Analysis of Bank Distress and Failure Predictability in Nigeria

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Abstract

After the 2005 banking sector reform and consolidation exercise, Nigerian banks were deemed to be strong and resilient to shocks. However, the global financial crisis of 2007–2009 and ensuing widespread economic instability brought in its wake incidences of bank distress and failure globally, and Nigeria was not spared. Since the 2007–2009 global financial crisis, there has been renewed interest in bank failure and financial system vulnerability analysis. Considering the far-reaching negative consequences of bank failure, especially the loss of jobs, loss of investment by shareholders, and erosion of confidence in the banking sector, it has become most pertinent to determine if it is possible to identify early warning signs of frailty (distress) in the Nigerian banking sector with a view to predicting the likely incidence of future failure. Therefore, this study analyses bank distress and failure predictability in Nigeria using financial covariates and non-financial variables between 2006 and 2015. Using quarterly data of all Nigerian banks from BankScope, and employing the Cox proportional hazards model and Kaplan-Meier estimate, the study identified the financial covariates and non-financial variables that contribute to bank distress and failure in Nigeria, and predicted the probable time to failure of Nigerian banks.

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Executive Summary

The liberalisation of Nigeria's financial services sector in 1986 as part of the conditionality for the Structural Adjustment Programme (SAP) essentially eased the requirements for banking licences in Nigeria. Consequently, there was a dramatic increase in the number and variety of financial institutions operating in the country. From 1985 to 1992, the number of commercial banks increased from 40 to 120 banks, the highest number to that point in time. The sheer number of commercial banks and their inability to naturally combine their operations to become more efficient posed a serious problem in the Nigerian financial services sector. The consequence of the inefficiency arising from increased number of banks was increasing incidence of bank failures and distress in the Nigerian banking sector in the 1990s. The inability of the banks to voluntarily embark on consolidation in line with the global trend necessitated the adoption of appropriate legal and supervisory frameworks as well as a comprehensive incentive package to facilitate mergers and acquisition as a crisis resolution option and to promote the soundness, stability and enhanced efficiency of the system.

Consequently, the Central Bank of Nigeria (CBN), announced a banking industry reform on July 6th, 2004 to strengthen Nigerian banks and enhance their competitiveness in the international financial markets. The major thrust of the reform was the requirement that the minimum capitalisation for banks should be NGN25billion, up from NGN2billion with full compliance before end-December 2005 (that is, about 18 months from the policy announcement). The clear intent of the banking sector consolidation exercise was to consolidate the existing banks into fewer, larger, and financially stronger banks. At the close of the first phase of the consolidation programme on December 31st, 2005, twenty-five (25) banks emerged having met the minimum capitalisation requirement. The successful banks accounted for about 93.5% of the deposit liabilities of the banking system. About NGN406billion was raised by banks from the capital market, while the consolidation process led to the inflow of Foreign Direct Investment (FDI) of US$652 million- and 162,000-pounds sterling. At the expiration of the December 31, 2005 timeline for recapitalisation, fourteen banks (14) failed to secure merger partners and were not also able to make the minimum capitalisation requirement on their own. Consequently, the operating licenses of the fourteen (14) affected banks were revoked.

The global financial crisis of 2007-2009 and ensuing widespread economic instability however brought in its wake incidences of bank distress and failure globally and Nigeria was not spared. The re-emergence of the ugly phenomenon of bank distress and failure has once again brought to the fore the issue of bank distress and predictability of bank failure.

Literature on bank distress and failure predictability identifies a number of bank-specific characteristics that aid prediction of bank distress and failure, especially in developed countries with limited focus on developing economies. It is likely that bank distress and failure can be predicted not only by bank-specific financial covariates. However, efforts have so far been focused only on financial covariates in bank distress and failure prediction in Nigeria. The effort in this paper is geared towards exploring the financial covariates and non-financial variables that predict bank distress and failure in Nigeria using quarterly data from the Bankscope Database. The study also explored the probable time to failure of Nigerian banks.

The study analyses bank distress and failure predictability in Nigeria using financial covariates and non-financial variables between 2006 and 2015. Using quarterly data of all Nigerian banks from BankScope, and employing the Cox proportional hazards model and Kaplan-Meier estimate, the study identified the financial covariates and non-financial variables that contribute to bank distress and failure in Nigeria, and predicted the probable time to failure of Nigerian banks.

Within the period 2006-2009 (early post-consolidation period), the ratio of impaired loans to bank equity holdings, ratio of impaired loan to equity, and loan loss reserve were significant predictors of bank failure in Nigeria. Also, the ratio of impaired loans to gross loan increases the risk of bank failure. Similarly, loan loss reserve had the probability of reducing the risk of bank failure in Nigeria between 2006 and 2009. However, higher loan loss reserve indicates poor quality of loan portfolio of banks. Return on Average Equity (ROE) has been found not to have contributed significantly to the survival of banks within the post-consolidation period. This is understandable because ROE has been found not to be the necessary and sufficient conditions for bank survival in some cases, especially during financial crisis. In some cases, banks may record good return on equity and return on assets, yet, may still experience problems. In addition, although the “traditional” decomposition of the ROE measure (looking at bank operational performance, risk profile and leverage) may have been useful to assess bank’s performance under normal circumstances, this approach has clearly not proven adequate in an environment of much higher volatility – such as during the global financial crisis, where fluctuations have been caused entirely by operational performance, which does not aid our understanding of the potential trade-off between risk and return in performance.

The study also found that impaired or non-performing loans significantly increases the risk of bank distress and failure, while cost to income ratio increases the risk of bank failure in Nigeria. Loan loss reserve has the probability of reducing the risk of bank failure. This study provides additional evidence and corroborates earlier findings on bank-specific financial covariates that predict bank distress and failure in Nigeria. The study is one of the few to incorporate non-financial variables in the bank distress and failure prediction literature. A significant insight from this study is the role of the structure of bank ownership on distress/failure or survival of a bank. That is, whether the Chief Executive of the bank is the founder can significantly predict bank distress and failure. At 5% level of significance, ownership structure reduces the probability of incidence of distress, while at 10% level of significance, ownership structure has the probability of reducing both bank distress and failure. The study found that the average survival time of small Nigerian banks ranges from about 23 quarters to 40 quarters, while big Nigerian banks take a longer time to fail and their average survival time cannot be easily determined.

In line with the findings, the study recommends as follows:

- The Banking Supervision Directorate of the Central Bank of Nigeria (CBN) should go beyond the use of Return on Equity (ROE) as a performance indicator, more especially in periods of crisis. In benign times, ROE may be applied but may not be a sufficient performance indicator in a volatile environment. Other indicators like operational efficiency should be incorporated.
- The Central Bank of Nigeria (CBN) should set and strictly enforce a maximum limit for loan loss reserve provision as well as proportion of impaired/non-performing loan. This should be followed with strict regular periodic supervision, preferably quarterly. Penalty for infractions should be clearly stipulated.
- The Central Bank of Nigeria (CBN) should allow/encourage owners or major promoters of banks to be Chief Executives of banks for a stipulated period of time from inception. This should however not detract from close and effective monitoring to ensure strict compliance with best corporate governance practices, and avoidance of unethical practices.
- Survival models such as Cox Proportional Hazards model should be used for periodic stress test and off-site supervision of Nigerian banks to assess the health of the banking sector, and aid on-site supervision. Early warning signals emanating from such exercise will reveal potentially vulnerable banks and make for proactive intervention to avert incidences of bank distress and failure, and mitigate systemic risk.
- The Central Bank of Nigeria (CBN) should ensure sound and robust credit risk management and discourage excessive risk by banks.

1.0 Introduction

1.1 Background to the study

The liberalization of Nigeria's financial services sector in 1986, as part of the conditions of the Structural Adjustment Programme (SAP), essentially eased the requirements for banking licences in Nigeria. Consequently, there was a dramatic increase in the number and variety of financial institutions operating in the country (Soyibo, Alashi and Ahmad, 2004). From 1985 to 1992, the number of commercial banks increased from 40 to 120 banks, the highest number of banks recorded until that year(Alford, 2010). The sheer number of commercial banks and their inability to naturally combine their operations to become more efficient posed a serious problem to the Nigerian financial services sector. According to Soludo (2004), the inability of the Nigerian banking system to voluntarily embark on consolidation in line with the global trend necessitated the adoption of appropriate legal and supervisory frameworks as well as a comprehensive incentive package to facilitate mergers and acquisition as a crisis resolution option and to promote the soundness, stability and enhanced efficiency of the system.

Consequently, the Central Bank of Nigeria (CBN), announced banking industry reform on 6 July 2004 to strengthen Nigerian banks and enhance their competitiveness in the international financial markets. The major thrust of the reform was the requirement that the minimum capitalization for banks should be NGN25 billion, up from NGN2 billion with full compliance before the endof December 2005 (that is, about 18 months from the policy announcement). The clear intent of the policy was to consolidate the existing banks into fewer, larger, and financially stronger banks (Alford, 2010). At the close of the first phase of the consolidation programme on 31 December 2005, 25 banks emerged having met the minimum capitalization requirement (Soludo, 2006). The successful banks accounted for about 93.5% of deposit liabilities of the banking system. About NGN406 billion was raised by banks from the capital market, while the consolidation process led to a foreign direct investment (FDI) inflow of US$652 million and £162,000 Sterling. At the expiration of the 31 December 2005 timeline for recapitalization, 14 banks failed to secure merger partners and were also not able to meet the minimum capitalization requirement on their own. Consequently, the operating licenses of the 14 banks were revoked.

After the banking consolidation exercise, Nigerian banks generally showed an improvement in their operations in terms of branch expansion, deposit mobilization and profitability. According to Soludo (2006), aside from the reduction in the number of banksand the heavy capital mobilization, other benefits of the consolidation exercise included: greater depositor confidence, reduced interest rate due to high liquidity, and lending to the private sector rose by 40%. There is no doubt that the consolidation exercise had some positive impacts on the banking sector (Sanusi, 2010). However, the global financial crisis of 2007–2009 and ensuing widespread economic instability brought in its wake incidences of bank distress and failure globally, and Nigeria was not spared. The re-emergence of the ugly phenomenon of bank distress and failure has once again brought to the fore the issue of bank distress and the predictability of bank failure. Consequently, and as is common in times of financial turmoil, interest in bank failures and ways of averting these failures have been rekindled.

Literature on bank distress and failure predictability identifies a number of bank-specific characteristics that aid prediction of bank distress and failure, especially in developed countries but with limited focus on developing economies. It is likely that bank distress and failure can be predicted not only by bank-specific financial covariates. Nonetheless, efforts have so far been focused only on financial covariates in bank distress and failure prediction in Nigeria. This paper is geared towards exploring the financial covariates and non-financial variables that predict bank distress and failure in Nigeria. The paper is subdivided into five key sections. Section 1 sets out the research issue/problem statement, as well as the objectives of the study. Section 2 examines the extant literature – conceptual and empirical. Section 3 sets out the methodology – conceptual issues and theoretical framework, the model specification as well as the choice of variables used in the study. Section 4 discusses the empirical results, and Section 5 presents the summary, conclusion and policy recommendations.

1.2 Research issue/problem statement

Despite several financial services sector reforms and regulatory tightening, Nigeria experienced another wave of bank failures in 2009 in the wake of the global financial crisis. As the global financial crisis raged and its impact on the Nigerian economy and the banking system became apparent, it became obvious that the Nigerian banking system was in a dire situation. According to Sanusi (2011), the balance sheet of banks became eroded to the extent that some of them remained for some time on "life support" provided by the Central Bank of Nigeria (CBN). Interbank rates spiked as banks tried to borrow at any rate to remain afloat, the size of non-performing loans significantly increased, customer panic re-emerged and several instances of unethical conduct among the managements of banks were revealed. Consequently, the CBN and the Nigerian Deposit Insurance Corporation (NDIC) ordered a special examination of Nigerian banks. The result of the CBN/NDIC special examination revealed that nine banks were in a dire state.

