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Causes of Bank Failures on a Global Perspective, With Major Reference to Nigeria

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I. Introduction

The banking system in Nigeria has recently been under scrutiny, not only because of its intermediation functions, but also because of the problems plaguing the industry in terms of failures and eventual bank distress. The issue of bank failure has risen in prominence throughout time as a result of the growing recognition of the banking sector's continued importance to effective economic functioning, growth, and development (Marshal, 2017). The scope and depth of bank failure might be either broad (generalised) or systemic. When the occurrence of failure spreads quickly and cuts throughout the industry in terms of the ratio of total deposits of failed institutions to total deposits of the industry, it is known as generalised failure (Aliero and Ache, n.a). on the other hand, the problem is considered systemic if its prevalence and contagious effects become endemic, posing a threat to the entire system' stability. Thus, public's trust in the system is utterly eroded (Egbo, 2012). As a result, it's only logical that topics relating to bank operations, as well as their challenges, would reverberate among academics and researchers.

Bank failures almost always have negative effects for stakeholders outside of the collapsed banks. The non-banking system as a whole sometimes bears the brunt of the consequences. A failure can have serious consequences for employment, earnings, financial development, and other public interests. The string of failures in the banking sector over the years can be summarised by the number of insolvent banks, the rash of nonperforming loans, the debt and required capitalisation, the loss of depositor funds, and the overall impact on the economy; all highlighting the sector's importance (Marshal, 2017). While acknowledging the causes of banks failure in Nigeria, Marshal (2017) opined that the number of failed banks, spate of nonperforming loans, debt and extent of required capitalization, loss of depositor's funds, and overall impact on the economy can all be captured by the number of failed banks, nonperforming loans, debt and extent of required capitalization, loss of depositors' funds, and the general impact on the economy, all of which underscore the importance of the sector.

In most empirical studies on banking failures, a financial institution (bank) is considered to have failed if it received external support or was shut down immediately (Egbo, 2012). In addition, a financial institution is considered to have failed if it falls into one of the following categories (Bongini, Claessens, and Ferri 200): the financial institution was recapitalised by the central bank or an agency specifically created to address the crisis, and/or required a liquidity injection from the monetary authority; the financial institution's operations were temporarily suspended ("frozen") by the government; the financial institution's operations were temporarily suspended ("frozen") by the government; the government. These categories encompass a broader definition of economic failure than the stricter definition of de jure failure (closure) (González *et al.,* 2019). One potential drawback is that group (iv) could include banks that were merged or absorbed for strategic reasons rather than bankruptcy reasons during the crisis era.

Nigeria's financial services sector began to liberalise in 1986 as part of the Structural Adjustment Programme's requirements (SAP). The conditions for banking licenses in Nigeria were substantially relaxed as a result of this. Thus, on July 6, 2004, the Central Bank of Nigeria (CBN) announced banking reform to strengthen Nigerian banks and improve their competitiveness in international financial markets (Sunday and Innocent, 2021). The reform's main focus was the requirement that banks have a minimum capitalisation of NGN25 billion, up from NGN2 billion, with complete compliance expected by the end of December 2005. (that is, about 18 months from the policy announcement). The policy's stated goal was to merge existing banks into fewer, larger, and financially stronger institutions (Alford, 2010). On the 31st of December 2005, the first phase of the consolidation program came to an end, with 25 banks having reached the minimum capitalization requirement (Soludo, 2006). The successful banks accounted for 93.5 percent of the banking system's deposit liabilities. Banks raised over NGN406 billion from the capital market, while the consolidation process resulted in a US$652 million and £162,000 Sterling infusion of foreign direct investment (FDI).

