062
LLTA	0.342	NITAa	-0.114	MVEBVTLa	-0.057
WCTAa	0.319	PCTAa	-0.112	NCFTLa	-0.056
SETAa	0.302	BD_MEETa	0.109	EDYRa	0.052
TLTAa	-0.296	NCFSEa	-0.108	EPS_MPSa	0.048
FCGEa	-0.291	YEARSa	0.094	CREYRa	-0.045
SETLa	0.289	INFLa	0.087	GETAa	-0.045
LALLa	0.244	CEO_FINLITa	-0.085	DDYRa	-0.041
IETAa	-0.225	WOMEN_Ra	-0.081	CEO_Ga	-0.038
NICCa	-0.21	NEM_TBDa	-0.078	CEXPYRa	-0.02
FCTLa	-0.194	DDTDa	0.077	NIDSEa	-0.013
NETAa	-0.19	AMVS_NETa	0.077	LATAa	0.004

Track 1: ESG/ CSR and Sustainability of Africa Continental Free Trade Area

Aderin, A. (2024). Modelling Financial Distress in the Nigerian Banking Sector. In: Owusu-Manu, D., Adesi, M. and Acheampong, A. (Eds) Proceedings of the 1st International Conference on Environment, Social, Governance and Sustainable Development of Africa (ICESDA-2024), 26-29 March 2024, Kwame Nkrumah University of Science and Technology (KNUST)-Kumasi, Ghana, Green Communities International, 1-20.

Note: a = not included in model.

`Eventually, the five ratios included in the predictive model on the basis of the MDA are the ratio of net income to total liabilities (NITL), ratio of primary capital to loan liabilities (PCLL), ratio of loan liabilities to total assets (LLTA), ratio of net income to total assets (NITA), and ratio of cash and short-term funds to total assets (CSTA). Thus, all the ratios in the predictive model are accounting ratios, with two profitability ratios, one liquidity ratio, one capital adequacy ratio, and one leverage ratio. These ratios are included in the model given their unique ability to best discriminate between the exclusive groupings of distressed and non-distressed banks.

It is instructive to note that the included ratios are spread across the accounting ratio groupings and that profitability ratios dominate the other groups. It is apparent that decreasing profitability is always a foundational factor in determining financial distress in any organisation. However, the prediction model excludes corporate governance and market-based ratios, suggesting that the role of these factors may only be prerequisites or aftermaths of the influences of the accounting-based factors in predicting banks' financial distress. Accounting ratios therefore provide requite stakeholders with a clear peek into the future stability of banks in Nigeria.

Having established the predictive ratios for banks' financial distress, the estimated equation from the ratios is shown in equation 2 (z-statistics are in parentheses). From the resulting model, it is seen that the profitability ratios of NITL and NITA have the heavier discriminating influences in terms of magnitude, though the coefficient of NITA is negative and fails the significance test at the 5% level. The resulting model is presented in equation 2 as follows:

$$Yscore = -0.12 + 1.18NITL + 0.34pcll + 0.51llta - 0.74NITA + 0.38CSTA \quad (2)$$

$$(2.96) \quad (2.69) \quad (3.79) \quad (-0.43) \quad (1.98)$$

The estimated model discriminates between distinct groupings by classifying banks into their distressed and non-distressed categorisations. This it does by utilising zero (0) as its cut-off point. The zero cut off point is arrived at through the inculcation of a constant value of 0.12 in the model. The constant value is the product of the mean values of the discriminant variables when applied in the estimated model. The implication of the cut-off point is that banks with negative Yscore values are categorised as distressed banks, while those with positive Yscore values are categorised as non-distressed banks.

It is necessary to further investigate the effectiveness of the predictive model. We utilise several simulation tests to determine the overall effectiveness and adequacy of the model. The first simulation test entails the test of the individual discriminating ability of the five selected variables. This is based on an F-test on the variations of the means for both discriminant groupings. This test relates the difference between the average values of the ratios in each group to the variability (or spread) of ratio values within each group. The resulting F-statistics test is presented in table 3. NITL, PCLL, and NITA are all significant at the 1% level, while LLTA passed the significance test at the 5% level. This shows that these variables are highly different in their overall means between the two discriminant groups of distressed and non-distressed banks. When the univariate conditions are considered, it is seen that the average ratios for the distressed group are much lesser than the average ratios for the non-

Aderin, A. (2024). Modelling Financial Distress in the Nigerian Banking Sector. In: Owusu-Manu, D., Adesi, M. and Acheampong, A. (Eds) Proceedings of the 1st International Conference on Environment, Social, Governance and Sustainable Development of Africa (ICESDA-2024), 26-29 March 2024, Kwame Nkrumah University of Science and Technology (KNUST)-Kumasi, Ghana, Green Communities International, 1-20.