The initial measures/initiative taken by the CBN in conjunction with the NDIC and the Federal Ministry of Finance included injection of NGN620 billion into the nine banks and the replacement of the chief executive/executive directors of eight of the nine banks. Notwithstanding these measures, three out of the nine rescued banks continued to show signs of weakness. Subsequently, the federal government, through the NDIC, assumed ownership of three banks through the "Bridge Bank" mechanism following the revocation of their licences by the CBN (Sanusi, 2010). Also, the Asset Management Corporation of Nigeria (AMCON) was established in 2010 to be a key stabilizing and revitalizing tool to revive the financial system by efficiently resolving the non-performing loan assets of banks in the Nigerian economy. The net financial cost of stabilizing the Nigerian financial system, sequel to the global financial crisis, is estimated at NGN1.75 trillion, which represented 5.85% of Nigeria's GDP of NGN29.498 trillion as at end December 2010.

The re-emergence of the ugly phenomenon of bank failure has once again brought to the fore the issue of predictability of bank failure and financial system vulnerability in the Nigerian financial services sector. The failure of a bank is fundamentally different from the failure of other types of businesses because of the interconnectedness of banking institutions and systemic risk. The failure of any firm may create externalities and losses in output, but because of banks' importance in the intermediation process, the costs and externalities associated with a bank failure are likely to be much larger than those associated with the failure of a non-bank entity (Kupiec and Ramirez, 2009). According to Kaufman (1996), bank failures are widely perceived to have greater adverse effects on the economy and thus are considered more important than the failure of other types of businesses. In part, bank failures are viewed as more damaging than other failures because of a fear that their failure may spread in domino fashion throughout the banking system, felling solvent as well as insolvent banks. The spiral effects of bank failure create difficulties in raising funds/credits and the deteriorating interests in safekeeping with banks acts as a disincentive to savings and investments, which, of course, hinders the performance of small and medium scale industries that serve as the engine of growth in the economy (Olaniyi, 2007).

Considering the far-reaching negative consequences of bank failure for the Nigerian economy, especially job losses, loss of investment by shareholders, and erosion of confidence in the banking sector, it is most pertinent to determine if it is possible to identify early warning signs of frailty in the Nigerian banking sector with a view to predicting the likely incidence of future failure. Previous studies on bank failure in Nigeria include: Olaniyi (2007); Adeyeye et al. (2012); Amadasu (2012); Oforegbunam (2011); Okezie (2011); Pam (2013); and Farinde (2013). More recent attempts to predict bank failure and distress in Nigeria include: Adeyeye and Oloyede 2014; Adeyeye and Migro, 2015; Babajide et al., 2015; and Ozurumba, 2016). This study extends the analysis, first, by considering the components of distress and failure (looking at the possibilities of predicting bank distress and failure). Secondly, this study incorporates non-financial variables in 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). The inclusion of these non-financial variables is to examine the influence of non-financial characteristics of banks in predicting distress and failure in the Nigerian bank system. Furthermore, this study extends the frontier of analysis by estimating the probable time to failure of small and big Nigerian banks.

1.3 Objectives of the study

The broad objective of this study is to analyses bank distress and failure predictability in Nigeria.
Specifically, the study seeks to:

1. explore the possibility of predicting distress and failure of Nigerian banks using banks' financial covariates and non-financial attributes;
2. identify bank-specific financial covariates and non-financial variables that explain the probability of bank distress and failure in Nigeria; and
3. estimate the probable time to failure of Nigerian banks.

2.0 Literature Review

2.1 Conceptual literature

The failure of a bank is not happenstance and does not occur in one day. It is organic as well as systemic and can therefore be predicted ahead of time based on the identification of the early warning signals; thereby providing a sustainable framework for bank management and regulatory authorities to take decisive actions to nip the problem in the bud (Oforegbunam, 2011). Early warning systems identify the causes of the failures and signal a possible bank failure ahead of time. Early signals of distress may include an increasing portfolio of non-performing loans, sustained drop in earnings per asset, high turnover of staff, consistent sourcing of funds from the interbank market, turnover of depositors, growing incidence of fraud, inability to meet statutory requirements, and instability in corporate management (Donli, 2003). Identification of these early warning signals are therefore of great interest to regulatory authorities throughout the world.

Conceptually, a bank is said to have failed when it is unable to meet its obligations to its depositors or other creditors because it has become insolvent or too illiquid to meet its liabilities. A bank fails economically when the market value of its assets declines below the market value of its liabilities, so that the market value of its capital (net worth) becomes negative (Kaufman, 1996). Unlike other profit maximizing entities, which are regarded as failed when their liabilities outweigh their assets (i.e., a negative net worth position), making it impossible for them to honour their financial obligations when due, a broader view of failure is usually adopted for banks because of the impact of bank failures on the economy.

2.2 Empirical literature

The earliest interest in predicting bank failures was the seminal contribution of Secrist (1938) who examined 741 national banks that failed in the late 1920s and early 1930s and 111 banks that did not fail prior to 1933 to secure indications of likely survival or collapse. This comparative analysis was the first of its kind and sought to discover the symptoms of failure and non-failure of banks (Barr and Siems, 1996). However, Beaver (1966) and Altman (1968) are some of the most widely cited in the early corporate bankruptcy literature. Beaver's (1966) was a univariate analysis on how accounting information in corporate financial statements affects security prices. Altman's (1968) was the first multivariate study of bankruptcy prediction and was particularly popular because of its success in predicting the bankruptcy of manufacturing firms using the 'Z-score' in a multivariate discriminant analysis.

After the initial attempts by Beaver (1966) and Altman (1968) to predict bankruptcy, the body of literature on the subject continued to grow as the unfortunate occurrence of bank failure persisted. The body of empirical literature of knowledge on bankruptcy prediction gained further momentum after academics and practitioners realized that the problem of asymmetric information between banks and firms lies at the heart of an important market failure such as credit rationing and that the improvement in monitoring technologies represents a valuable alternative to any incomplete contractual arrangement aimed at reducing borrowers' moral hazard (Stiglitz and Weiss, 1981, 1986 and 1992; De Meza-Webb, 1987; and Milde and Riley, 1988). More than ever before, the emphasis shifted to the development of more effective prediction models, such as early warming models. In the view of Barr and Siems (1996), while an early warning system cannot replace an on-site examination, which allows for personal interaction with the bank's management and employees and permits first-hand evaluation of operating procedures, levels of risk-taking, and long-range strategic planning, it can complement the on-site examination process by identifying troubled institutions that need early examination or possible intervention.

Olaniyi (2006) and Pam (2013) employed a multiple discriminant analysis (MDA) model in measuring bankruptcy status and ascertaining the state of health of Nigerian banks. These studies concluded that liquidity, profitability, operating efficiency and total assets turnover are very potent tools in the determination of the strength of Nigerian banks. Other parameters like earnings per share, dividend per share and the ratio of interest earned to interest paid also serve as potent collaborative tools (alongside MDA) in the determination of the strength of banks. Olaniyi (2007) evaluated the susceptibility of Nigerian banks to failure employing a multivariate analysis of Z-scores and found that the model can measure accurately potential of failure of unhealthy banks but inaccurately measures failure status of sound banks.

Adeyeye, Fajembola, Olopete, and Adedeji (2012), Adeyeye and Migro (2015), and Adeyeye and Oloyede (2014) used principal component analysis (PCA), discriminant models and enhanced discriminant models to predict the probability of bank failure and develop early warning signals of bank failure in Nigeria. These studies found measures of profitability, liquidity, credit risk and capital adequacy as key predictive financial ratios. These studied concluded that differences in profitability, liquidity, credit risk (asset quality) and capital adequacy (sustenance) are the major distinguishing characteristics between the healthy and failed banks. They also found that variables for management quality and other bank characteristics such as economic conditions and staff productivity are potentially not important predictors of financial problems in Nigerian banks, but might make a difference for the group of banks facing difficulties.

Amadasu (2012) examined corporate bankruptcy of Nigerian banks using four methodologies: Z-score, ordinary least squares (OLS) regression, correlation matrix, and logit and probit regression. The study found that working capital/total assets, sales/total assets, and retained earnings/total assets are significant variables for survival. Oforegbunam (2011) applied Altman's model in the prediction of distress in the Nigerian banking industry and found that the levels of capital adequacy; asset quality; earnings strength; liquidity sufficiency and management competency are critical indices for measuring the health of banks in Nigeria.

Okezie (2011) and Ozurumba (2016) examined the relationship between capital ratios and bank distress, and the impact of non-performing loans on the performance of Nigerian banks employing the OLS method. These studies found that the three capital ratios: risk-weighted, leverage and gross revenue ratios, predicted bank distress significantly and that there is no significant difference in the level of efficiency of the three capital ratios in distress prediction. Also, it was found that return on asset and return on equity have an inverse relationship with non-performing loans and loan loss provision, respectively, while they are positively related to loans and advances.

Farinde (2013) evaluated the susceptibility of Nigerian banks to failure using the multilayer perceptron neural network analysis. Ratios found to be sensitive to solvency of banks include: total equity/liabilities (without equity), earnings before tax/total assets, working capital/total assets, earnings before tax/working capital, and earnings before tax/gross earnings. Babajide, Olokoyo and Adebayo (2015) employed the Cox proportional hazards model to predict the failure of banks in Nigeria using financial covariates and found that banks that are high on non-performing loans to total loans plus lease, and with high operating expenses to average total assets have a very high tendency of failure.

Nurazi and Evans (2005) investigated whether CAMEL(S) ratios can be used to predict bank failure in Indonesia. The study found that logistic regression in tandem with multiple discriminant analysis could function as an early warning system for identifying bank failure and as a complement to on-site examination. The results of the study suggest that the variables adequacy ratio, assets quality, management, earnings, liquidity, and bank size are statistically significant in explaining bank failure. Zaghdoudi (2013) used the binary logistic regression method to develop a predictive model of Tunisian bank failures and found that the most pertinent ratios in the explanation of the failure of Tunisian banks are decrease in profitability, and the ability of banks to repay their debts.

Author	Methodology applied	Country examined and period covered	Key findings	Significant explanatory variables
Cole and Wu (2009**)**	Simple hazard model with time-varying covariates	United States 1980–1992	The study found that incorporating time-varying covariates enabled the utilization of macroeconomic variables, which cannot be used in a one-period model. The model significantly outperformed the simple static probit model and substantially improved the out-of-sample prediction of bank failures.	CAMELS risk ratios, particularly those related to capital adequacy, liquidity and asset quality.
Whalen (2005)	Cox proportional hazards model	United States 1997–1999	The study found that hazard models are considerably more accurate than two simpler supervisory screens out-of-sample. In particular, the estimated models do a much better job of correctly flagging high-risk banks.	Ratio of total equity to total assets, management quality, bank size measure (the log of total assets), interest rate risk (total assets repricing in 15 years or more divided by total assets), net gains on loans sold divided by total assets.
Olaniyi (2007)	Multivariate analysis of Z-scores	Nigeria 1998–2003	The model was able to measure accurately potential of failure of unhealthy banks, but inaccurately measured failure status of sound banks.	Working capital to total assets, retained earnings to total assets, earnings before interest and taxes to total asset, value of equity to total book debt, gross earnings to total assets.
Amadasu (2012)	Z-score, OLS regression, correlation matrix and logit, probit regression	Nigeria 2003–2007	The study found that adequate supervision and treatment are given to working capital efficiency to ensure survival.	Working capital/total assets, sales/total assets, and retained earnings/total assets.
Oforegbunam (2011)	Altman's model	Nigeria 2004–2008	The study found that the levels of capital adequacy, asset quality, earnings strength, liquidity sufficiency and management competency are critical indices for measuring the health of banks in Nigeria. Nigeria.	Capital adequacy, asset quality, earnings strength, liquidity sufficiency and management competency.
Okezie (2011)	OLS regression	Nigeria 1991–2004	The study shows that the three capital ratios predicted bank distress significantly and that there is no significant difference in the level of efficiency of the three capital ratios in distress prediction.	Risk-weighted, leverage and gross revenue ratios.

