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Abstract

This study aimed to examine the impact of CAMEL indicators on the financial health of selected banks in Nigeria. Access bank, First bank, Zenith bank, Fidelity bank, Unity bank, Union bank and Wema bank were examined from 2012 to 2020. Data for the study was collected from the audited annual reports of investigated banks. The study applied multiple discriminant (Z-score) technique and censored logistic regression to capture the effects of CAMEL indicators. The discriminant analysis revealed that about 69.84% of the studied banks fall into distress status, while only 30.16% are financially sound. The censored regression indicates that liquidity, asset quality, earnings and management quality significantly and negatively impact on bank financial health. This study concludes that CAMEL variables are potent instrument for assessing bank financial soundness and recommend that bank management should improve on their CAMEL indicators as they have the potential to guarantee banks financial stability.

Keywords: ***Bank Financial Health, Censored Logistic Regression, CAMEL Indicators, Multiple Discriminant Analysis***

Introduction

Banks as financial institutions play a vital role in the development of any nation. It mobilizes funds from the surplus unit of the economy to the deficit unit, thus making funds available not only to the private sector but the government as well as for developmental purposes. Banking business is a risky venture because its performance or failure is influenced to some extent by a variety of internal and external factors. Banks failure will have adverse consequences on economic activities, hence it is the most strictly regulated and supervised sector of the economy (Sahut and Mili, 2011). Those saddle with the management and supervision of banks need to be abreast with the risk factors confronting it and ensure that banks are adequately managed (Basel, 1997). Banks differ from other corporate organisations primarily because the failure or distress of banks negatively impinges on depositor rights, other industries and the economy at large, and therefore can stimulate international financial crises because of the spillover effects. As such, appraising bank activities and detecting early signals are the top priority of regulators and global financial authority (Huang, Chang & Liu, 2012).

A bank is distressed when its total liabilities is more than total assets - a situation often described as technical insolvency (Umoh, 1997). A financial institution is distressed when it experiences several financial, operational and managerial weaknesses which prevent the institution from meeting its obligation to

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customers, shareholders and the economy as a whole (Ojo, 2010). When a relatively large proportion of banks are having liabilities exceeding the market value of its total assets which may lead to runs, the banking system may be described as distressed (CBN/NDIC, 1995). SirElkhatim and Salim (2015) identified distressed banks as: First, bank whose operation are suspended. Secondly, bank recapitalized or those that received liquidity from monetary authority. Thirdly, bank which eventually merge with healthy bank due to financial distress, and lastly, those close by the regulatory agency.

Studies have pin-point a wide range of determinants of company failure and have formulated models for forecasting company failure. Majority of distress prediction techniques are intended to capture firm's inability to cater for its financial commitments. To evaluate this capability, models are designed to measure a gap involving the financial situation of the firm in a critical situation (Jardin & Severin, 2013). This method of prediction depends on the assessment of a value that appraises a distance to bankruptcy (see Altman, 1968; Sueyoshi & Goto, 2009).

Attempts have been made to predict bank distress conditions in Nigeria using Z-score. For instance, Pam (2013) employed discriminant analysis to predict the state of health of some banks in Nigeria from 1999-2003. Specifically, he analysed two failed banks and two existing banks. Z-score below 1.80 is considered ill-health, while those above 1.80 are described as healthy. The study merely considers the state of financial health of the banks, not the factors responsible for that condition of health. Unuafe and Afolabi (2014) applied multiple discriminant model on CAMEL and stock market information to predict bank failure in Nigeria from 2006 to 2010. The period of the study differs from the current one and the study did not engage censored regression to differentiate heathy banks from unhealthy ones nor consider the signs effect of the variables which make it different from the ongoing investigation. Rostami (2015) used CAMELS indicators to gauge bank failure situation in Iran from 2009-2013. The study merely calculates CAMELS ratios of each firm and compare with average banking industry ratios.

The gaps identified are geographical and methodological gaps and this study intend to fill these gaps using Z-score technique to classify the financial institutions into their respective financial health conditions and apply the Logic regression which has the capacity to differentiate healthy from unhealthy banks and determine the sign effects of CAMEL variables on bank financial health. With these techniques, it is possible to pinpoint the actual factor(s) responsible for the state of health of the banks looking at the signs effect. The main objective of the study is to determine the sign effects of CAMEL indicators as tools for predicting bank distress conditions. The outcome of the study will aid regulatory authorities, investors, creditors and managers in their judgment.