ICESDA 2024 **PROCEEDINGS**
ISSN -3057-3912 PRINT
3057-3920 ONLINE

distressed groups. Apparently, the non-distressed banks performed better for each of the discriminant groupings (as shown in table 3). The test for CSTA shows no significant difference of means between the two groups, indicating that there is actually no difference in the variable variations between the distressed and non-distressed banks. This however does not absolve the CSTA of its importance in the model as its presence helps to improve the overall predictive powers of the model.

Table 3: Discriminant Variable Means and Test of Significance

Discriminant Variable	Distressed group mean	Non-distressed group mean	F-ratio	Prob.
NITL	0.93%	5.49%	0.876	0.003
PCLL	5.25%	93.80%	0.894	0.006
LLTA	0.63%	1.79%	0.931	0.028
NITA	1.47%	4.63%	0.894	0.006
CSTA	25.71%	31.11%	0.982	0.265

As Altman (1968) noted, an effective technique used to determine the relative contribution of each variable to the total discriminating power of the function as well as the interaction between them is devised by observing relevant statistics based on a scaled vector. These statistics, shown in table 4, are obtained by weighting the scaled vectors with appropriate measures which then gives the relevant contribution of each of the variables in determining whether a bank would be distressed or not. From table 4, it is observed that the large contributors to group separation of the discriminant function are profitability and capital adequacy ratios, each with over 40% proportional contribution. This again confirms the casual empirics that less profitable banks are the most prone to financial distress among banks in Nigeria.

Table 4: Relative Contribution of the Discriminant Variables

Variable	Scaled vector	Rank
NITL	0.473	1
PCLL	0.433	2
NITA	0.432	3
LLTA	0.342	4
CSTA	0.171	5

Aderin, A. (2024). Modelling Financial Distress in the Nigerian Banking Sector. In: Owusu-Manu, D., Adesi, M. and Acheampong, A. (Eds) Proceedings of the 1st International Conference on Environment, Social, Governance and Sustainable Development of Africa (ICESDA-2024), 26-29 March 2024, Kwame Nkrumah University of Science and Technology (KNUST)-Kumasi, Ghana, Green Communities International, 1-20.

ISSN -3057-3912 PRINT
3057-3920 ONLINE

A particularly important consideration for the formulated prediction model from the MDA procedure is to test the effectiveness of the selection process for the five discriminant variables included in the model. In table 5, the predictive ability of the discriminant model is examined. This shows how well the five variables discriminate between distressed and non-distressed banks in Nigeria and it yields the measure of success of the MDA in classifying the banks. In essence, table 5 shows both the number and the percentage of banks correctly classified as either distressed or non-distressed. It can be seen from table 5 that 77.1% of the non-distressed banks were correctly classified as non-distressed and 91.4% of the distressed banks were correctly classified as distressed. This gives an indication of a very low margin of error in the classification of distressed banks as the MDA model for predicting banks' financial distress produced a prediction accuracy of 91.4%; which can be regarded as appreciably high.

Table 5: Examination of the Predictive Ability of the Discriminant Model

Actual group membership (banks' financial distress)		**Predicted Group Membership**		**Total**
		Non-distressed	Distressed	
Count	Non-distressed	27	8	35
	Distressed	3	32	35
%	Non-distressed	77.1	22.9	100.0
	Distressed	8.6	91.4	100.0

The previous results in the MDA analysis shows the initial evidence of the reliability of the conclusions derived from the prediction of banks' financial distress. It is however imperative to strengthen the effectiveness of the predictive capacity of the MDA formulations by using varied time periods for the analysis, including annual estimates and longer periods (prior to distress) of prediction. Thus, annual data for one to five years prior to bank distress are used in reformulating the MDA and the test results are presented in the following analysis. The accuracy of the prediction model can further be evaluated by using univariate analysis of the trend of the five predictive variables in the model. We therefore consider the mean and standard deviations for each of the years among the discriminant variables, the test of equality, the unstandardized estimates as well as the case-wise prediction tests.