Author	Methodology applied	Country examined and period covered	Key findings	Significant explanatory variables
Pam (2013)	Multiple discriminant analysis (MDA)	Nigeria 1999–2003	The study found that the MDA model is a potent tool in the prediction of the potential of failure; the key variables in the Altman model are positive indicators in the analysis.	Liquidity, profitability, operating efficiency and total assets turnover, earnings per share, dividend per share and the ratio of interest earned to interest paid.
Farinde (2013)	Multilayer perceptron neural network analysis	Nigeria 2008–2011	The study evaluated the susceptibility of Nigerian banks to failure and identified ratios and financial data that are sensitive to the solvency of the bank.	Total equity/liabilities (without equity), earnings before tax/total assets, working capital/total assets, earnings before tax/working capital, and earnings before tax/gross earnings.
Adeyeye and Oloyede (2014)	Enhanced discriminant model	Nigeria 2007–2009	The study found that differences in financial ratios are the major distinguishing characteristics between non-failed and failed banks.	Profitability, liquidity, credit risk and capital adequacy ratios.
Adeyeye and Migro (2015)	PCA pooled with logit and probit	Nigeria 1986–2010	The study investigated the status of Nigerian banks and developed an integrated early warning system (IEWS).	Profitability, liquidity, credit risk and capital adequacy ratios.
Babajide, Olokoyo and Adebayo (2015)	Cox proportional hazards model	Nigeria 2003–2011	The study used financial covariates from financial statements of banks to predict incidence of bank failure.	Non-performing loan to total loan plus lease, operating expense to average total assets, ratio of operating expenses to average total assets. ratio.
Ozurumba (2016)	OLS regression	Nigeria	The study used financial covariates.	Bank non-performing loans.
Nurazi and Evans (2005)	Logit model	Indonesia	The study used financial covariates.	Ratio of operating expense to operating income, net.
Zaghdoudi (2013)	Logit regression	Tunisia	Financial ratios.	Banking operation, leverage ratio, bank profitability per employee.

Bank failure and survival analysis

Survival analysis (SA), also known as failure time analysis and event history analysis, is used to analyze data on the length of time it takes a specific event to occur (Kalbfleish and Prentice, 1980). Also known as time-to-event analysis, SA is a statistical method for analyzing survival data, and is widely used in the social and economic sciences, as well as in insurance (longevity, time-to-claim analysis) (Luyang and Hongyuan, 2013). The SA technique is used in a variety of contexts sharing a common characteristic: interest centres on describing whether, or when, events occur (Stepanova and Thomas 2000).

Survival analysis is used to analyze data where the outcome variable is the time until the occurrence of an event of interest. Examples of such events of interest include bank failure, death, the onset of disease, marriage, divorce, and failure of a machine. It is also called "Time to Event" Analysis. The thrust of the SA is to analyse the time for an event of interest (bank failure) to occur and to estimate the variables that might explain the behaviour of this time. Objects of interest in SA (in the case of this paper, Nigerian banks) are usually monitored over a specified time period and the focus is on the time at which the event of interest occurs. The time-to-event or survival time can be measured in days, weeks, months or years.

According to Karina, Aquiles, and Alberto (2006), Kiefer (1988) presents a highly informative and introductory research on this type of analysis, where he describes clearly and objectively the main concepts of SA: the survival function and probability of failure conditional function, also known as hazard function. The hazard function represents the central concept of this statistical analysis. This function is the estimation of conditional probabilities of a particular event to occur at different moments. The analysis of survival not only considers the probability of the event itself, but also the likelihood that the same event may occur with a previous condition.

Shumway (2001) applied the first survival analysis model to a data set of significant size. Consistent with previous studies, Shumway noted the theoretical superiority of SA techniques over the more popular techniques (discriminant analysis and logit analysis). In addition, Shumway's SA model was shown to empirically outperform both discriminant analysis and logit analysis in hold-out predictions. King, Nuxoll and Yeager (2005) as cited in Babajide et al. (2015) provide empirical evidence to show that the characteristics of failing banks have changed considerably in the last ten years. They also argue that the time is right for new research employing new empirical techniques. In particular, dynamic models that utilize forward-looking variables and address various types of bank risk individually are promising lines of inquiry.

Whalen (2005) developed a Cox proportional hazards model that is designed to predict the probability that a low-risk community bank will be downgraded to high-risk status over an eight-quarter time horizon. Cole and Wu (2009) modified Shumway's (2001) methodology using a simple dynamic hazard model with time-varying covariates to develop a bank failure early warning model, and then tested the out-of-sample forecasting accuracy of this model relative to a simple one-period probit model, such as is used by U.S. banking regulators. The model incorporated time-varying covariates thereby enabling the utilization of macroeconomic variables, which cannot be incorporated into a one-period model. The authors found that the model significantly outperforms the simple probit model with or without the macroeconomic variables.

Functions in survival analysis

The dependent variable in survival analysis is composed of two parts: one is the time to event and the other is the event status, which records if the event of interest occurred or not, that is the survival and hazard functions. The survival and hazard functions are key concepts in survival analysis for describing the distribution of event times. The survival function gives, for every time, the probability of surviving (or not experiencing the event) up to that time. The hazard function gives the potential that the event will occur, per time unit, given that an individual has survived up to the specified time. The hazard function represents the central concept of survival analysis.

Following Karina et al. (2006), the survival function given in probabilistic terms is set as below:
The survival function $S(t)$ is defined by:

$$S(t) = P(T \geq t) \tag{1}$$

and is equal to $1-F(t)$, where $F(t)$ is the cumulative distribution function of T. (Note $P(X=t)=0$ for each number t in case of a density function.)

Since the cumulative distribution function $F(t)$ specifies the distribution of T, the distribution of T is also specified by the survival function $S(t)=1-F(t)$.

The hazard function $\lambda(t)$ specifies the instantaneous rate of failure at $T=t$ conditional upon survival to time t and is defined by the limit for $\delta \downarrow 0$ of the following ratio:

$$\frac{P(t \leq T < t+\delta \mid T \geq t)}{\delta} = \frac{P(t \leq T < t+\delta)}{P(T \geq t) \times \delta} = \frac{S(t)-S(t+\delta)}{\delta} \times \frac{1}{S(t)} \tag{2}$$

Taking this limit we get

$$. \ \lambda(t) = \frac{f(t)}{S(t)} \tag{3}$$

Note that the derivative of the survival function $S(t)$ is equal to $-f(t)$. The distribution of T is specified by its hazard function as well because the survivor function is determined by the hazard function:

$$\frac{d}{dt}\ln\left(S(t)\right) = -\frac{f(t)}{S(t)} = -\lambda(t) \tag{4}$$

$$\ln\left(S(t)\right) = -\int_0^t \lambda(u)du \qquad \text{(Note: } S(0) = 1\text{)} \tag{5}$$

$$S(t) = \exp\left(-\int_0^t \lambda(u)du\right) \tag{6}$$

In this study, the event of interest is bank failure and a bank is said to have failed if any of the four conditions mentioned in Section 2.1 has been met.

3.0 Methodology

3.1 Conceptual issue

To better situate the two concepts – bank distress and bank failure, as used in the study, a broader definition of bank failure is adopted. A bank is considered to have failed if it fits into any of the following categories (Gonzalez-Hermosillo, 1999; Bongini, Claessens and Ferri, 2001; Heffernan, 2005):

- The bank was recapitalized by either the central bank or an agency specifically created to address the crisis, and/or required a liquidity injection from the monetary authority;
- the bank's operations were temporarily suspended ("frozen") by the government;
- the government closed the bank, due to bankruptcy, dissolution, liquidation or negative net worth; or
- the bank was absorbed or acquired by another financial institution, through involuntary merger or acquisition.

This study categorizes a bank as being in distress using the Central Bank of Nigeria's prudential threshold. In this case, a bank is considered as being in distress using the capital adequacy ratio (CAR) threshold – a bank is in distress if the ratio of equity to total assets is less than 10%.

3.2 Theoretical framework

This study aims to develop an Early Warning Signal (EWS) model for bank distress and failure prediction in Nigeria. The indicators of early warning models are closely related to supervisory rating system of banks. The most widely known rating system is CAMELS – capital adequacy, asset quality, management, earnings, liquidity, and sensitivity to market risk. CAMELS ratings are primarily proxies for market information (Cargill, 1989). This study incorporates non-financial variables (bank category, bank listing status on the Nigerian Stock Exchange, banks' ownership structure and banks' merger status) to examine the influence of non-financial bank characteristics in predicting distress and failure in the Nigerian banking system.

This study employs a survival analysis approach using the Cox proportional hazards model as used by Alves, Kalatzis and Maties (2009), Pereira (2014) and Babajide et al. (2015) in predicting distress and failure of banks in Nigeria. Shumway (2001) demonstrated that a hazard model provides more consistent in-sample estimations and more accurate out-of-sample predictions for corporate bankruptcies than traditional static bankruptcy prediction models. The study combined data sets from failed and sound banks, and assigned the value of 1 if the bank has failed and assigned the value of 0 if the bank is sound. This enables the regression to be assessed based on the interaction of the two types of data and further provides a better explanation of the significance and magnitude of each independent variable. The Cox proportional hazards survival analysis enables a deeper investigation of bank failure and captures time variations in assessing the probability of a bank failing. In estimating the probable time to failure, the study employed the Kaplan-Meier survival estimate.

3.3 Model specification

This section presented the model specification and estimations for the study. It began by given the justification for the use of Cox Proportional Hazard model for the survival analysis. This is followed with an explanation of different steps involved in the estimation of the model as well as the description of the data and variable used for the study.

Cox proportional hazards model (for Objectives 1 and 2)

Following Pereira (2014), the Cox proportional hazards model was used to analyze the survival or failure of Nigerian banks using financial covariates and non-financial variables. Hazard models correct for period at risk and allow for time-varying covariates; it utilizes all information available for each bank at every point in time, producing consistent estimates and avoiding bias inherent in static models. According to Shumway (2001), hazard models resolve the problems of static models by explicitly accounting for time. The dependent variable in a hazard model is the time spent by a firm in the healthy group. When firms leave the healthy group for some reason other than bankruptcy (e.g., a merger), they are considered censored, or no longer observed.

According to Pereira (2014), there are two main reasons for modelling survival data. One is to determine which combination of potential explanatory variables affects the shape of the hazard function. Another is to obtain an estimate of the hazard function for a particular company.

The Cox proportional hazards model, also known as the Cox regression model, has become the most widely used in survival analysis. The key to understanding the Cox model is the concept of the hazard rate or hazard functions – the rate of change of probability over an interval conditional on survival until the start of the interval.

The definition of the model can be as follows: Assuming that the hazard of "failure" for a given time period depends on the values $x_1, x_2, \ldots, x_p$ of p explanatory variables $X_1, X_2, \ldots X_p$, the set of values of explanatory variables in the proportional hazard model will be represented by the vector x, so $\mathbf{x} = (x_1, x_2, \ldots, x_p)$.

