

**CREDIT RISK MODELING TECHNIQUES AND PERFORMANCE  
OF LIFE INSURANCE FIRMS IN NIGERIA**



**BY**

**FAVOUR ABIEYUWA OSAMWONYI**

**MG2104713**

**DEPARTMENT OF ACTUARIAL SCIENCE AND INSURANCE,  
FACULTY OF MANAGEMENT SCIENCES,  
UNIVERSITY OF BENIN,  
BENIN CITY,**

**NOVEMBER, 2025.**

**CREDIT RISK MODELING TECHNIQUES AND PERFORMANCE  
OF LIFE INSURANCE FIRMS IN NIGERIA**

**BY**

**OSAMWONYI FAVOUR ABIEYUWA**

**MGS2104713**

**BEING A PROJECT SUBMITTED TO THE DEPARTMENT OF ACTUARIAL  
SCIENCE, FACULTY OF MANAGEMENT SCIENCES, UNIVERSITY OF  
BENIN, BENIN CITY IN PARTIAL FULFILMENT OF THE REQUIREMENTS  
FOR THE AWARD OF BACHELOR OF SCIENCE (B.Sc.) DEGREE IN  
ACTUARIAL SCIENCE.**

**NOVEMBER, 2025.**

## CERTIFICATION

This is to certify that this project titled “**Credit Risk Modeling Techniques and Performance of Life Insurance Firms in Nigeria**” was carried out by **Favour Abieyuwa Osamwonyi** with matriculation number **MGS2104713**. It has been read and recommended for acceptance in partial fulfilment of the requirement for the award of Bachelor of Science (B.Sc.) Degree in Actuarial science.

\_\_\_\_\_  
**Dr. B.I. Oni**

(Project Supervisor)

**Date:** \_\_\_\_\_

\_\_\_\_\_  
**Mrs. Izedomi**

(Project Co-Ordinator)

**Date:** \_\_\_\_\_

\_\_\_\_\_  
**Dr .O.I. Omoruyi-Aigbovo**

(Head of Department)

**Date:** \_\_\_\_\_

## **DEDICATION**

This work is dedicated to the almighty God who made me all I am today and granted me the required strength, wisdom and knowledge needed in carrying out this work. I also specially dedicate this work to my amazing parents, Mr and Mrs. Osamwonyi and my siblings for always believing in me and pushing me to be my best in my academic pursuit.

## **ACKNOWLEDGMENT**

First and foremost, I am grateful to God Almighty for His endless love, mercy and unwavering support throughout my life and academic journey. His favour and unwavering support has sustained me throughout every phase of this project.

I would like to appreciate my supervisor, Dr. B. I. Oni for his guidance, timely feedback and continuous encouragement. My gratitude extends to the faculty Dean, Prof.(MRS)E.I. Evbayiro-Osagie and to the exceptional lecturers in the Department of Actuarial Science and Insurance. I also want to appreciate my wonderful H.O.D, Dr. O.I. Omoruyi-Aigbovo for her kindness and leadership. And also, my course advisor, Dr .E.H. Iroh for his teachings and guidance.

To my parents, Mr and Mrs Osamwonyi, I express my heartfelt gratitude for your support and encouragement in the course of writing my project. May God continue to bless you both.

To my friends and well-wishers, thank you all for your support, prayers and encouragement. I do not take any of it for granted.

## **TABLE OF CONTENTS**

**Pages**

Title page	i
Certification	iii
Dedication	iv
Acknowledgments	v
Table of contents	vi
List Of Table	x
List Of Figure	xi
Abstract	xii

**CHAPTER ONE: INTRODUCTION**

1.1	Background of the study -----	1
1.2	Statement of research problem -----	3
1.3	Research Questions -----	5
1.4	Objectives of the study-----	5
1.5	Hypotheses of the Study -----	6
1.6	Significance of the study -----	7
1.7	Scope of the study -----	9

## **CHAPTER TWO: LITERATURE REVIEW**

2.0	Introduction -----	10
2.1	Conceptual Review -----	10
2.1.1	Performance of Life Insurance Firms -----	10
2.2	Credit Risk Modeling Techniques -----	13
2.2.1	Credit Scoring Models -----	16
2.2.2	Structural Models -----	17
2.2.3	Altman Z-Score Model -----	19
2.2.4	Conceptual Framework -----	22
2.3	Theoretical Review -----	23
2.3.1	Structural Theory of Credit Risk -----	23
2.3.2	Agency Theory -----	24
2.3.3	Signaling Theory -----	24
2.3.4	Theoretical Framework -----	25
2.4	Empirical Review -----	26
2.5	Gap in Literature -----	46

## **CHAPTER THREE: METHODOLOGY**

3.1	Introduction -----	47
-----	--------------------	----

3.2	Research Design -----	47
3.3	Population of the study -----	48
3.4	Sample Size and Sampling Technique -----	48
3.5	Sources of Data -----	49
3.6	Method of Data Analysis -----	50
3.7	Model Specification -----	50
3.8	Measurement of Variable -----	53