The mean and standard deviation of the variables for each of the five years prior to financial distress of the banks are shown in table 6. For both groups, the mean values appear to be declining as the distress year gets closer (apart from LLTA which appears to actually be rising as the distress year gets closer). There is therefore indication that during the run up to financial distress, the banks tend to perform less in terms of the five discriminant variables. This further gives credence to the usefulness

Aderin, A. (2024). Modelling Financial Distress in the Nigerian Banking Sector. In: Owusu-Manu, D., Adesi, M. and Acheampong, A. (Eds) Proceedings of the 1st International Conference on Environment, Social, Governance and Sustainable Development of Africa (ICESDA-2024), 26-29 March 2024, Kwame Nkrumah University of Science and Technology (KNUST)-Kumasi, Ghana, Green Communities International, 1-20.

ICESDA 2024 PROCEEDINGS
ISSN -3057-3912 PRINT
3057-3920 ONLINE

of the included variables in the MDA structure.

Table 6: Mean and Standard Deviation for Annual Data Series

Status	**Variable**	**Year 5**		**Year 4**		**Year 3**		**Year 2**		**Year 1**	
non-distressed	NITA	0.06	0.05	0.05	0.03	0.04	0.03	0.04	0.02	0.04	0.02
	NITL	0.06	0.05	0.06	0.04	0.05	0.03	0.05	0.03	0.06	0.03
	CSTA	0.37	0.18	0.34	0.17	0.36	0.25	0.24	0.23	0.24	0.26
	PCLL	0.28	0.42	1.67	3.24	1.15	1.76	1.16	1.87	0.43	0.57
	LLTA	0.01	0.02	0.01	0.02	0.01	0.01	0.03	0.04	0.02	0.03
distressed	NITA	0.03	0.01	0.02	0.01	-0.02	0.11	0.03	0.01	-0.02	0.11
	NITL	0.03	0.01	0.03	0.01	-0.01	0.10	0.03	0.01	-0.01	0.11
	CSTA	0.41	0.17	0.35	0.15	0.28	0.17	0.14	0.15	0.11	0.12
	PCLL	0.00	0.00	0.00	0.00	0.00	0.00	0.15	0.24	0.11	0.18
	LLTA	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.02	0.03

The test of equality of means for the discriminant variables are shown in table 7. The F-test on the variations of the means for both discriminant groupings of the banks show little variations in the five variables for each year prior to the distress announcement. Only LLTA maintained any form of significant variation in means for each of the years based on the F-statistics. This implies that on an individual annual basis for the univariate analysis, there is no significant difference between the means of the variables. The estimates of the structural MDA model using the variables in the analysis is also reported in table 8. The results show that the variables had no particular trend in terms of size and signs. Thus, there is little evidence to show that a univariate evaluation of the individual years prior to financial distress of the banks produces effective grounds for measuring the predictive capacity of the MDA models.

Aderin, A. (2024). Modelling Financial Distress in the Nigerian Banking Sector. In: Owusu-Manu, D., Adesi, M. and Acheampong, A. (Eds) Proceedings of the 1st International Conference on Environment, Social, Governance and Sustainable Development of Africa (ICESDA-2024), 26-29 March 2024, Kwame Nkrumah University of Science and Technology (KNUST)-Kumasi, Ghana, Green Communities International, 1-20.

Table 7: Test of Equality of Means

Variable	Years prior to financial distress									
	Year 5		Year 4		Year 3		Year 2		Year 1	
	F	Sig.	F	Sig.	F	Sig.	F	Sig.	F	Sig.
NITA	2.34	0.15	5.35*	0.03	1.83	0.20	2.08	0.18	1.88	0.20
NITL	2.18	0.17	5.58*	0.02	2.07	0.18	1.72	0.21	2.44	0.14
PCLL	2.99	0.11	1.87	0.20	2.97	0.11	2.00	0.18	2.08	0.17
LLTA	5.66*	0.02	5.43*	0.03	5.67*	0.02	1.14	0.31	0.07	0.79
CSTA	0.20	0.66	0.01	0.93	0.58	0.46	1.07	0.32	1.45	0.25

Note: * indicates significance at the 5% level.