At the end of the deadline for recapitalisation on December 31, 2005, 14 banks had failed to find merger partners and were unable to achieve the minimum capitalisation requirement on their own (Soludo, 2006). As a result, the 14 banks' operating licenses were revoked. Nigerian banks improved their operations in terms of branch expansion, deposit mobilisation, and profitability after the banking consolidation process (Sunday and Innocent, 2021). However, the worldwide financial crisis of 2007–2009, as well as the resulting widespread economic instability caused by the outbreak of Covid-19 in the year 2020, resulted in bank difficulty and failure all across the world, including Nigeria. The ugly phenomena of bank distress and collapse has resurfaced, bringing the problem of bank hardship and the predictability of bank failure to the fore once more. As a result, and as is typical in times of financial upheaval, interest in bank failure to avoid them has resurfaced.

Many earlier research on bank failure in Nigeria have existed over time (see Farinde 2013; Pam 2013; Adeyeye et al. 2012; Amadasu 2012; Oforegbunam 2011; Okezie 2011; and Olaniyi 2007). More recently, Ozurumba (2016), Adeyeye and Migro (2015), Babajide et al. (2015) and Adeyeye and Oloyede (2014) sought to anticipate bank failure and hardship in Nigeria using various variables and techniques. However, this study aims to improve on previous research by incorporating non-financial variables into the failure prediction model (bank listing status on the Nigerian Stock Exchange, banks' ownership structure, banks' merger status, bailout status, consolidation status, and number of merged banks) and by considering the components of distress and failure (looking at the possibilities of predicting bank distress and failure) by drawing from the earlier study carried out by Sunday and Innocent (2021). These additions will aid in the investigation of the role of non-financial bank characteristics in predicting bank hardship and failure in the Nigerian banking sector.

Thus, the underlying objectives of this study are to:

i. investigate the possibility of predicting bank distress and failure in Nigerian banks using financial covariates and non-financial attributes;
ii. identify bank-specific financial and non-financial characteristics that influence the likelihood of bank distress and failure in Nigeria;

II. Literature Review

A bank's failure is not an accident, and it does not happen overnight. It is both organic and systemic, and so may be predicted ahead of time based on the discovery of early warning signals, offering a long-term framework for bank management and regulatory agencies to take decisive action to avert the problem (Oforegbunam, 2011). The seminal contribution of Secrist (1938) sparked the first interest in predicting bank collapses, and many research have sought to follow suit since then. Olaniyi (2006) and Pam (2013), for example, used a multiple discriminant analysis (MDA) model to determine the bankruptcy status and health of Nigerian banks. Liquidity, profitability, operating efficiency, and total assets turnover are all powerful indicators of a bank's success in Nigeria, according to these studies.

Principal component analysis (PCA), discriminant models, and augmented discriminant models were used by Adeyeye *et al* (2012), Adeyeye and Migro (2015), and Adeyeye and Oloyede (2014) to forecast the chance of bank failure and produce early warning signals in Nigeria. Profitability, liquidity, credit risk, and capital sufficiency were identified as crucial predictive financial parameters in these investigations. Profitability, liquidity, credit risk (asset quality), and capital sufficiency (sustenance) are the primary distinguishing features between healthy and unsuccessful banks, according to this research. Amadasu (2012) used four approaches to investigate corporate bankruptcy in Nigerian banks: Z-score, ordinary least squares (OLS) regression, correlation matrix, and logit and probit regression. Working capital/total assets, sales/total assets, and retained earnings/total assets are all key determinants for survival, according to the study. The levels of capital adequacy, asset quality, earnings strength, liquidity sufficiency, and management competency are essential indices for gauging the health of banks in Nigeria, according to Oforegbunam (2011), who used Altman's model to anticipate distress in the Nigerian banking system.