$h_0(t)$ is designated as the hazard function of a firm, for which the values of all variables that make the vector **x** is zero. The function $h_0(t)$ is called the baseline hazard function. The hazard function for i companies can then be written as:

$$h_i(t) = \psi(x_i)h_0(t), \tag{7}$$

where $\psi(x_i)$ is the function of the values of the vector of explanatory variables for i firms.

The function $\psi(x_i)$ can be interpreted as the risk over time t for a firm whose vector of explanatory variables is $\mathbf{x}_i$ on the risk for a firm whose $\mathbf{x}=0$.

Since the relative risk $\psi(x_i)$ cannot be negative, it is written as $\exp(\eta_i)$, where η_i is a linear combination of p explanatory variables in $\mathbf{x}_i$. Therefore,

$$\eta_i = \beta_1 x_{1i} + \beta_2 x_{2i} + \ldots + \beta_p x_{pi}, \tag{8}$$

which is equivalent to

$$\eta_i = \sum_{j=1}^{p} \beta_j x_{ji}. \tag{9}$$

The quantity η_i is called the linear component of the model, also known as risk score or prognostic index for i firms. The proportional hazard model can generally be expressed as follows:

$$h_i(t) = exp(\beta_1 x_{1i} + \beta_2 x_{2i} + \ldots + \beta_p x_{pi}) h_0(t) \tag{10}$$

Hence, the Cox regression model for this study is specified as follows:

$h_i(t) = \exp(\beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \beta_4 x_{4i} \ldots + \beta_{20} x_{20i}) h_0(t)$
(11)

where β is the vector of coefficients of the $x_1, x_2, \ldots, x_p$ explanatory variables in the model. X takes the form of $x_1 \ldots\ldots x_{23}$

The predictor variables that were used in this study include:

x_1	=	(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	=	(BAILUT)	–	bailout
x_6	=	(IMPLOAN)	–	ratio of impaired loans to gross loan (%)
x_7	=	(EQTYASS)	–	ratio of equity to total assets (%)
x_8	=	(EQTYNET)	–	ratio of equity to net loans (%)

x_9 = (EQYCUS) – ratio of equity to customer and short-term funding (%)

x_{10} = (EQYLIAB) – ratio of equity to liabilities (%)

x_{11} = (ROAA) – return on average assets (%)

x_{12} = (ROAE) – return on average equity (%)

x_{13} = (COSINC) – ratio of cost to income ratio (%)

x_{14} = (NETLNS) – ratio of net loans to total assets

x_{15} = (NETLNDEP) – ratio of net loans to depositor and short-term funding

x_{16} = (LIQASS) – ratio of liquid assets to customer short-term funding

x_{17} = (GROTHLN) – growth in gross loan

x_{18} = (IMPLNEQ) – ratio of impaired loans to equity

x_{19} = (BNKCAT) – whether bank is owned by multinational

x_{20} = (BNKCONS) – bank merger status at consolidation

x_{21} = (BNKCONSM) – number of banks that merged

x_{22} = (LSTSTAT) – listing status of bank on the Nigerian Stock Exchange (NSE)

x_{23} = (OWNSTR) – whether the bank MD/CEO is the founder of the bank

Kaplan-Meier survival estimate (for Objective 3)

A Kaplan-Meier estimate was employed to estimate the probable time to failure of Nigerian banks. The Kaplan-Meier (or KM) estimator is probably the most popular approach. The Kaplan-Meier estimate is one of the best options to be used to measure the fraction of subjects living for a certain amount of time after treatment (Goel, Khanna, and Kishore, 2010).

The Kaplan-Meier estimator is defined only at times when events occur. It is defined as:

$$S(t) = \prod_{j:t_j \le t} [1 - \frac{d_j}{n_j}] \qquad (12)$$

of firms that are still at risk at time t_j and d_j is the number of ɖ at time t_j. The Kaplan-Meier estimator provides a reading on the likelihood of survival at time t based on the survival history of all firms.

k distinct event times $t_1 < t_j < \ldots < t_k$

At each event time tj, there are nj individuals at risk

d_j is the number who have the event at t_j

3.4 Steps in estimation

Following Pereira (2014), this study first employed a Cox proportional hazards model to forecast the likelihood of failure of Nigerian banks from banks' financial covariates and non-financial variables. Secondly, a survival analysis of all 24 Nigerian banks, including the failed banks, rescued, and sound banks, was performed to provide an estimate of bank-specific financial covariates and non-financial variables factors that explain the probability of distress and failure. Thirdly, a Kaplan-Meier estimator was used to estimate the probable time to failure of Nigerian banks. In identifying the covariates, the study considered the variables that have been used in the extant literature and the most recent variables used by Andrianova et al. (2015) in constructing a new international database on financial fragility, in which Nigeria was part of the African sample.

3.5 Choice and description of variables

The choice of variables for the model was informed by extant literature on financial sector fragility and failure prediction. When testing the superiority of the hazard model over the static probit model, Cole and Wu (2009) incorporated macroeconomic variables into their survival model. Also, Andrianova et al. (2015) constructed a new international database on financial fragility, in which Nigeria was part of the African sample, by using some relevant financial variables. This study drew from these studies in constructing the covariates. However, unlike Cole and Wu (2009), this study controlled for the following non-financial variables: banks' listing status on the Nigerian Stock Exchange, banks' ownership structure, banks' merger status, bailout status, consolidation status, and number of merged banks. The choice of these non-financial variables was informed by the financial services sector reforms, especially the consolidation exercise of 2004, which was meant to strengthen Nigerian banks and make them resilient to shocks.

The use of financial ratios as proxies for fundamental bank attributes provides information about the symptoms rather than the causes of financial difficulty, in that they provide leading indicators of incipient crises. Bank financial ratios reflect the variation in bank asset risk and leverage, because they capture the market, credit, operational, and liquidity risk faced by banks. In this sense, bank balance sheets and income statements convey information about the ex post consequences of management's decisions (i.e., they provide an indirect measure of managerial performance) (Sinkey, 1975). Consequently, this study constructed financial covariates as bank-level variables that proxy for bank capital adequacy, asset quality, management quality, earnings ability, liquidity and sensitivity to market risk. Additional variables that were used included loans growth rate.

3.6 Data for the study

This study utilized secondary data sourced from the BankScope Database (Bureau Van Dijk database). The BankScope Database covers all the banks currently operating in Nigeria, including failed banks. Bank level data were constructed using bank level information obtained from BankScope, which included annual and quarterly financial reports of both publicly-listed banks and private commercial banks over the: (i) full sample period (2006–2015); (ii) in-sample period (2006–2009); and (iii) out-of-sample period (2009–2015). Conversely, the non-financial variables were obtained using dummies. The estimation was carried out using STATA software.

4.0 Empirical Results and Discussion

This section provided the empirical results of the study based on data from Bankscope database. First, we provided the summary/descriptive of the key variables used in the regression. In addition, the session discussed the results of the survival analysis**.**

4.1 Descriptive statistics

Descriptive statistics of the financial variables used in the study are presented in Table 1 and were decomposed by category of banks and failure. The first decomposition is by distress threshold, which takes the value 1 if the bank has reached distress threshold, and 0 if otherwise. The other decompositions are by bank size and failure. From the result, the ratio of loan loss reserve to gross loan (LNLOSS) is 7.95% for banks on the threshold of distress, compared to 3.60% for banks that are not at the threshold; the average for big banks is 2.33%, compared to 4.04% for small banks, while it is 14.43% for failed banks, compared to 1.98% for sound banks. Increasing loan loss reserve may suggest that historically a large proportion of gross loans has not been performing, which is not healthy for the survival of a bank. For big banks the average percentage of impaired to gross loans (IMPLOAN) is 1.81%, while for small banks it is as high as 15.01%; for failed banks the average is 17.50%, while it is 7.81% for surviving banks. Banks that are not at the distress threshold were found to have higher average impaired loan ratio percentages compared to banks that are at the distress threshold.

Estimates of the equity ratios from Table 1 indicate that sound or large banks have higher average equity ratios. For example, the equity to total assets ratio (EQTYASS), equity to net loans ratio (EQTYNET), equity to customer short-term funding (EQYCUS) and equity to liabilities (EQYLIAB) ratios for sound banks are 14.85, 37.13, 20.78, and 17.62, respectively. They are not only small for distressed banks but are also negative, just as they are for distressed banks. These ratios for larger (compared to small banks) are 6.58(4.7), 20.6(7.22), 9.1(8.47), and 7.66(7.44), respectively. These figures suggest that equity ratios are pertinent in assessing the health status of Nigerian banks.

The study examined two types of returns: return on average assets (ROAA) and return on average equity (ROAE). Table 1 shows that return on average assets is higher for sound banks and larger banks compared to distressed, small or failed banks, while it is negative for distressed banks. On the other hand, return on average equity is higher for distressed, small and failed banks. These two variables were alternated in the regression results since they are likely to have different effects on the probability of distress or failure. The results show that the cost to income ratio (COSINC) for banks that are on the distress threshold is 78.01, compared to 60.26 for sound banks. Also, small banks have a cost to income ratio of 48.9, compared to 38.27 for large banks, while the cost to income ratio for failed banks is 65.17, compared to 13.78 for surviving banks. This finding suggests that the cost to income ratio could be a predictor of bank survival or failure in Nigeria.

Financial covariates that indicate the risk appetite or risk-taking attitude of banks were also captured in the study. These include the ratio of net loans to total assets (NETLNS), ratio of net loans to depositor and short-term funding (NETLNDEP), ratio of liquid assets to customer short-term funding (LIQASS), growth of gross loan (GROTHLN), and ratio of impaired loans to equity (IMPLNEQ). The results indicate that banks on the distress threshold, small banks and failed banks do not necessarily take more risk compared to sound and large banks. For instance, while the average net loans to assets for banks at the distress threshold is 39.27, it is 44.42 for sound banks. However, it could be argued that profit is greater where the risk is higher. Conversely, while the average ratio of impaired loans to equity is 12.8 for distressed banks, it is 10.36 for sound banks. Similarly, while this ratio is only 3.526 for large banks, it is as high as 9.595 for small banks. This suggests that the ratio of impaired loans to equity in small banks is three times larger than that of large banks.

The correlation matrix of the variables is reported in Table 2. The results show that all equity ratios are highly correlated and the coefficient of correlation is at least 0.94. This suggests that these variables cannot enter the regression model at the same time to avoid multicollinearity problems in the estimations. Return on average assets and return on average equity are negatively correlated, suggesting that they measure returns differently. Also, there is possible and high correlation among the variables that measure bank risk-taking attitude.