Table 8: Estimates of the MDA Structural Model

Variable	Year 5		Year 4		Year 3		Year 2		Year 1	
	ND	D	ND	D	ND	D	ND	D	ND	D
NITA	1067.77	729.51	-861.62	-776.46	-780.38	-447.43	-539.58	-991.74	-230.52	-80.41
NITL	-870.32	-596.11	888.73	761.50	867.75	490.77	624.11	984.94	245.54	82.86
CSTA	19.85	17.66	35.68	31.51	13.60	8.92	9.85	6.51	10.09	4.43
PCLL	-19.23	-11.39	0.21	-0.29	1.31	0.26	1.41	0.34	0.94	-0.03
LLTA	500.39	268.30	95.89	21.33	287.06	86.14	71.39	37.67	44.53	26.09
(Constant)	-7.50	-5.01	-12.77	-7.89	-10.24	-3.68	-7.13	-3.75	-4.59	-1.33

Note: ND = non-distressed; D = distressed.

The clear test for the predictive ability of the MDA estimates is fully demonstrated by considering the number of correctly predicted banks in terms of distressed or non-distressed categorisations for each of the years. The goal is to observe how the accuracy of prediction behaves as the time period tails

Aderin, A. (2024). Modelling Financial Distress in the Nigerian Banking Sector. In: Owusu-Manu, D., Adesi, M. and Acheampong, A. (Eds) Proceedings of the 1st International Conference on Environment, Social, Governance and Sustainable Development of Africa (ICESDA-2024), 26-29 March 2024, Kwame Nkrumah University of Science and Technology (KNUST)-Kumasi, Ghana, Green Communities International, 1-20.

ICESDA 2024 PROCEEDINGS
ISSN -3057-3912 PRINT
3057-3920 ONLINE

away from the distress period. Table 9 shows the case-wise highlights of the pattern of prediction for bank financial distress on the basis of the MDA using the five selected discriminant variables. It can be observed that much of the predictions for bank financial distress were accurately made, especially with respect to the distressed banks.

Table 9: Case-wise Statistics

Case Number	Years prior to financial distress									
	Year 5		Year 4		Year 3		Year 2		Year 1	
	Actual Group	Predicted Group	Actual Group	Predicted Group	Actual Group	Predicted Group	Actual Group	Predicted Group	Actual Group	Predicted Group
Access Bank	0	0	0	0	0	0	0	0	0	0
First Bank	0	0	0	0	0	0	0	0	0	0
FCMB	0	1**	0	0	0	0	0	0	0	0
Fidelity Bank	0	1**	0	1**	0	1**	0	1**	0	1**
Guaranty Trust Bank	0	0	0	0	0	0	0	0	0	0
UBA	0	0	0	1**	0	0	0	0	0	1**
Zenith Bank	0	0	0	1**	0	0	0	0	0	0
Afribank	1	1	1	1	1	1	1	1	1	1
Finbank	1	1	1	1	1	1	1	1	1	1
Intercontinental Bank	1	1	1	1	1	1	1	1	1	1
Oceanic Bank	1	1	1	1	1	1	1	1	1	1
PHB	1	1	1	1	1	1	1	1	1	1
Skye Bank	1	1	1	1	1	1	1	0**	1	1
Union Bank	1	1	1	1	1	1	1	1	1	1

Note: ** indicates the wrongly predicted cases.

The proportion of correctly predicted group of banks both for the non-distressed and distressed banks for each of the years are shown in table 10. The analysis reveals that in five years, four years, three years and one year prior to distress, 100% of the distressed banks were correctly predicted by the

Track 1: ESG/ CSR and Sustainability of Africa Continental Free Trade Area

Aderin, A. (2024). Modelling Financial Distress in the Nigerian Banking Sector. In: Owusu-Manu, D., Adesi, M. and Acheampong, A. (Eds) Proceedings of the 1st International Conference on Environment, Social, Governance and Sustainable Development of Africa (ICESDA-2024), 26-29 March 2024, Kwame Nkrumah University of Science and Technology (KNUST)-Kumasi, Ghana, Green Communities International, 1-20.

ICESDA 2024 **PROCEEDINGS**
ISSN -3057-3912 PRINT
3057-3920 ONLINE

Track 1: ESG/ CSR and Sustainability of Africa Continental Free Trade Area

MDA. For the second year prior to distress, 85.7% of the distressed banks were correctly predicted.