Conceptual Review

Bank Distress in Nigeria

The first recorded bank failure in Nigeria can be traced to 1930, followed by the failure of Nigerian Mercantile Bank in 1936, and the Nigerian Perny Bank in 1946 (Foluso, 1985 in Olukotun, 2013). Ashamu (2015) asserted that distress in Nigerian banking industry is not a new event neither accidental, it is both organic and systemic and have adverse consequences on the economy. For instance, the number of banks in the country drop by 200 to as low as 89 in 1998. Out of the 89 banks, 14 were considered fairly sound, 11 unsound. Ojo (2010) stated that 34 banks out of 120 failed in Nigeria between 1994 and 2000. By September 2004, 25 banks were reported to have shown signs of distress and 14 that could not be recapitalized at the end of 2005 had their license revoked. Indeed, at the end of 2005 only 25 banks out of 89 survived. Soludo (2004) cited in Ashamu (2015) identified the challenges in the Nigerian banks to include lack of liquidity, poor asset quality, weak capital base, weak corporate governance among others.

Bank distress in Nigeria may be attributed to both micro and macro factors. For instance, it is reported that government policy to withdraw public fund (deposits) from banks in addition to government monetary policy resulted in liquidity crises in the banking sector in 1989. And this led to the collapse of many banks in Nigeria between 1994 and 1996 (Olukotun et al, 2013). Kama (2010) identified political interference and ownership structure are some of the causes of bank distress in Nigeria. He added that going to the capital market more than once a year to source for fund is a sign of ineffective bank management and symptom of bank distress. Ojo (2010) stated that certain macroeconomic changes often paved the way for bank crises. He enumerated the macro-indicators to include balance of payment, inflation, interest rate, changes in asset prices, growth in credit etc. Banking system engulf in crises can hardly perform it intermediation function if credit creation is hindered owing to low capital adequacy, drop in liquidity (Olukotun, Olusegun & Olorunfemi, 2013). Hence, the need to assess these banks' specific factors to ascertain their adequacy or otherwise.

CAMEL Indicators

CAMEL is an acronym for capital adequacy, asset quality, management qualities, earnings and liquidity. These indicators are the most popular methods of analyzing and assessing of financial soundness globally. Financial soundness indicators are calculated for the purpose of aiding the evaluating and monitoring of the strengths and vulnerabilities of the financial system. To ensure for easy comparability of banks and data at international level, the IMF published in March, 2006 the compilation guide on financial soundness indicators. The aim of financial soundness variables is to enhance the financial stability and help to minimize the possibility of failure of the financial institutions in the national economy (www.Oecd.com). Saiya and Pandowo (2015) asserts that bank soundness can influence customers' loyalty to the bank, hence the need to be given serious consideration.

Review of Empirical Literature

Studies have inquired into the factors responsible for bank failure both in developed and developing countries (Oshinsky & Olin, 2006; Bongini, Claessens & Ferri, 2001). Bettz, Oprica, Peltonen and Sarlin (2013) employed early warning model to predict bank distress in European banks and posits that combining macro-financial indicators with bank indicators produced vital outcome for predicting bank distress. Sahut and Mili (2011) applied multivariate logit model on cross-sectional data from 2000 to 2007 in MENA countries and reported that CAMEL proxy variables are predictors of bank distress but find no significant link between economic fundamental and bank distress**.** It is generally agreed that the CAMEL indicators are essential tools for assessing banks' financial vulnerability and soundness (Cihak and Poghosyam, 2009). Unuafe and Afolabi (2014) applied multiple discriminant model on CAMEL and stock market information to predict bank failure in Nigeria from 2006 to 2010. The summary of the study is that bank failure is due to poor CAMEL and unwarranted risk taking.