Using the OLS approach, Okezie (2011) and Ozurumba (2016) investigated the relationship between capital ratios and bank distress, as well as the influence of non-performing loans on the performance of Nigerian banks. These studies discovered that the three capital ratios, risk-weighted, leverage, and gross revenue ratios, accurately predicted bank distress and that there was no significant difference in the efficiency of the three capital ratios in predicting distress. Farinde (2013) used a multilayer perceptron neural network approach to assess the susceptibility of Nigerian banks to failure. Total equity/liabilities (without equity), earnings before tax/total assets, working capital/total assets, earnings before tax/working capital, and profits before tax/gross earnings have all been found to be sensitive to a bank's solvency. Babajide *et al* (2015) used the Cox proportional hazards model to predict bank failure in Nigeria using financial covariates. They discovered that banks with a high ratio of non-performing loans to total loans plus lease, as well as high operating expenses to average total assets, have a high risk of failure.

III. Methodology

3.1.1 Theoretical Framework

This study will rely on the Early Warning Signal (EWS) model for predicting bank difficulty and failure in Nigeria, as employed by (Sunday and Innocent 2021). Early warning model indications are strongly linked to bank regulatory grading systems. CAMELS – capital adequacy, asset quality, management, earnings, liquidity, and sensitivity to market risk (is the most well-known rating system). Non-financial variables (bank category, bank listing status on the Nigerian Stock Exchange, bank ownership structure, and bank merger status) will also be included in this study to investigate the impact of non-financial bank characteristics on predicting distress and failure in the Nigerian banking system.

Furthermore, the study will apply a survival analysis approach based on the Cox proportional hazards model, as employed by Pereira (2014) and Babajide et al. (2015) in forecasting bank distress and failure in Nigeria. Hazard model prediction models produce more consistent in-sample estimations and more accurate out-of-sample predictions for corporate bankruptcies than the traditional static bankruptcy (Shumway 2001). The Cox proportional hazards survival analysis allows for a more in-depth assessment of bank failure while also accounting for time fluctuations in determining the likelihood of a bank collapsing.

3.1.2 Model Specification

To be able to achieve the stated objectives, this study intends leaning on the Cox proportional hazards model as used by Pereira (2014), Babajide et al. (2015) and Sunday and Innocent (2021). Assuming that the probability of "failure" at a given time period is proportional to the values of p explanatory variables $x_i, x_2, ... x_p$ the set of explanatory variable values in the proportional hazard model is represented by the vector x, which equals $X_i, X_2, ... X_p$

The hazard function of a firm is $h_0(t)$ which has zero values for all variables that make up the vector x. The baseline hazard function is referred to as $h_0(t)$. As a result, the danger function of i can then be written as:

$$h_t(t) = \delta(x_i)h_0(t) \ldots\ldots\ldots\ldots\ldots\ldots (3.1)$$

where $\delta(x_i)$ represents the function of the values of the vector of explanatory variables for i firm. The function $\delta(x_i)$ could be described as the risk over time t for a firm whose vector of explanatory variables is x_i on the risk for a firm whose $x = 0$. Because the relative risk $\delta(x_i)$ cannot be negative, it is expressed as exp (γ_i), where γ_i is a linear combination of the p explanatory variables in x_i. Therefore,

$$\gamma_i = \alpha_i\alpha_{1i} + \alpha_2\alpha_{2i} + \cdots \alpha_p\alpha_{pi} \ldots\ldots\ldots\ldots\ldots\ldots (3.2)$$

which is corresponding to

$$\gamma_i = \sum_{j=1}^{p} \alpha_j x_{ji} \ldots\ldots\ldots\ldots\ldots\ldots (3.3)$$

The quantity γ_i, is called the linear component of the model otherwise known as risk score or prognostic index for i firm. The proportional hazard model can generally be expressed as:

$h_i(t) = \exp\,(\alpha_i\alpha_{1i} + \alpha_2\alpha_{2i} + \cdots \alpha_p\alpha_{pi})h_0(t) \ldots\ldots (3.4)$

Thus, the Cox regression model for this study is written as:

$h_i(t) = \exp\,(\alpha_i\alpha_{1i} + \alpha_2\alpha_{2i} + \alpha_3\alpha_{3i} + \alpha_4\alpha_{4i} \ldots \alpha_{10}\alpha_{10i})h_0(t) \ldots (3.5)$

where α represents the vector coefficient of the $x_i, x_2, ... x_p$ explanatory variables in the model. X assumes the form of $x_i, x_2, ... x_{10}$. Thus, the variables of interest to this study are:

x_i = (AGE) – age of the bank
x_2 = (SURVTM) – survival time
x_3 = (SUVSTA) – survival status
x_4 = (LNLOSS) – ratio of loan loss reserve to gross loan (%)
x_5 = (EQTYASS) – ratio of equity to total assets (%)
x_6 = (EQYLIAB) – ratio of equity to liabilities (%)
x_7 = (ROAA) – return on average assets (%)
x_8 = (ROAE) – return on average equity (%)
x_9 = (COSINC) – ratio of cost to income ratio (%)
x_{10} = (BNKCAT) – whether bank is owned by multinational
x_{11} = (BNKCONS) – bank merger status at consolidation
x_{12}= (BNKCONSM) – number of banks that merged
x_{13} = (LSTSTAT) – listing status of bank on the Nigerian Stock Exchange (NSE)
x_{14} = (OWNSTR) – whether the bank MD/CEO is the founder of the bank

3.1.2 Data Choices and Sources

Extant studies on financial sector fragility and failure prediction guided the selection of variables for the model. In order to generate the covariates, this study will use the estimating approaches of Cole and Wu (2009) and Andrianova et al. (2015). Unlike Cole and Wu (2009), however, this analysis took into account the

following non-financial variables: banks' Nigerian Stock Exchange listing status, ownership structure, merger status, bailout status, consolidation status, and the number of combined banks. The financial services sector changes, particularly the 2004 consolidation exercise, influenced the selection of these nonfinancial variables. The consolidation exercise was designed to strengthen Nigerian banks and make them more resilient to shocks.
This study will make use of secondary data from the BankScope Database (Bureau Van Dijk database). The BankScope Database contains information on all active and failed banks in Nigeria. Bank level data will be compiled using data from BankScope, which includes annual and quarterly financial reports from both publicly traded and private commercial banks for the following time periods: I the full sample period (2006–2020); (ii) the in-sample period (2006–2009); and (iii) the out-of-sample period (2009–2020). Non-financial variables, on the other hand, will be calculated using dummies. STATA software will be used to perform the estimation.

IV. Results and Discussions

4.1.1 Descriptive Statistics

Table 4.1 shows descriptive statistics for the financial variables used in the study, which were broken down by bank category and failure. The first decomposition is by distress threshold, which is 1 if the bank has reached the threshold and 0 otherwise. Bank size and failure are the other decompositions. The ratio of loan loss reserve to gross loan (LonRes) is 6.53 percent for banks on the brink of distress, compared to 2.48 percent for banks that aren't; the average for big banks is 1.57 percent, compared to 3.03 percent for small banks; and it's 13.41 percent for failed banks, compared to 1.53 percent for sound banks, according to the findings.

Table 4.1: Descriptive Statistics by Banks Categories

Variables	Distress Threshold			Big bank			Failure		
	0	1	Total	0	1	Total	0	1	Total
Loan Reserve/gross Loan (%)	2.48	6.53	4.20	3.03	1.57	2.39	1.53	13.41	3.28
Equity loan/total asset	13.73	-4.48	7.19	3.69	5.82	4.35	8.81	-8.44	4.99
Equity/Liabilities	16.5	-1.77	9.94	6.43	6.9	6.49	10.32	-3.51	7.15
Return on average assets	1.86	-4.11	-0.13	-0.60	0.29	-0.39	1.39	-10.01	-1.31
Return on average equity	18.37	36.24	25.23	21.39	8.76	16.7	13.33	64.51	22.61
Ratio of cost to income	59.14	76.59	65.84	47.89	37.51	44.02	43.42	64.15	46.87