Table 10: Percentage Counts for Prediction of Group Membership

		Predicted Group Membership		
Year	**Status**	**non-distressed**	**Distressed**	**Total**
1	non-distressed	71.4	28.6	100
	Distressed	0	100	100
2	non-distressed	85.7	14.3	100
	distressed	14.3	85.7	100
3	non-distressed	85.7	14.3	100
	distressed	0	100	100
4	non-distressed	57.1	42.9	100
	distressed	0	100	100
5	non-distressed	71.4	28.6	100
	distressed	0	100	100

Finally, the results of the long-range predictive accuracy for financial distress of banks are shown in table 11. As shown in the preceding analysis, most of the prior years to distress produced 100% accuracy in terms of predicting financial distress of banks using the five discriminant factors of the estimated model. Based on the above results, we opine that the estimated prediction model is an accurate forecaster of bank financial distress for up to five years prior to the eventuality of the distress scenario. The accuracy does not seem to diminish as the lead time increases and hence, would suffice for longer term forecasts.

Table 11: Long-Range Predictive Accuracy

Year Prior to Distress	**Hits**	**Misses**	**Percent Correct**
1st	7	0	100
2nd	6	1	85.7
3rd	7	0	100
4th	7	0	100
5th	7	0	100

Aderin, A. (2024). Modelling Financial Distress in the Nigerian Banking Sector. In: Owusu-Manu, D., Adesi, M. and Acheampong, A. (Eds) Proceedings of the 1st International Conference on Environment, Social, Governance and Sustainable Development of Africa (ICESDA-2024), 26-29 March 2024, Kwame Nkrumah University of Science and Technology (KNUST)-Kumasi, Ghana, Green Communities International, 1-20.

ICESDA 2024 **PROCEEDINGS**
ISSN -3057-3912 PRINT
3057-3920 ONLINE

Conclusion and Recommendations

The study investigated the possibility of developing a model for the prediction of financial distress among Nigerian banks. In developing the proposed model, four variable groupings of interest were analysed. The variable groupings include accounting ratios, market-based ratios, corporate governance mechanisms and macroeconomic factors. The results of the study indicate that a discriminant model with high predictive powers for the forecasting of distress scenarios in the Nigerian banking sector can be empirically developed.

The model demonstrates that five important factors are critical in the prediction and determination of financial distress among Nigerian banks. The factors are ratio of net income to total assets, ratio of net income to total liabilities, ratio of loan liabilities to total assets, ratio of primary capital to loan liabilities, and ratio of cash and short-term funds to total assets. Simulation tests conducted on the developed model give further credence to its adequacy, accuracy and long-range forecast ability in the prediction of financial distress among Nigerian banks.

The developed model may however experience limitations due to dynamic and uncertain nature of the macro-economic environment. Despite the non-inclusion of any macro-economic factor in the model's variable selection, the important contribution of macro-economic indices on the survival of micro-economic units cannot be overemphasised. It is therefore advised that subsequent model developments should give consideration to the possibility of developing dynamic models that can cater to changes in macro-economic indices to a reasonable extent.

Our study contributes to knowledge by correcting for the inadequacy of extant models in accurately predicting the financial distress status of Nigerian banks, through the development of an ideal and concise model for the specificity of the Nigerian banking scenario. This has implication for the longevity of banks in particular and the banking sector in general which is unarguably one of the most critical sectors in any economy.

We recommend that relevant regulatory authorities such as the Central Bank of Nigeria (CBN) and the Nigeria Deposit Insurance Corporation (NDIC) should experiment this new model in testing the health status of banks at the end of every financial year to ascertain their true state of affairs. This would assist the relevant authorities to take proactive measures in correcting any form of inherent anomalies which could snowball into disastrous outcomes.

Aderin, A. (2024). Modelling Financial Distress in the Nigerian Banking Sector. In: Owusu-Manu, D., Adesi, M. and Acheampong, A. (Eds) Proceedings of the 1st International Conference on Environment, Social, Governance and Sustainable Development of Africa (ICESDA-2024), 26-29 March 2024, Kwame Nkrumah University of Science and Technology (KNUST)-Kumasi, Ghana, Green Communities International, 1-20.