Table 1: Descriptive statistics by categories of bank

Variables	Distress threshold			Big bank			Failure		
	0	1	Total	0	1	Total	0	1	Total
Loan loss reserve/gross loan (%)	3.596	7.949	5.213	4.044	2.326	3.421	1.978	14.43	4.363
Impaired loan/gross loan (%)	19.18	9.487	15.58	15.01	1.813	10.23	7.806	17.5	9.663
Equity/total assets	14.85	-3.057	8.198	4.7	6.577	5.38	9.263	-7.418	6.069
Equity/net loans	37.13	-15.44	17.6	7.219	20.6	12.07	20.83	-14.09	14.15
Equity/customer and short-term funding	20.78	-1.181	12.62	8.469	9.096	8.696	12.55	-2.447	9.677
Equity/liabilities	17.62	-0.354	10.95	7.438	7.657	7.517	10.77	-2.494	8.232
Return on average assets	2.983	-2.686	0.878	0.406	1.046	0.638	1.843	-8.987	-0.23
Return on average equity	19.49	37.66	26.24	22.4	9.519	17.73	13.78	65.53	23.69
Cost to income ratio	60.26	78.01	66.85	48.9	38.27	45.05	43.87	65.17	47.95
Net loans/total assets	44.42	39.27	42.51	33	21.65	28.89	32.13	26.6	31.07
Net loans/depositor and short-term funding	60.9	45.74	55.27	43.31	27.9	37.72	42.94	32.98	41.03
Liquid assets/customer short-term funding	30.05	21.78	26.98	20.88	12.54	17.86	20.05	16.1	19.29
Growth of gross loan	7.587	-1.912	4.059	1.868	3.61	2.499	5.586	-6.879	3.199
Impaired loans/equity	10.36	12.8	11.27	9.595	3.526	7.395	8.996	1.864	7.631

Table 2: Correlation matrix of the variables

	lnloss	imploan	eqtyass	eqtynet	eqycus	eqyliab	roaa	roae	cosinc	netlns	netlndep	liqass	grothln	implneq
lnloss	1													
imploan	0.4698	1												
eqtyass	-0.165	0.12	1											
eqtynet	-0.0781	0.0765	0.9414	1										
eqycus	-0.1212	0.1285	0.963	0.9439	1									
eqyliab	-0.1242	0.1525	0.9683	0.9285	0.9948	1								
roaa	-0.8949	-0.3656	0.3966	0.3265	0.4034	0.4	1							
roae	0.5661	0.2689	0.0365	0.0584	0.0255	0.033	-0.5401	1						
cosinc	0.1902	0.1776	-0.1122	-0.1593	0.0253	0.0411	0.0254	-0.075	1					
netlns	0.2033	0.3143	0.4205	0.2689	0.5049	0.5368	0.0674	0.2395	0.6758	1				
netlndep	0.166	0.2993	0.5202	0.3797	0.6158	0.6375	0.1167	0.2316	0.6107	0.984	1			
liqass	0.0992	0.1414	0.4631	0.3613	0.5418	0.5511	0.2501	0.0797	0.5615	0.7155	0.7348	1		
grothln	0.073	0.249	0.6656	0.6033	0.6014	0.6301	0.0529	0.0944	-0.0336	0.2879	0.3357	0.1625	1	
implneq	0.0972	0.2497	0.4148	0.351	0.4149	0.4209	0.1537	0.0177	0.2524	0.5278	0.5275	0.4518	0.3915	1

4.2 Survival analysis results

This subsection gives a detailed discussion of the results of the estimates of the factors that predict bank distress as well as failure in Nigeria. In addition, the section also provides an analysis of the probable time to failure of Nigerian banks based on the data from Bankscope database.

Estimating the factors that predict failure of Nigerian banks

The Cox proportional model results are reported in Table 3. The table presents the hazard ratios, which are standard for interpreting the results. Eight different specifications of the model were estimated to control for important variables as well as to alternate other variables to check the sensitivity of the estimates to various specifications of the model. For example, two equity ratios used in the model – ratio of equity to customer and short-term funding (EQYCUS) and ratio of equity to liabilities (EQYLIAB) – were alternated in all eight specifications due to the possibility of multicollinearity, while variables such as cost to income ratio (COSINC), growth of gross loan (GROTHLN), ratio of liquid assets to short-term funding (LIQASS), and ratio of loan loss to gross loan (LNLOSS) were kept constant.

The reported hazard coefficients show that the statistically significant variables are ratio of equity to customer and short-term funding (EQYCUS), ratio of equity to liabilities (EQYLIAB), cost to income ratio (COSINC), ratio of liquid assets to short-term funding (LIQASS), and ratio of loan loss to gross loan (LNLOSS). The results show that higher cost to income ratios (COSINC) increase the risk of failure by between 2.6% and 3.8% considering the coefficients in all eight specifications. Alternatively, the probability is calculated by the ratio of the hazard coefficient to one, plus the hazard coefficient. This probability is about 0.51, which means the probability of failure to increasing cost to income ratio is about 0.51. This corroborates the findings of Nurazi and Evans (2005) and Babajide et al. (2015).

Another statistically significant predictor of bank failure in Nigeria is liquid assets to short-term funding (LIQASS). The hazard ratio is less than unity which implies that a higher liquid asset to short-term funding ratio decreases the risk of bank failure in Nigeria, other things remaining constant. In probability terms, a higher liquid asset to short-term funding ratio reduces the probability of failure by 0.469, or by 46.9%. This is because banks with higher liquidity are better able to meet customers' short-term demand for cash, and are better able to avoid bank runs, which may culminate in systemic distress and hence individual bank failure. This result agrees with Zaghdoudi (2013) who found that a bank with the ability to repay its debt, high bank profitability, and leverage ratio has high probability of survival and less probability to fail . On the other hand, excess liquidity could imply that banks are not efficient in lending and are likely to earn less.

Growth in gross loan (GROTHLN) has hazard coefficients of less than one that are also statistically significant, in models 1 to 6. These coefficients suggest that growth in gross loans leads to lower risk of bank failure in Nigeria. Banks with loan growth are likely to earn higher income and are able to meet short-term operating costs without having liquidity problems by funding their operations through other means. This probably explains why banks chase big, proven customers to borrow from them. This could sometimes result in an adverse selection problem, especially when lending is made without sufficient collateral. Growth in gross loan is important if the ratio of impaired loans is decreasing. On the other hand, the hazard coefficients of loan loss to gross loan are greater than 1 in models 1–6, after controlling for various covariates. This implies that increasing loan loss provision is historically associated with the rise of bad loans, which can make a bank go out of business, other things remaining the same. Specifically, increasing loan loss increases the probability that a bank will fail by 0.5265, or 52.65%.

Return on average equity and return on average assets are two profitability variables captured in the model. The two indicators were alternated in the estimated Cox proportional hazards models. The coefficient of return on average equity in the bank failure prediction model is positive and statistically significant in specification 8, and the corresponding hazard ratio is greater than one in the corresponding specification in Table 4. On the other hand, the coefficient of return on average asset is negative in model 7, with hazard ratio less than unity in the corresponding specification in Table 4. The implication of these results is that banks that earn most of their profits on return on average equity are not safer than banks that earn more profits based on return on average assets. Return on average assets measures how efficient management is by investing the bank's assets in more profitable ventures. The return on average equity in the context of Nigerian banks also includes capital profits earned through issue of shares at a premium even when the bank is capital-constrained. So, it does not show efficient management and, consequently, soundness. The signs of these coefficients therefore reflect the reality for Nigerian banks. These are consistent with the descriptive statistics that show that banks at the threshold of distress or failed banks earn higher returns on average equity but have negative returns on average assets, which shows inefficiency and likelihood of failure.

In the bank distress prediction models, the coefficient of return on average equity is consistently positive with a significant hazard greater than one, which is consistent with more risk of going into distress sooner than later. On the other hand, the coefficient of return on average assets is consistently negative and statistically significant with a hazard ratio less than unity, which is associated with low risk of going into distress. Hence, when a bank's profit comes from return on average equity rather than return on average assets, such a scenario raises cause for concern. Although this finding may appear somewhat counterintuitive and at variance with a preponderance of extant studies on bank performance measurement, a European Central Bank report (2010) supports the finding.

According to the European Central Bank report (2010), the most common measure for bank performance, i.e., return on equity (ROE), is only part of the story, as a good level of ROE may either reflect a good level of profit or more limited equity capital. In addition, although the "traditional" decomposition of the ROE measure (looking at bank operational performance, risk profile and leverage) may have been useful to assess banks' performance during benign times, this approach has clearly not proven adequate in an environment of much higher volatility – such as during the global financial crisis, where fluctuations have been caused entirely by operational performance, which does not aid our understanding of the potential trade-off between risk and return in performance. This, according to the ECB report, may explain why some of the high-ROE firms have performed particularly poorly over the crisis, dragged down by a rapid leverage adjustment. It is pertinent to note that this study covered the period of the global financial crisis that was characterized by high volatility and other factors that may have affected the performance of banks.

The results in Table 3 also indicate that the non-financial variables (including, among others, listing status of the banks on the Nigerian Stock Exchange, bank category – whether foreign or locally owned, banks' merger status at consolidation, and ownership structure) included in the model did not predict bank failure at a 5% level of significance. However, bank ownership structure (whether the founder is the MD/CEO of the bank) and the listing status of banks (whether or not the bank is listed on the Nigeria Stock Exchange), predicted bank failure at a 10% level of significance.

Table 3: Hazard ratios of effects of bank level financial covariates and non-financial variables on bank failures in Nigeria

Variables	model1	model2	model3	model4	model5	Model6	model7	model8
eqycus	1.125*			1.122*	1.041			
	(0.014)			(0.014)	(0.405)			
roae	1.004	1.004	1.004	1.004	1.007	1.007		1.012*
	(0.145)	(0.161)	(0.189)	(0.158)	(0.089)	(0.083)		(0.013)
cosinc	1.029*	1.029*	1.026*	1.027*	1.037*	1.038*	1.179*	1.033*
	(0.024)	(0.034)	(0.032)	(0.023)	(0.018)	(0.018)	(0.040)	(0.016)
age	1.005	1.007						
	(0.681)	(0.572)						
liqass	0.883*	0.885*	0.893*	0.888*	0.902*	0.902*		
	(0.023)	(0.027)	(0.023)	(0.019)	(0.049)	(0.047)		
grothln	0.890*	0.886*	0.892*	0.894*	0.874*	0.869*	0.743	1.006
	(0.015)	(0.017)	(0.014)	(0.012)	(0.039)	(0.037)	(0.053)	(0.885)
lnloss	1.112**	1.115**	1.111**	1.111**	1.125**	1.128**		
	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)		
eqyliab		1.161*	1.151*			1.055		
		(0.024)	(0.022)			(0.385)		
netlns					0.666	0.655*		
					(0.060)	(0.047)		
netlndep					1.318	1.330		
					(0.066)	(0.054)		
roaa							0.606*	
							(0.032)	
eqtynet							1.340*	1.019
							(0.045)	(0.260)
implneq							0.201	0.876
							(0.051)	(0.150)
ownstr							11.79	0.0950
							(0.306)	(0.198)
bnkconsm							0.865	0.467
							(0.915)	(0.529)
N	160	160	160	160	160	160	160	160
ll	-16.03	-16.49	-16.64	-16.11	-14.20	-14.16	-10.87	-17.63
chi2	17.33	16.42	16.12	17.17	20.99	21.08	27.66	14.14
r2_p	0.351	0.332	0.326	0.348	0.425	0.427	0.560	0.286

Exponentiated coefficients; p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Estimating the factors that predict distress of Nigerian banks

Table 4: Hazard ratios of effects of bank level characteristics, and non-financial variables on bank distress in Nigeria

Variables	model1	model2	model3	model4	model5	Model6	model7	model8
Cost to income ratio	1.012*	1.018*	1.017*	1.027*	1.166**	1.148*	1.357*	1.176**
	(0.048)	(0.006)	(0.038)	(0.005)	(0.000)	(0.001)	(0.012)	(0.000)
Return on average assets	0.961*		0.953*		0.884*			0.928
	(0.025)		(0.014)		(0.002)			(0.294)
Return on average equity		1.006*		1.009*		1.012*	1.015+	
		(0.006)		(0.004)		(0.012)	(0.062)	
Impaired loans/equity			1.015	1.011				
			(0.513)	(0.644)				
Whether the bank MD/CEO is the founder			0.457	0.295	0.118+	0.131+	0.00454*	0.107+
			(0.366)	(0.197)	(0.067)	(0.096)	(0.029)	(0.057)
Equity/total assets					26.05**	13.29*	227.5*	31.83*
					(0.001)	(0.003)	(0.005)	(0.001)
Equity/ customer and short-term funding					0.310+	0.406	0.197*	0.280+
					(0.091)	(0.166)	(0.044)	(0.089)
Equity/ liabilities					0.118*	0.176*	0.0195*	0.107*
					(0.003)	(0.010)	(0.030)	(0.003)
Impaired loan/gross loan (%)							1.127*	1.039
							(0.021)	(0.468)
Observations	195	195	195	195	195	195	195	195
ll	-31.15	-30.86	-30.27	-29.46	-17.20	-19.46	-14.91	-17.03
chi2	8.991	9.580	10.75	12.37	36.89	32.38	41.46	37.23
r2_p	0.126	0.134	0.151	0.174	0.517	0.454	0.582	0.522

Exponentiated coefficients; p-values in parentheses
+ $p < 0.10$, * $p < 0.05$, ** $p < 0.001$, *** $p < 0.0001$

The Cox proportional model results in Table 4 show that the statistically significant variables are cost to income ratio, return on average assets, ratio of equity to customer and short-term funding, ratio of impaired loan to gross loan, and bank ownership structure (whether the MD/CEO is the founder). The result shows that higher cost to income increases the risk of distress by between 12% and 17.6%. The result also shows that a higher ratio of equity to customer and short-term funding reduces the risk of distress. This is because the more the equity fund, the higher the possibility of the bank's ability to meet customers' demand for short-term funding. On the other hand, the result indicates that the ratio of impaired loans to gross loan increases the probability of distress in the Nigerian banking sector.