And for the estimates of equity ratios, results in Table 4.1 shows that sound or large banks have higher average equity ratios. For sound banks, the equity to total assets (EQTASS), and equity to liabilities (EQTLIAB) ratios are respectively 13.73 and 16.50. They are not only minor for distressed banks, but they are also negative for distressed banks. These values implies that equity ratios are important in determining the soundness of Nigerian banks (Sunday and Innocent, 2021). Return on average assets is higher for sound banks and larger banks compared to troubled, tiny, or failed banks, but it is negative for distressed banks for the two categories of returns evaluated. Return on average equity, on the other hand, is higher for distressed, tiny, and bankrupt banks. Because these two variables are anticipated to have different effects on the likelihood of distress or failure, they were alternated in the regression results. The cost to income ratio (R_COSINC) for banks on the brink of failure is 76.59, compared to 59.14 for sound banks, according to the findings.

Table 4.2 shows the correlation matrix of the variables. The equity ratios are significantly connected, with a coefficient of correlation of at least 0.51. The table also show the existence of a negative correlation between return on average assets and return on average equity, which suggests that they assess returns differently.

Table 4.2: Correlation Matrix of the Variables

	LonRes	EqtAss	EqtLiab	ROAA	ROAE	R_CosInc
LonRes	1					
EqtAss	-0.279	1				
EqtLiab	-0.238	0.5083	1			
ROAA	-0.643	0.0634	0.224	1		
ROAE	0.4521	-0.0232	0.0113	-0.3401	1	
R_CosInc	0.0762	-0.1722	0.0089	0.0114	-0.037	1

4.1.2 Survival Analysis Results

The subsection discusses in details the results of the estimations of the factors that predict bank failure in Nigeria.

4.1.2.1 Factors Predicting Banks Failure in Nigeria

Table 4.3 presents the findings of the Cox proportional model. The hazard ratios, which are conventional for understanding the data, are shown in the table. In a similar version to several models employed by Sunday and Innocent (2021), three alternative model specifications were estimated in order to account for important factors as well as to alternate other variables in order to test the sensitivity of the estimates to other model specifications. Due to the possibility of multicollinearity, the two equity ratios used in the model ratio of equity to customer and short-term funding (EQTASS) and ratio of equity to liabilities (EQTLIAB) were alternated in all three specifications. The ratio of equity to assets (EQTASS), ratio of equity to liabilities (EQYLIAB), Loan reserves/ gross loans (LONRES), Returns on average assets (ROAA) and cost to income ratio (R_COSINC) are the statistically significant variables, according to the reported hazard coefficients (LNLOSS). The results show that higher cost to income ratios (R_COSINC) increase the risk of failure by between 0.9% and 3.0% considering the coefficients in all eight specifications.

Table 4.3: Bank level financial covariates and non-financial variables on bank failures in Nigeria

	Model 1	Model 2	Model 3
Age	1.007	1.113	
	(0.448)	(0.567)	
EqtAss	17.54***	14.37***	18.19***
	(0.002)	(0.004)	(0.000)
LonRex	1.021**	1.011**	1.015***
	(0.012)	(0.010)	(0.008)
EqtLiab	1.116**	1.115*	1.005
	(0.012)	(0.024)	(0.448)
ROAA	0.903*		
	(0.022)		
ROAE	1.001		
	(0.248)		
R_CosInc	1.009***	1.103**	1.003**
	(0.004)	(0.013)	(0.011)
BnkConsm		0.846	0.778
		(0.644)	(0.584)
Ownstr		9.85	1.436
		(0.305)	(0.087)
N	10	10	10
ll	-5.31	-6.15	-5.42
Chi_2	6.34	6.44	6.36
r2_p	0.215	0.187	0.204

The model captures two profitability variables: return on average equity and return on average assets. In the Cox proportional hazards models, the two indicators were alternated. In the two models, the coefficient of return on average equity in the bank failure prediction model in Tables 4.3 is positive and statistically significant, and the corresponding hazard ratio in Table 4.4 is greater than one. However, the coefficient was not significant in model three. These findings imply that banks that make the majority of their earnings from return on average equity are not necessarily safer than banks that make more profits from return on average assets. By investing the bank's assets in more successful projects, return on average assets gauges how efficient management is. Even when the bank is capital-constrained, capital profits gained through the issue of premium shares are included in the return on average equity of Nigerian banks.