Track 1: ESG/CSR and Sustainability of Africa Continental Free Trade Area

References

Abdullah, N. A., Halim, A., Ahmad, H. and Rus, R. M. (2008). Predicting corporate failure of Malaysia listed companies: Comparing multiple discriminant analysis, logistic regression and the hazard model. *International Research Journal of Finance and Economics, 15*, pp. 201-217.

Adekanmbi, M. O. (2017). Causes and effects of banking distress in Nigeria banking industry. *International Academic Journal of Accounting and Financial Management, 4*(1), pp. 100-105.

Alford, D. E. (2010). Nigerian banking reform: Recent actions and future prospects. *Journal of International Banking Law and Regulation, 25*, pp. 337-355.

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance, 23*(4), pp. 589-609.

Altman, E. I. (2013). Predicting financial distress of companies: Revisiting the Z-score and ZETA models. In M. L. Heine (Ed.), *Handbook of research methods and applications in empirical finance*, pp. 428-456.

Altman, E. I., Iwanicz-Drozdowska, M., Laitinen, E. K. and Suvas, A. (2014). *Distressed firm and bankruptcy prediction in an international context: A review and empirical analysis of Altman's Z-score model*. Retrieved from: http://dx.doi.org/10.2139/ssrn.2536340

Aziz, M. and Dar, H. (2006). Predicting corporate bankruptcy: Where we stand? *Corporate Governance, 6*(1), pp. 18-33.

Bauer, J. and Agarwal, V. (2014). Are hazard models superior to traditional bankruptcy prediction approaches? A comprehensive test. *Journal of Banking and Finance, 40*, pp. 432-442.

Beaver, W. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research, 4*(3), pp. 71-111.

Boratynska, K. and Grzegorzewka, E. (2018). Bankruptcy prediction in the agribusiness sector: Lessons from quantitative and qualitative approaches. *Journal of Business Research, 89*(8), pp. 175-181.

Boritz, J. E., Kennedy, D. B. and Sun, J. Y. (2007). Predicting business failure in Canada. *Accounting Perspectives, 6*(2), pp. 141-165.

Cao, Y. and Chen, X. (2012). An agent-based simulation model of enterprises financial distress for the enterprise of different life cycle stages. *Simulation Modelling Practice and Theory, 20*, pp. 70-88.

Charitou, A. and Trigeorgis, L. (2004). *Explaining bankruptcy using option theory*. Retrieved from: http://dx.doi.org/10.2139/ssrn.675704

Chava, S. and Jarrow, R. (2001). *Bankruptcy prediction with industry effects, market versus accounting variables, and reduced from credit risk models*. Retrieved from: http://dx.doi.org/10.2139/ssrn.287474

Chen, W. and Du, Y. (2009). Using neural networks and data mining techniques for the financial distress prediction model. *Expert Systems with Applications, 36*, pp. 4075-4086.

Aderin, A. (2024). Modelling Financial Distress in the Nigerian Banking Sector. In: Owusu-Manu, D., Adesi, M. and Acheampong, A. (Eds) Proceedings of the 1st International Conference on Environment, Social, Governance and Sustainable Development of Africa (ICESDA-2024), 26-29 March 2024, Kwame Nkrumah University of Science and Technology (KNUST)-Kumasi, Ghana, Green Communities International, 1-20.

ICESDA 2024 **PROCEEDINGS**
ISSN -3057-3912 PRINT
3057-3920 ONLINE

Eriki, P. O. and Udegbunam, R. (2013). Predicting corporate distress in the Nigerian stock market: Neutral network versus multiple discriminant analysis. *African Journal of Business Management, 7*(38), pp. 3856-3863.

Gupta, V. (2014). An empirical analysis of default risk for listed companies in India: A comparison of two prediction models. *International Journal of Business and Management, 9*(9), pp. 223-233.

Hillegeist, S., Keating, E., Cram, D. and Lundstedt, K. (2004). Assessing the probability of bankruptcy. *Review of Accounting Studies, 9*(1), pp. 5-34.

Jones, S. (2017). Corporate bankruptcy prediction: A high dimensional analysis. *Review of Accounting Studies, 22*(3), pp. 1366-1422.

Kouki, M. and Elkhaldi, A. (2011). Toward a predicting model of firm bankruptcy: Evidence from the Tunisian Context. *Middle Eastern Finance and Economics, 14*, pp. 26-43.