Ashamu (2015) used linear regression on macro-economic variables to determine bank distress in Nigeria from 1986-2013. The result shows that M2, inflation has negative effect on bank distress proxy by M2/GDP. Charalambakis (2013) employed accounting and stock market variables for the prediction of failure in Greece using discrete hazard. The study documented that discrete hazard model which combine three accounting ratios components of Z-score and three stock market variables is recommended for predicting distress of financial firms. Arabi (2013) determined bank failure in Sudan from 2000 to 2009 using logistic regression and discriminant analysis. The result showed earning indicator exerts the most dominating effect on bank failure, followed by asset quality, liquidity and capital adequacy. Rostami (2015) used CAMELS indicators to gauge bank failure situation in Iran from 2009-2013. The study merely calculates CAMELS ratios of each firm and compare with average banking industry ratio and conclude that CAMELS model is effective and accurate technique for performance evaluation in banking industry.

Methodology

This study aims to investigate the financial health of deposit money banks in Nigeria. To achieve this, the multiple discriminant and censored logic regression techniques were applied on CAMEL variables of selected banks for the period 2012 to 2020. However, loan growth variable data was extended to 2021 to enable us estimate loan growth. Data for the analysis were collected from the annual financial report of the banks and Nigerian Stock Exchange daily official list. The banks investigated are; Access bank, First bank, Zenith bank, Union bank, Wema bank, Fidelity bank, Unity bank and First City Monument bank. The study adopts Unafe and Afolabi (2014) model which estimate Z-score thus:

$Z= 1.02X_1 + 0.14X_2 + 0.033X_3 + 0.006X_4 + 0.0999X_5$ …………………………………………..(1)

Where,

Z = Overall index

X_1 = working capital/total Assets

X_2 = retained earnings/total Assets

X_3 = earnings before interests and taxes/total Assets

X_4 = market value of equity/book value of total liabilities

X_5 = sales/total Assets

However, this study focus on CAMEL variables, therefore the above model was modified and Z-score estimated as follows:

$Z= 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5$ ……………………………………………………(2)

Where:

Z = overall index

X_1= capital adequacy (total debt/total assets)

X_2 = liquidity (total deposit/total assets)

X_3 = asset quality (loan growth)

X_4 = earnings (gross earnings/total assets)

X_5 = management quality (total expenses/earning before tax)

The Z-score index discriminates firms on the distress zone from the healthy ones. To this end, we used cutoff rate of $Z < 3.4217$ for bank in distressed conditions and $Z > 3.4217$ for healthy banks. 3.4217 in this study is the average of the Z-score of each banks divided by the number of years investigated.

To ascertain the effect of the CAMEL variables on bank financial health, the study followed Sahut and Mili (2011) Logit model stated thus:

$$P(Y_i = 1) = \frac{1}{1 + e^{-H_i}} \quad \text{...(3)}$$

Where Y_i is the dependent variable that take value of 1 if firm is distressed and 0 otherwise,

P is probability function, and

$H_i = \emptyset_0 + \sum_{j=1}^{m} \emptyset j X i j$, where X_i is explanatory variables for firm_i and $\emptyset$ the parameters to be estimated.

In this study, we used panel data and dummy variable which we assigned 1 if the Z-score is < 3.4217 and 0 otherwise. At the end, there were a total of 63 observations, made up of 44 distressed conditions and 19 healthy states. Since all the banks are not in distress zone, the need for censoring then arises. Therefore, we run censored logistic regression. The relationship between the bank financial health (regressand) and the explanatory variables is stated thus:

$$POD_{it} = b_0 + b_1CA_{it} + b_2LQ_{it} + b_3AQ_{it} + b_4EN_{it} + b_5MQ_{it} + U_{it} \quad \text{...(4)}$$

Where:

POD_{it} is the dummy variable which take the value of 1 if bank is in a distress zone and 0 otherwise (1 for Z-score < 3.4217 and 0 for Z-score > 3.4217). The regressand (POD in this study) is a dummy variable that discriminates between banks in distress state and non-distressed condition in line with Sahut and Mili, (2011).

CA_{it}= capital adequacy (total debt/total assets) of firm_i at time t

LQ_{it}= liquidity (total deposit/total assets) of firm_i at time t

AQ_{it} = asset quality (loan growth) of firm_i at time t (in line with Sahut & Mili, 2011)

EN_{it} = earnings (gross earnings/total assets) of firm_i at time t (see Jayade, 2006)

MQ_{it} = management quality (total expenses/total assets) of firm_i at time t. (Li et al, 2011) showed that successful banks have low expenses-to-assets ratios.

b_0 = intercept term, b_1 - b_5 are the coefficient of regression.