The coefficient of return on average equity in bank distress prediction models is continuously positive, with a substantial hazard greater than one, indicating a higher chance of entering into distress sooner rather than later. On the other hand, with a hazard ratio less than unity, the coefficient of return on average assets is continually negative and statistically significant, indicating a low danger of going into trouble. As a result, when a bank's profit is derived from return on average equity rather than return on average assets, this is cause for concern. Despite the fact that this finding appears paradoxical and goes against the majority of existing studies on bank performance monitoring, a European Central Bank report (2010) backs it up. The most frequent indicator of bank performance, return on equity (ROE), according to a European Central Bank report (2010), is just part of the picture, as a high level of ROE might represent either a high level of profit or a low amount of equity capital.

Table 4.4: Bank level characteristics and non-financial variables on bank distress in Nigeria

	Model 1	Model 2	Model 3
Whether the bank MD/CEO is the founder	0.331	0.343**	0.107+
	(0.166)	(0.019)	(0.054)
Equity/total asset	17.54***	14.37***	18.19***
	(0.002)	(0.004)	(0.000)
Equity/Liabilities	0.116***	0.125***	0.179***
	(0.004)	(0.001)	(0.000)
Return on Average Assets	1.003**	1.114***	1.010**
	(0.012)	(0.007)	(0.010)
Return on Average Equity	0.967**	0.986**	0.928
	(0.028)	(0.019)	(0.103)
Ratio of cost to income	1.109***	1.113***	1.003**
	(0.006)	(0.003)	(0.010)
N	10	10	10
ll	-4.11	-3.32	-4.28
Chi_2	5.48	6.13	5.38
r2_p	0.131	0.116	0.124

The cost-to-income ratio, return on average assets, return on average assets and bank ownership structure (whether the MD/CEO is the founder) are all statistically significant variables, according to the Cox proportional model results in Table 4.4. The findings suggest that a higher cost of living raises the probability of distress by between 0.3% and 11.3%. This outcome is consistent with apriori expectations, because when the MD/CEO is also the founder, he or she goes to great lengths to safeguard the money and investment by employing every method available to guarantee that the bank survives.

V. Summary and Conclusion

This study empirically explored causes of bank failure in Nigeria. Using quarterly data from the BankScope Database, bank-level financial variables were utilised to assess the predictors of bank failure, in order to meet the study’s objectives. Findings of the showed that cost-to-income ratio, return on average assets, return on average assets and bank ownership structure (whether the MD/CEO is the founder) were all important predictors of bank failure in Nigeria. The results also revealed that return on average equity in bank distress prediction is continuously positive, with a substantial hazard greater than one, indicating a higher chance of entering into distress sooner rather than later.

Policy Implications/Recommendations

i. The Nigerian Central Bank should establish and tightly enforce a maximum ceiling for loan loss reserve provision, as well as a percentage of impaired/non-performing loans. This should be followed by severe periodic oversight, preferably on a quarterly basis. Infraction penalties should be explicitly defined.

ii. The Central Bank of Nigeria should allow/encourage bank owners or key promoters to serve as CEOs for a set length of time after the bank's founding. This should not, however, detract from the importance of thorough and effective monitoring to ensure strict adherence to excellent corporate governance practices and the avoidance of unethical behaviour.

iii. To measure the health of the banking industry and to enhance on-site supervision, survival models such as Cox proportional hazards models should be employed for periodic stress testing and off-site monitoring of

Nigerian banks. Early warning signals generated by such an endeavour will identify potentially weak banks, allowing for proactive intervention to prevent bank distress and failure, as well as lessen systemic risk.

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