Lin, F., Liang, D. and Chu, W. (2010). The role of non-financial features related to corporate governance in business crisis prediction. *Journal of Marine Science and Technology, 18*(4), pp. 504-513.

Mizdrakovic, V. and Bokic, M. (2016). Reassessment of corporate bankruptcy prediction models efficiency: Evidence from Serbia. *TEME Journal for Social Sciences, 40*(4), pp. 1367-1382.

Monnasoo, K. (2007). *Determinants of firm sustainability in Estonia*. Eesti Pank Working Paper. Retrieved from: https://www.eestipank.ee/en/publication/working-papers/2007/42007-kadri-mannasoo-determinants-firm-sustainability-estonia

Ohlson, J. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research, 18*(1), pp. 109-131.

Rodriguez, J. C. (2007). Measuring financial contagion: A copula approach. *Journal of Empirical Finance, 14*, pp. 401-423.

Sabela, S. W., Brummer, L. M., Hall, J. H. and Wolmarans, H. P. (2018). Using fundamental, market and macroeconomic variables to predict financial distress: A study of companies listed on the Johannesburg Stock Exchange. *Journal of Economic and Financial Sciences, 11*(1), pp. 1-11.

Sensini, L. (2016). An empirical analysis of financially distressed Italian companies. *International Business Research, 9*(10), pp. 75-85.

Shah, N. (2014). Developing financial distress prediction models using cutting edge recursive partitioning techniques: A study of Australian mining performance. *Review of Integrative Business and Economics Research, 3*(2), pp. 103-143.

Singh, B. P. and Mishra, A. K. (2016). Re-estimation and comparisons of alternative accounting based bankruptcy prediction models for Indian companies. *Financial Innovations, 2*(6), pp. 1-28.

Smaranda, C. (2014). Scoring functions and bankruptcy prediction models: Case study of Romanian companies. *Procedia Economics and Finance, 10*, pp. 217-226.

Stanisic, N., Mizdrakovic, V. and Knezevic, G. (2013). Corporate bankruptcy prediction in the Republic of Serbia. *Industrija, 41*(4), pp. 145-159.

Taffler, R. J. (1983). The assessment of company solvency and performance using a statistical model.

Aderin, A. (2024). Modelling Financial Distress in the Nigerian Banking Sector. In: Owusu-Manu, D., Adesi, M. and Acheampong, A. (Eds) Proceedings of the 1st International Conference on Environment, Social, Governance and Sustainable Development of Africa (ICESDA-2024), 26-29 March 2024, Kwame Nkrumah University of Science and Technology (KNUST)-Kumasi, Ghana, Green Communities International, 1-20.

ICESDA 2024 **PROCEEDINGS**
ISSN -3057-3912 PRINT
3057-3920 ONLINE

Accounting and Business Research, 13(52), pp. 295-308.

Ugurlu, M. and Aksoy, H. (2006). Prediction of corporate financial distress in an emerging market: The case of Turkey. *Cross Cultural Management: An International Journal, 13*(4), pp. 277-295.

Wang, Y. and Campbell, M. (2010). Financial ratios and the prediction of bankruptcy: The Ohlson model applied to Chinese publicly traded companies. *The Journal of Organisational Leadership and Business, 17*(1), pp. 1-15.

Wanke, P., Barros, C. P. and Faria, J. R. (2015). Financial distress drivers in Brazilian banks: A dynamic slack approach. *European Journal of Operational Research, 24*(1), pp. 258-268.

Yang, Z. R., Platt, M. B. and Platt, H. D. (1999). Probabilistic neural networks in bankruptcy prediction. *Journal of Business Research, 44*(1), pp. 67-74.

Zmijewski, M. E. (1984). Methodological issues related to the estimation of financial prediction models. *Journal of Accounting Research, 22*(1), pp. 59-82.