The introduction of non-financial variables (dummies) in the study provided insights and added value to the study. For instance, while the listing status of the banks was significant at 10%, the structure of bank ownership, that is, whether the MD/CEO is the founder of the bank, significantly predicted bank distress at a 5% level of significance. The result therefore shows that banks with the MD/CEO as founder reduces the probability of distress. This result is in line with a priori expectations, because when the MD/CEO is the founder, he or she makes every effort to protect the fund and investment by adopting every possible strategy to ensure that the bank survives. Also, the listing status of the banks (whether a bank is listed on the Nigerian Stock Exchange) significantly predicted bank distress at a 10% level of significance.

4.3 Predicting bank failure, 2006–2009

Table A7 in the appendix shows the results of the model on the predictors of bank failure in Nigeria in the early post-consolidation era (2006–2009). The model was constrained to elicit factors that could predict the probability of bank failure after the banking sector consolidation exercise. The Cox proportional hazards coefficients revealed that the ratio of impaired loans to bank equity holdings, ratio of impaired loan to equity, and loan loss reserve are all significant predictors of bank failure in Nigeria in the early post-consolidation period (2006–2009). The result shows that the ratio of impaired loans to gross loan increases the risk of bank failure, and agrees with Ozumrumba (2016) who found that the ratio of impaired loan to gross loans reduces the performance of banks. The study's findings reveal that loan loss reserve had the probability of reducing the risk of bank failure in Nigeria between 2006 and 2009. This also conforms with a priori expectations as an increase in loan loss reserve indicates how much of the total loan portfolio had been provided for but charged off. However, a higher loan loss reserve indicates a poor-quality loan portfolio.

4.4 Estimating the probable time to failure of Nigerian banks

In estimating the probable time to failure of Nigerian banks, the study employed the Kaplan-Meier survival estimate and a curve as shown in the Appendix. In comparing the survival of big and small banks, big banks take the dummy 1 while small banks take the value 0. The Kaplan-Meier curve shows that small banks fail much faster and therefore have lower survival time than big banks that have higher survival times. For instance, the graph shows that the average survival time for small banks ranges from about 23 quarters to 40 quarters. On the other hand, the graph shows that big banks take a longer time to fail and the average survival time of big banks cannot be easily determined.

The results in Table A1 & A2 suggest that the probability of having failure in quarter 8 as well as quarter 23 are 25% and 50% respective while the probabilities of experiencing distress in quarters 8, 23, and 26 are 25%, 50% and 75%% respectively. On the other hand, the adequacy of the fitted Cox survival model was also assessed by testing the assumption of the proportional-hazards model as a diagnostic procedure. This can be tested using the log-minus-log plot, by comparing the probabilities and the rho values, etc. The result as shown in Table A5 where probability values are greater than the rho values led to the rejection of the hypotheses that the assumption of the proportional hazard models was violated, thereby accepting the alternative that the assumption was not violated. We therefore conclude that the models are well fitted and that the factors contributing to failure and distress in the Nigerian banking sector can be predicted. Similarly, the Log-rank test for equality of survivor functions as shown in Table A6 compares the survival of banks based on size and ownership structure. The results indicate no difference in the probability of failure and distress between big and small banks as well as between banks whose managing directors are the founders and those whose MDs are not founders. This is shown by the value of the Chi2 probability value that is more than 0.05 which lead to the acceptance of the null hypothesis that there is no difference in the time to distress and failure across the two measures. The implication of the result is that the regulatory authorities should look beyond the financial reports of big and small banks irrespective of whether the MDs are founders or not.

5.0 Summary, Conclusions and Policy Recommendations

This paper provided empirical evidence on the financial and non-financial factors that predict bank distress and failure based on data from Bankscope database. In addition, the paper has highlighted the policy implications of the empirical results obtained from the study.

5.1 Summary and conclusions

This study empirically examined bank distress and failure predictability in Nigeria in the post-banking sector reform and consolidation period of 2006 to 2015. To achieve the set objectives of the study, bank-level financial covariates were used to determine the predictors of bank distress and failure as well as estimating the probable time to failure of Nigerian banks using quarterly data from the BankScope Database. There have been attempts to address similar objectives by earlier researchers (Whalen, 1991, Cole and Wu, 2009, Pereira, 2014, Adeyeye and Migro, 2015, Babajide et al., 2015). This study extended the knowledge frontier of bank distress and failure predictability in Nigeria by incorporating non-financial variables into the model (bank ownership structure, bank listing on the Nigerian Stock Exchange, and bank category as well as bank merger status at consolidation). These non-financial variables represent the idiosyncratic attributes of banks in the post-consolidation period. The non-financial variables were included to examine the influence of other extraneous variables on bank distress and failure prediction aside from bank-level financial covariates. This study further extended the frontier of analysis by exploring the probable time to failure of small and big Nigerian banks.

This study showed that in the period 2006–2009 (early post-consolidation period), the ratio of impaired loans to bank equity holdings, ratio of impaired loan to equity, and loan loss reserve were significant predictors of bank failure in Nigeria. The results also indicate that the ratio of impaired loans to gross loan increases the risk of bank failure, while loan loss reserve had the probability of reducing the risk of bank failure in Nigeria between 2006 and 2009. High return on average equity was found not to have contributed significantly to the survival of banks in Nigeria in the post-consolidation period. This is understandable because return on equity has been found not to be a necessary and sufficient condition for bank survival, especially during periods of financial crisis. Consequently, while it is pertinent to consider return on equity as a measure of banks' strength, it is only part of the story, as a good level of return on equity may either reflect a good level of profit or more limited equity capital. The study found that impaired or non-performing loans significantly increases the risk of bank distress and failure, while cost to income ratio increases the risk of bank failure in Nigeria. Loan loss reserve has the probability of reducing the risk of bank failure. The study found that the average survival time of small Nigerian banks ranges from about 23 quarters to 40 quarters, while big Nigerian banks take a longer time to fail and their average survival time cannot be easily determined.

This study provides additional evidence and corroborates earlier findings on bank-specific financial covariates that predict bank distress and failure in Nigeria. The study is one of the few to incorporate non-financial variables in the bank distress and failure prediction literature. A significant insight from this study is the role of the structure of bank ownership on distress/failure or survival of a bank. That is, whether the chief executive of the bank is the founder can significantly predict bank distress and failure. At a 5% level of significance, ownership structure reduces the probability of incidence of distress, while at a 10% level of significance, ownership structure has the probability of reducing both bank distress and failure.

5.2 Policy implication/recommendations

In line with the findings of the study, the following recommendations are put forward:

4. The Banking Supervision Directorate of the Central Bank of Nigeria should go beyond the use of ROE as a performance indicator, more especially in periods of crisis. In benign times, ROE may be applied but may not be a sufficient performance indicator in a volatile environment. Other indicators, such as operational efficiency, should be incorporated.
5. The Central Bank of Nigeria should set and strictly enforce a maximum limit for loan loss reserve provision as well as a proportion of impaired/non-performing loan. This should be followed with strict regular periodic supervision, preferably quarterly. Penalties for infractions should be clearly stipulated.
6. The Central Bank of Nigeria should allow/encourage owners or major promoters of banks to be Chief Executives of banks for a stipulated period of time from inception. However, this should not detract from close and effective monitoring to ensure strict compliance with best corporate governance practices, and avoidance of unethical practices.
7. Survival models, such as Cox proportional hazards models, should be used for periodic stress testing and off-site supervision of Nigerian banks to assess the health of the banking sector, and to aid on-site supervision. Early warning signals emanating from such an exercise will reveal potentially vulnerable banks and make for proactive intervention to avert incidences of bank distress and failure,

and mitigate systemic risk.

8. The Central Bank of Nigeria should ensure sound and robust credit risk management and discourage excessive risk by banks.

References

Adeyeye, P.O., O.D. Fajembola, M.O. Olopete and D.B. Adedeji. 2012. “Predicting bank failure in Nigeria using Principal Component Analysis and D-Score Model”. Research Journal of Finance and Accounting. 3(8): 159–70.

Adeyeye, P.O. and J.A. Oloyede. 2014. “Forecasting bank failure in Nigeria: An application of Enhanced Discriminant Model”. International Journal of Finance and Accounting, 3(1): 37–48. Retrieved from www.sapub.org/global/showpaperpdf.aspx?doi=10.5923/j.ijfa.20140301.05

Adeyeye, P.O. and S.O. Migro. 2015. “An investigation on Nigerian banks’ status using early-warning signal”. Banks and Bank Systems, 10(1): 53–64. Retrieved from http://businessperspectives.org/journals_free/bbs/2015/BBS_en_2015_01_Olufemi.pdf

Alford, D. 2010. “Nigerian banking reform: Recent actions and future prospects”. SSRN Electronic Journal, 19 April. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1592599

Altman, E.I. 1968. “Financial ratios, discriminant analysis and the prediction of corporate bankruptcy”. The Journal of Finance, 23(4): 589–609

Amadasu, D. E. 2012. Bank Failure Prediction. International Journal of Arts and Humanities. 1(4), November, 250-265. Retrieved from http://www.ajol.info/index.php/ijah/article/viewFile/106426/96374

Andrianova, S., B. Baltagi, T. Beck, P. Demetriades, D. Fielding, S. Hall, S. Koch, R. Lensink, J. Rewilak and P. Rousseau. 2015. “A new international database on financial fragility”. University of Leicester Working Paper No. 15/18. University of Leicester Department of Economics, Leicester, July.

Alves, K. L., Kalatzis, A. E. and Matias, A. B. (2009). Survival Analysis of Private Banks in Brazil.

Available online at http://ecomod.net/sites/default/files/documentconference/ecomod2009/1058.pdf

Babajide, A.A., F.O. Olokoyo and F.B. Adegboye. 2015. “Predicting bank failure in Nigeria using survival analysis approach”. Journal of South African Business Research, 2015(2015)

Bankscope database. Bureau Van Dijk. www.bankscope.bvdep.com

Barr, R.S. and T.F. Siems. 1996. Bank Failure Prediction Using DEA to Measure Management Quality. Retrieved from http://faculty.smu.edu/barr/pubs/bsPredict.pdf?origin=publication_detail

Beaver, W. H. 1966. “Financial ratios as predictors of failure”. Journal of Accounting Research, 4: 71–111.