U = error term

Discussion of Findings

The multiple discriminant (Z-score) result revealed that about 69.84% of the banks investigated are likely to experience distress in the near future if urgent care is not taking, while about 30.16% are in a sound financial health. Specifically, First Bank Z-scores for the period under investigation were below the cut off rate of 2.675 on the average except in 2018. The same is true of Zenith Bank throughout the period investigated. The result further revealed that Unity Bank and Union Bank are above the cutoff point for during the period under investigation. However, Access Bank is financially sound during the period of the study. Similarly, Fidelity Bank have a Z-score greater than 3.4217 for the period under study except in 2014.

Based on this outcome, the censored logistic regression was run to ascertain the effect of the explanatory variables on bank financial health, using the panel data. The Wald test statistic was applied to determine the overall significance of the explanatory variable. The results of the investigation are presented in table 1 and 2 below.

Table 1: Censored logistic regression outcome.

Dependent variable = POD(Dummy variable)		
Independent variables	Coefficient	z. Statistic
C	1.5371	6.3158(0.0000)*
CA	-0.4268	-0.7872(0.4311)
LQ	-0.0060	-0.0195(0.9845)
AQ	-0.6967	-3.4355(0.0000)*
EN	-0.2481	-5.3306(0.0000)*
MQ	-0.5366	-6.4061(0.0008)*
Convergence achieved after 7 iterations * = significant at 0.01 % (Probability reported in parenthesis)		

Researcher's estimation using E-view 9.0 software

The result in table 1 above exposes that all the CAMEL variables negatively and significantly influence bank financial health, indicating that a boost in the indicators will help to militate bank distress in Nigeria. It also implies that the current amount of these proxy indicators are grossly inadequate. The table 1 further reveals that capital adequacy (CA) has a negative and but not significant impact on bank financial health condition. The result signify that the current level of bank capital adequacy is not enough to immune banks from experiencing financial distress. Similarly, liquidity ratio negatively influenced bank distress status.

But the result is not significant at 5% level, which tends to mean that bank managers should embrace financial inclusion in order to attract more deposits because the current liquidity position is not sufficient to keep the banks stable. On the contrary, asset quality, earnings and management quality negatively and significantly impact bank health status within the period under investigation. The result which is significant at 5%, implies that an improvement in asset quality, management quality and earnings of the banks will help in alleviating bank distress in Nigeria. Therefore, the regulatory authorities and banks managers should pay devoted attention to these indicators because the hold the potential to guarantee bank stability in Nigeria.

The overall result indicates that CAMEL variables are important predictor and useful indicators in guiding against bank distress if appropriately applied. The result provide support for Sahut and Mili (2011) that CAMEL indicators are useful in predicting bank failure.

To test for the level of integration of the indicators incorporated in the model, the Wald test was applied on the regression output. The outcome of the test is as presented in Table 2 below:

Table 2: Wald Test Estimation Results.

Statistics Tested	Value	Probability
T. Statistic	3.0174*	0.0038
F. Statistic	9.1048*	0.0038
Chi^2 Statistic	9.1048*	0.0025
*= Significant at 5% level		

Researcher's estimation with the aid of Eview software.

The result in table 2 above revealed the F-statistic is significant at 1%. Similarly, Chi^2 is also significant at 1% level, signifying that there is a linear relationship between the dependent and explanatory variables, suggesting that the model is reliable for predictive purposes.

Conclusions

This study examined the financial health of selected banks in Nigeria from 2012 to 2020. Data for the study was collected from bank audited annual reports of investigated banks. The study applied multiple discriminant (Z-score) technique and censored logistic regression to scrutinize the effect of CAMEL variables on bank distressed conditions. Specifically, the effect of capital adequacy, liquidity, asset quality, earnings and management quality on bank financial health conditions were considered. The discriminant analysis revealed that about 69.84% of the banks investigated may fall into distress status in near future if adequate measures are not applied, while only 30.16% are financially sound. The study found that CAMEL indicators such as asset quality, earnings and management quality negatively and significantly impact bank financial health in Nigeria. This study concludes that CAMEL indicators are potent instruments for scrutinizing bank financial health status. This study recommend that bank managers should devote attention towards the management of their CAMEL indicators to avoid distress and that the supervisory authorities should intensify surveillance and exercise regulatory discipline especially on the big banks as no bank is too big to experience financial crises.

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