Appendix

Appendix 1: Operationalization of Variables

S/N	Variable Groupings	Variables Sub-groupings	Proxy/Measurement
1	Accounting Ratios	Profitability Ratios	Ratio of net income to gross earnings
		Profitability Ratios	Ratio of net income to core equity capital
		Profitability Ratios	Ratio of interest income to total assets
		Profitability Ratios	Ratio of interest expenses to total assets
		Profitability Ratios	Ratio of non-interest income to total assets
		Profitability Ratios	Ratio of non-interest expenses to total assets
		Profitability Ratios	Ratio of net income to total assets
		Profitability Ratios	Ratio of net income to total liabilities
		Profitability Ratios	Ratio of gross earnings to total assets
		Liquidity Ratios	Ratio of liquid assets to liquid liabilities
		Liquidity Ratios	Ratio of liquid assets to total assets
		Liquidity Ratios	Ratio of cash and short term funds to total assets

Aderin, A. (2024). Modelling Financial Distress in the Nigerian Banking Sector. In: Owusu-Manu, D., Adesi, M. and Acheampong, A. (Eds) Proceedings of the 1st International Conference on Environment, Social, Governance and Sustainable Development of Africa (ICESDA-2024), 26-29 March 2024, Kwame Nkrumah University of Science and Technology (KNUST)-Kumasi, Ghana, Green Communities International, 1-20.

ICESDA 2024 **PROCEEDINGS**
ISSN -3057-3912 PRINT
3057-3920 ONLINE

		Liquidity Ratios	Ratio of working capital to total assets
		Liquidity Ratios	Ratio of demand deposits to term deposits
		Liquidity Ratios	Ratio of net cash flow to total assets
		Liquidity Ratios	Ratio of net cash flow to total liabilities
		Liquidity Ratios	Ratio of net cash flow to shareholders' equity
		Capital Adequacy Ratios	Ratio of net income minus dividend to shareholders' equity
		Capital Adequacy Ratios	Ratio of primary capital to total asset
		Capital Adequacy Ratios	Ratio of primary capital to loan liabilities
		Capital Adequacy Ratios	Ratio of shareholders' equity to total assets
		Capital Adequacy Ratios	Ratio of shareholders' equity to total liabilities
		Leverage Ratios	Ratio of loan liabilities to total assets
		Leverage Ratios	Ratio of total liabilities to total assets
		Operating Structure Ratios	Ratio of financial charges to gross earnings
		Operating Structure Ratios	Ratio of financial charges to total liabilities
2	Market-based Ratios	Market Value Ratios	Ratio of market value of equity to book value of equity
		Market Value Ratios	Ratio of earnings per share to market price per share
		Market Value Ratios	Ratio of average market value per shares to net cash flow per share
		Market Value Ratios	Market value of equity to book value of total liabilities
3	Corporate Governance Mechanisms	CEO Attributes	Ratio of CEO shareholdings to total board shareholdings
		CEO Attributes	Ratio of no. of years on the position to maximum tenure

Track 1: ESG/ CSR and Sustainability of Africa Continental Free Trade Area

Aderin, A. (2024). Modelling Financial Distress in the Nigerian Banking Sector. In: Owusu-Manu, D., Adesi, M. and Acheampong, A. (Eds) Proceedings of the 1st International Conference on Environment, Social, Governance and Sustainable Development of Africa (ICESDA-2024), 26-29 March 2024, Kwame Nkrumah University of Science and Technology (KNUST)-Kumasi, Ghana, Green Communities International, 1-20.

		CEO Attributes	Gender of the CEO (Female = 1; Male = 0)
		CEO Attributes	Degree of CEO financial literacy
		Board Attributes	Ratio of board shareholdings to total shareholdings
		Board Attributes	Ratio of the non-executive members to total board members
		Board Attributes	Ratio of women on the board to total board members
		Board Attributes	Number of existing board sub-committees
		Board Attributes	Number of board meeting for the financial period
4	Macroeconomic Factors	Government Factors	Capital expenditure of government as a percentage of GDP
		Government Factors	Government domestic debt as a percentage of GDP
		Government Factors	Government external debt as a percentage of GDP
		Financial Deepening Indicators	Inflation rate
		Financial Deepening Indicators	Money Supply as a percentage of GDP
		Financial Deepening Indicators	Credit to private sector as a percentage of GDP

Aderin, A. (2024). Modelling Financial Distress in the Nigerian Banking Sector. In: Owusu-Manu, D., Adesi, M. and Acheampong, A. (Eds) Proceedings of the 1st International Conference on Environment, Social, Governance and Sustainable Development of Africa (ICESDA-2024), 26-29 March 2024, Kwame Nkrumah University of Science and Technology (KNUST)-Kumasi, Ghana, Green Communities International, 1-20.