Bongini, P., S. Claessens and G. Ferri. 2001. “The political economy of distress in East Asian financial institutions.” Journal of Financial Services Research, 19(1): 5–25. Retrieved from http://www1.fee.uva.nl/fm/PAPeRS/Claessens/eastAsia_JFSR.pdf

Cargill, T.F. 1989. “CAMEL ratings and the CD market”. Journal of Financial Services Research, 3(4): 347–358.

Cole, R. and Q. Wu. 2009. “Predicting bank failures using a simple dynamic hazard model”.Retrieved from https://pdfs.semanticscholar.org/2f8f/52e4f3d8a1ff0e8df2c9c61fbaa747ca1bfe.pdf

De Meza, D. and D.C. Webb. 1987. “Too much investment: A problem of asymmetric information”. Quarterly Journal of Economics, 101: 282–92. Retrieved from qje.oxfordjournals.org/content/102/2/281.full.pdf

Donli, P. 2003. “Corporate governance in Nigeria. A status report the financial services sector”. In O. Alo, ed., Issues in Corporate Governance. Lagos, Finad Servea Institutions Training Centre: 18–39.

European Central Bank. 2010. “Beyond ROE – How to measure bank performance”. Appendix to the Report on EU Banking Structures. Retrieved from https://www.ecb.europa.eu/pub/pdf/other/beyondroehowtomeasurebankperformance201009en.pdf

Farinde, D.A. 2013. “A statistical prediction of likely distress in Nigeria banking sector using a neural network approach”. International Journal of Social, Management, Economics and Business Engineering, 7(10): 2720–5. Retrieved from http://waset.org/publications/17098/a-statistical-prediction-of-likely-distress-in-nigeria-banking-sector-using-a-neural-network-approach

Goel, M.K., Khanna, P., & Kishore (2010). Understanding Survival Analysis: Kaplan Meier Estimate. International Journal of Ayurveda Research, Vol 1(4) 274-279

Gonzalez-Hermosillo, B. 1999. “Determinants of ex-ante Banking System Distress: A Macro-Micro Empirical Exploration of Some Recent Episodes. International Monetary Fund Working Paper No. 33. International Monetary Fund, Washington, D.C., March. Retrieved from https://www.imf.org/en/Publications/WP/Issues/2016/12/30/Determinants-of-Ex-Ante-Banking-System-Distress-A-Macro-Micro-Empirical-Exploration-of-Some-2908

Heffernan, S.A. 2005. Modern Banking. Chichester, England: John Wiley & Sons.

Kalbfleish, J.D. and R.L. Prentice 1980. The Statistical Analysis of Failure Time Data. New York: John Wiley.

Karina, L., E.G. Aquiles and B.M. Alberto. 2006. “Survival analysis of private Banks in Brazil”. Technical Report, University of São Paulo, Brazil. Retrieved from http://ecomod.net/sites/default/files/document-conference/ecomod2009/1058.pdf

Kaufman, G.G. 1996. “Bank failures, systemic risk, and bank regulation”. Cato Journal, 16(1): 17–45. Retrieved from http://object.cato.org/sites/cato.org/files/serials/files/cato-journal/1996/5/cj16n1-2.pdf

Kiefer, N.M. 1988. "Economic duration data and hazard functions". Journal of Economic Literature, 26(2): 646–79. Retrieved from http://qed.econ.queensu.ca/pub/faculty/ferrall/econ861/papers/kiefer.pdf

Kupiec, P.H. and C.D. Ramirez. 2009. Bank Failures and the Cost of Systemic Risk: Evidence from 1900-1930. FDIC Center for Financial Research Working Paper No. 2008-09. Federal Deposit Insurance Corporation Center for Financial Research, Arlingon, VA. Retrieved from https://www.fdic.gov/bank/analytical/cfr/2008/wp2008/2008-09.pdf

Luyang, F. and W. Hongyuan. 2013. "Estimate attrition using survival analysis". Casualty Actuarial Society Spring Meeting, Vancouver, Canada, May 2013. Retrieved from https://cas.confex.com/.../Estimate%20Attrition%20Using%20Survival%

Milde, H. and J.G. Riley. 1988. "Signalling in credit markets". Quarterly Journal of Economics, 103: 101–29.

Nurazi, R. and M. Evans. 2005. "An Indonesian study of the use of CAMEL(S) ratios as predictors of bank failure". Journal of Economic and Social Policy, 10(1), Article 6.

Oforegbunam, T.E. 2011. "Benchmarking incidence of distress in the Nigerian banking industry on Altman Scale". Serbian Journal of Management, 6(2): 221–30. Retrieved from http://www.sjm06.com/SJM%20ISSN1452-4864/6_2_2011_November_123-282/6_2_221-230.pdf

Okezie, A.C. 2011. "Capital ratios as predictors of distress: A case study of the Nigerian banking system". Global Journal of Human Social Science, 11(3), version 1.0, April. Retrieved from https://globaljournals.org/GJHSS_Volume11/6-Capital-Ratio-as-Predictors-of-Distress.pdf

Olaniyi, T.A. 2006. "Bankruptcy prediction through financial strength analysis: A case study of Trade Bank PLC. The Journal of Department of Business Administration University of Ilorin, Nigeria 5:(1).pp105-110

Olaniyi, T.A. 2007. Predicting Potential of Failure in Nigerian Banking Sector: A Comparative Analysis of First Bank Plc, and Trade Bank Plc. Babcock Journal ofManagement and Social Sciences, Babcock University, Vol.6, No.1, Pp:64-73.

Ozurumba, B.A. 2016. "Impact of non-performing loans on the performance of selected commercial banks in Nigeria". Research Journal of Finance and Accounting, 7(16).

Pam, W.B. 2013. "Discriminant analysis and the prediction of corporate bankruptcy in the banking sector of Nigeria". International Journal of Finance and Accounting, 2(6): 319–25. Retrieved from http://article.sapub.org/pdf/10.5923.j.ijfa.20130206.04.pdf

Pereira, J. (2014). Survival Analysis Employed in Predicting Corporate Failure: A Forecasting Model

Proposal. International Business Research, Vol 7(5)

Sanusi, L.S. 2011. "Banks in Nigeria and national economic development: A critical review". Keynote address at the Seminar Becoming An Economic Driver While Applying Banking Regulations, organized by the Canadian High Commission in joint collaboration with the Chartered Institute of Bankers of Nigeria and the Royal Bank of Canada, 7 March held in Lagosn Nigeria.

Sanusi, L.S. 2010. "Global financial meltdown and the reforms in the Nigerian banking sector". Full text of a public lecture delivered at Convocation Square, Abubakar Tafawa Balewa University, Bauchi, Friday, 10 December. Retrieved from https://www.cbn.gov.ng/out/speeches/2010/Gov_ATBU%20Convocation%20Lecture.pdf

Secrist, H. 1938. National Bank Failures and Non-Failures: An Autopsy and Diagnosis. Bloomington, Indiana: Principia Press.

Shumway, T. 2001. "Forecasting bankruptcy more accurately: A simple hazard model". The Journal of Business, 74(1): 101–24. Retrieved from http://homes.chass.utoronto.ca/~szhou/print/ForcastingBankruptcyHazardModel.pdf

Sinkey, J. 1975. "A multivariate analysis of the characteristics of problem banks". The Journal of Finance, 30, March: 21–36.

Soludo, C.C. 2006. "The outcome of the banking sector recapitalization and the way forward for the undercapitalized banks". Press conference statement by the Governor of the Central Bank of Nigeria, 16 January. Retrieved from https://www.cbn.gov.ng/OUT/SPEECHES/2006/GOVADD%2016-1-06.PDF

Soludo, C.C. 2004. "Consolidating the Nigerian banking industry to meet the development challenges of the 21st century". Address by Mr Charles Chukwuma Soludo, Governor of the Central Bank of Nigeria, at the Special Meeting of the Bankers' Committee, Abuja, 6 July. BIS Review 43/2004. Retrieved from http://www.bis.org/review/r040727g.pdf

Soyibo, A. S.O. Alashi and M.K. Ahmad. 2004. A Positive and Normative Analysis of Bank Supervision in Nigeria. AERC Research Paper No. 145. African Economic Research Consortium, Nairobi, November. Retrieved from https://opendocs.ids.ac.uk/opendocs/bitstream/handle/123456789/2583/RP%20145.pdf?sequence=1

Sprague, O.M.W. 1910. "History of crises under the national banking system". Washington, D.C.: National Monetary Commission.

Stepanova, M. and L. Thomas. 2000. "Survival analysis methods for personal loan data". Operations Research, 50(2): 277–89.

Stiglitz, J. and A. Weiss. 1992. "Asymmetric information in credit markets and its implications for macroeconomics". Oxford Economic Papers, 44: 694–724.

Stiglitz, J. and A. Weiss. 1986. "Credit rationing: Reply". American Economic Review, 77: 228–31.

Stiglitz, J. and A. Weiss. 1981. "Credit rationing in markets with imperfect information". American Economic Review, 71: 912–27.

Whalen, G. (1991). A proportional hazards model of bank failure: An examination of its usefulness as an early warning tool. *Economic Review*, Federal Reserve Bank of Cleveland, vol. 27(Q I), pages 21-31

Whalen, G. 2005. A Hazard Model of CAMELS Downgrades of Low-risk Community Banks. OCC Economics Working Paper 2005-1, Office of the Comptroller of the Currency, Washington, D.C., May.

Zaghdoudi, T. 2013. "Bank failure prediction with logistic regression". International Journal of Economics and Financial Issues, 3(2): 537–43.

Appendix

Table A1: Summary of time to failure

	Time at risk	Incidence rate	No. of subjects subjects	Survival time 25%	50%	75%
total	470	0.019149	47	23	23	.

Table A2: Summary of time to distress

	Time at risk	Incidence rate	No. of subjects	Survival time 25%	50%	75%
total	470	0.025532	47	8	23	26

Table A3: Survival/failure function

Time	Beg. Total	Fail	Net Lost	Failure Function	Std. Error	[95% Conf	. Int.]
3	47	1	5	0.0213	0.021	0.003	0.1416
4	41	0	6	0.0213	0.021	0.003	0.1416
5	35	2	2	0.0772	0.0432	0.0253	0.2227
7	31	1	7	0.107	0.0511	0.0411	0.2626
8	23	1	6	0.1458	0.0619	0.062	0.3215
9	16	0	1	0.1458	0.0619	0.062	0.3215
10	15	0	1	0.1458	0.0619	0.062	0.3215
11	14	0	3	0.1458	0.0619	0.062	0.3215
19	11	0	2	0.1458	0.0619	0.062	0.3215
20	9	0	2	0.1458	0.0619	0.062	0.3215
22	7	0	1	0.1458	0.0619	0.062	0.3215
23	6	4	0	0.7153	0.1657	0.3975	0.9556
26	2	0	2	0.7153	0.1657	0.3975	0.9556

Table A4: Survival/failure function for bank distress

Time	Beg. Total	Fail	Net Lost	Failure Function	Std. Error	[95% Conf	. Int.]
3	47	1	5	0.0213	0.021	0.003	0.1416
4	41	1	5	0.0451	0.0313	0.0114	0.1692
5	35	3	1	0.127	0.0535	0.0546	0.2801
7	31	2	6	0.1833	0.0631	0.0914	0.3481
8	23	2	5	0.2543	0.075	0.1392	0.437
9	16	0	1	0.2543	0.075	0.1392	0.437
10	15	0	1	0.2543	0.075	0.1392	0.437
11	14	0	3	0.2543	0.075	0.1392	0.437
19	11	0	2	0.2543	0.075	0.1392	0.437
20	9	0	2	0.2543	0.075	0.1392	0.437
22	7	0	1	0.2543	0.075	0.1392	0.437
23	6	2	2	0.5029	0.152	0.2566	0.8074
26	2	1	1	0.7514	0.1915	0.3754	0.9837

Table A5: Test of proportional hazard assumption

	rho	chi2	df	Prob>chi2
roae	-0.26176	0.25	1	0.6189
cosinc	-0.29153	0.29	1	0.5887
liqass	-0.19521	0.21	1	0.6476
grothln	-0.30724	0.68	1	0.4085
lnloss	-0.13802	0.12	1	0.7341
ownstr	0.2753	0.25	1	0.6188
bnkconsm	0.10729	0.09	1	0.7704
global test		6.44	7	0.4895

Table A6: Log-rank test for equality of survivor functions

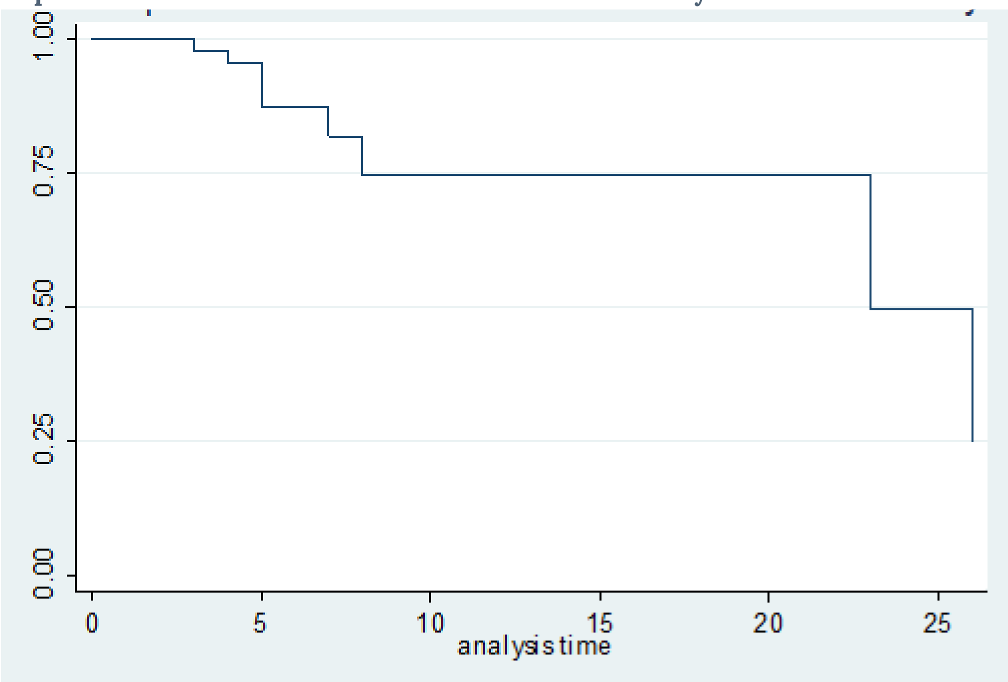
dthresh	Events observed	Events expected	bigbank	Events observed	Events expected	ownstr	Events observed	Events expected
0	1	2.98	0	6	6.42	0	6	5.93
1	5	3.02	1	3	2.58	1	3	3.07
Total	6	6	Total	9	9	Total	9	9
	chi2(1) =	3.35		chi2(1)	0.13		chi2(1) =	0
	Pr>chi2 =	0.0674		Pr>chi2	0.7227		Pr>chi2 =	0.9568

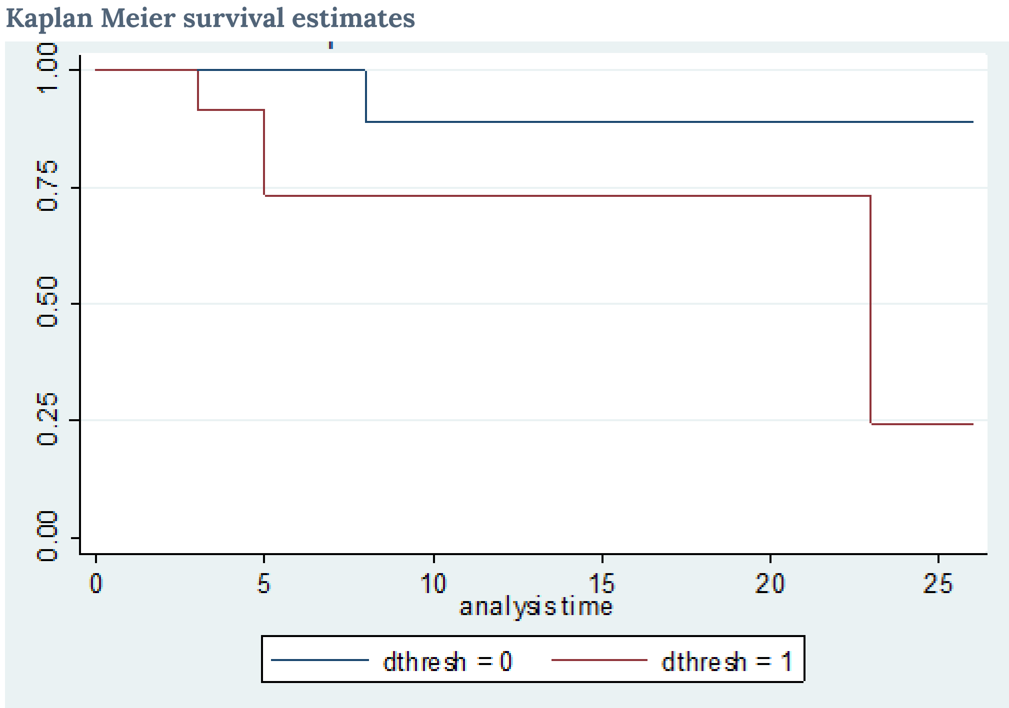
Table A7: Stcox hazard 2006–2009

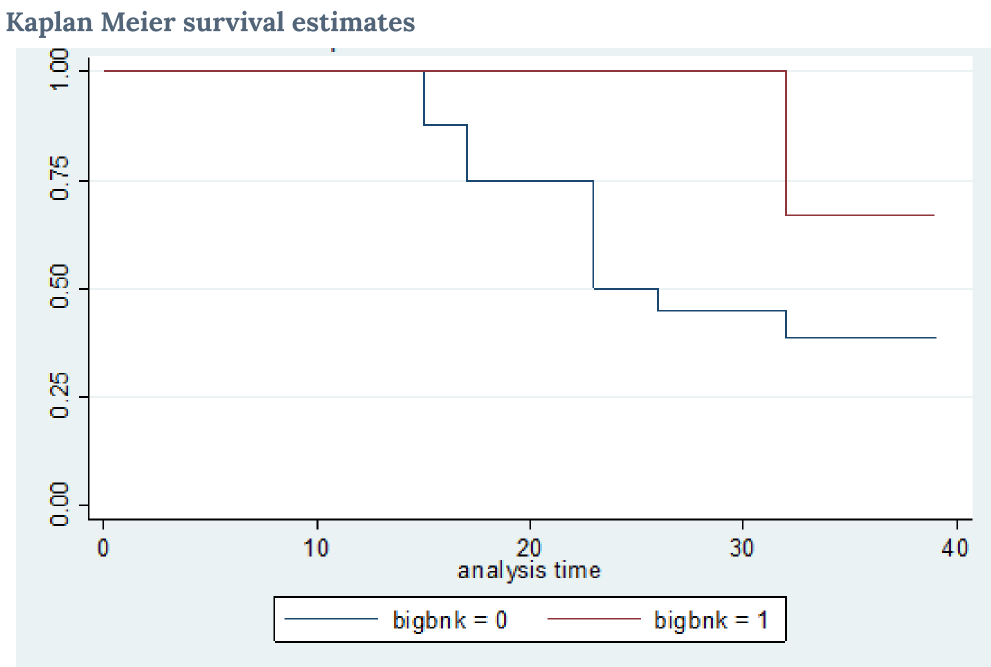
	_t	_t	_t	_t	_t
main					
ROAE	1.060***	1.070***	1.087***	0.953***	
	(0.000)	(0.000)	(0.000)	(0.000)	
implneq	1.125***	1.120***	1.124***	1.064***	1.075***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
liqass	1.073				
	(.)				
grothln	1.073***	1.078***	1.079***	1.050***	1.104***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
imploan	1.116	1.083	1.013	1.624***	1.569***
	(0.172)	(0.322)	(0.873)	(0.000)	(0.000)
lnloss	0.779**	0.814**	0.838*	0.717***	0.809**
	(0.001)	(0.008)	(0.022)	(0.000)	(0.007)
ROAA					1.171**
					(0.003)
Observations	9	9	9	9	9
ll	-10.75	-10.75	-10.75	-10.75	-10.75
chi2	4.866	4.866	4.866	4.866	4.866
r2_p	0.185	0.185	0.185	0.185	0.185

Exponentiated coefficients; p-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

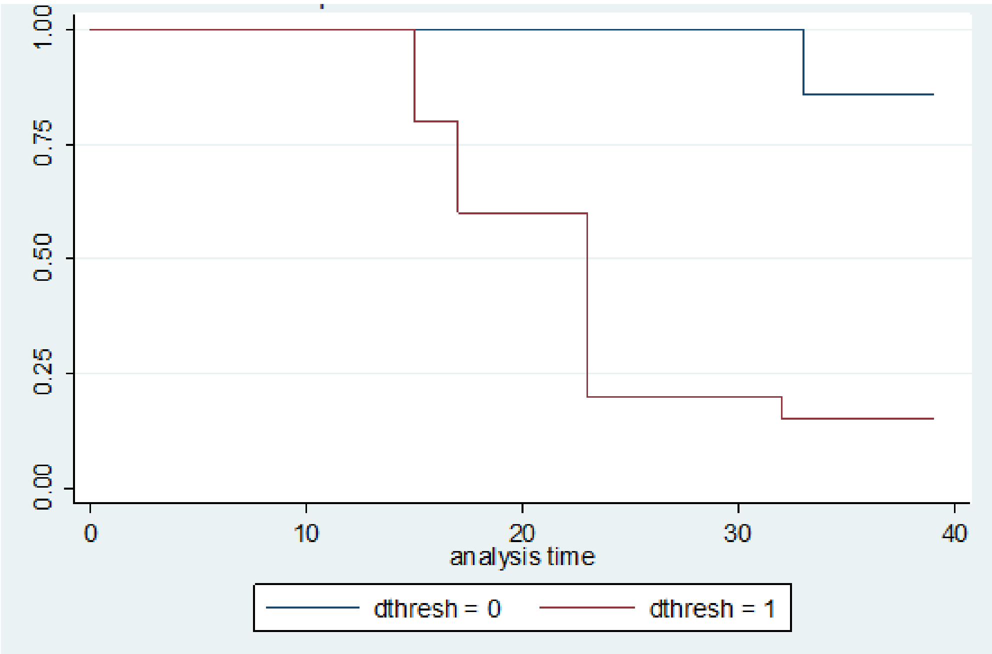
Kaplan-Meier survival estimate for Distress Probability




Kaplan Meier survival estimates
1.00
0.75
0.50
0.25
0.00
0
5
10
15
20
25
analysis time
dthresh = 0
dthresh = 1


Kaplan Meier survival estimates
1.00
0.75
0.50
0.25
0.00
0
10
20
30
40
analysis time
bigbnk = 0
bigbnk = 1

Kaplan Meier survival estimates



Mission

To strengthen local capacity for conducting independent, rigorous inquiry into the problems facing the management of economies in sub-Saharan Africa.

The mission rests on two basic premises: that development is more likely to occur where there is sustained sound management of the economy, and that such management is more likely to happen where there is an active, well-informed group of locally based professional economists to conduct policy-relevant research.

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