**CHAPTER FOUR: DATA PRESENTATIONANALYSIS AND INTERPRETATION**

4.1	Introduction -----	54
4.2	Descriptive Statistics -----	54
4.3	Correlation Analysis -----	60
4.4	Regression Diagnostics -----	46
4.5	Analysis of the Regression Result -----	62
4.6	Test of Hypothesis Model I -----	65
4.7	Test of Hypothesis Model II -----	70
4.8	Model Comparison and Evaluation -----	72
4.9	Discussion of Findings -----	74

**CHAPTER FIVE: SUMMARY OF FINDINGS, RECOMMENDATIONS AND CONCLUSION**

5.1	Summary of findings -----	77
5.2	Conclusion -----	78
5.3	Recommendations -----	79
5.4	Contribution to Knowledge -----	81
5.5	Suggestion for further Study -----	81
	References -----	82
	Appendix I -----	85
	Appendix II -----	86
	Appendix III -----	87
	Appendix IV -----	88
	Appendix V -----	89
	Appendix VI -----	90
	Appendix VII -----	91
	Appendix VIII -----	93

**LIST OF TABLE**

Table 2.1: Summary of Empirical Review.....	41
Table 4.1: Results of the Descriptive Analysis of the Regression Variables.....	53
Table 4.2: Result of the Correlation Analysis.....	55
Table 4.3: Test of Heteroskedasticity.....	60
Table 4.4: Result of the Breusch-Godfrey Test of Serial Correlation.....	62
Table 4.5: Results of the Hausman Test.....	63
Table 4.7: Result of the Regression Analysis.....	69

## LIST OF FIGURE

Fig 1: Result of the Histogram Normality Test.....	58
--	----

## **ABSTRACT**

This study examines the impact of credit risk modeling techniques on the performance of life insurance companies in Nigeria., focusing on a sample of 12 life insurance companies in Nigeria over the period 2018 to 2024. The variables analyzed included credit scoring, structural model and Altman Z-score model. Various statistical and econometric tools were applied to analyze the data. The findings revealed that credit scoring and Altman Z-score model have positive and statistically insignificant effects on the financial performance of life insurance companies in Nigeria, while the structural model has a negative and statistically insignificant influence on the financial performance of life insurance companies in Nigeria. Based on these findings, the study recommended that life insurance firms in Nigeria strengthen the adoption and integration of credit scoring systems using advanced data analytics and artificial intelligence and firms should review and customize structural models to better suit the operational and regulatory environment of the Nigerian insurance industry.

## **CHAPTER ONE**

### **INTRODUCTION**

#### **1.1 Background of the Study**

Life insurance companies' performance is getting more and more attention from both academics and people who work in the business. This is especially true in emerging markets like Nigeria, where the sector is very important for economic growth and financial inclusion. In the life insurance business, a company's success is usually judged by how stable its finances are, how profitable it is, how solvent it is, and how well it can meet the needs of its policyholders. All of these things are important for keeping stakeholders trust and achieving long-term growth (Osabohien et al., 2020). Nigeria has problems like low penetration rates, unstable economies, and changes in regulations that have made strong risk management strategies and good performance tracking even more important (Okeke et al., 2022). Because of these changes, life insurance companies are looking into more advanced risk modeling methods to protect their investments and improve their business results.

A big part of how well life insurance companies do is how well they can evaluate and handle credit risk, which is the chance that clients or other parties will not pay their debts.

Oluwatosin et al. (2023) say that credit risk modeling is now necessary for making choices about underwriting, investments, and reinsurance. Out of all the methods used, credit score models, structural models, and the Altman Z-Score model have become popular because they are good at figuring out and predicting the chances of default. Credit score models use statistical and machine learning algorithms to figure out how creditworthy a person or business is by looking at their past actions, demographic data, and information about their lifestyle. Credit scoring has been used in Nigerian insurance not only for screening but also to collect more premiums and reduce the number of loans that aren't being paid back (Omoriegbe et al., 2023). Based on the values of a company's assets and debts, structural models, which are based on financial theory, use that information to guess how likely it is that the company will go bankrupt. These models give a more complex picture of credit risk by including market dynamics and macroeconomic factors. This makes them very useful in markets that are always changing, like Nigeria's (Ajagbe et al., 2022).

The Altman Z-Score model was originally created to predict bankruptcy, but insurance companies have now added it to their list of early warning signs of financial trouble. It has been used successfully in the Nigerian insurance business to check if companies are solvent, help managers make decisions, and help regulators keep an eye on things

(Aladejebi, 2021). By using these credit risk modeling methods, Nigerian life insurance companies can better match their risk tolerance with their strategic goals. This will improve their financial performance, lower the number of defaults, and make them more resistant to market shocks. The way that advanced credit risk modeling techniques affect the performance of life insurance companies shows how important strong analytical models are in today's complicated financial world. Nigerian life insurance companies can lower credit risk and improve their overall performance and competitiveness in a market that is always changing by using credit scoring models, structural models, and the Altman Z-Score model and making them better all the time (Oluwatosin et al., 2022).

## **1.2 Statement of the Research Problem**

Although life insurance companies are very important to Nigeria's economic growth, they are still having trouble with credit risk management, which is holding them back. Life insurance companies in Nigeria are still having a hard time because they can't make enough money, a lot of people don't pay their premiums, and they have trouble staying solvent. Even though companies use different risk management methods, these issues are made worse by an unpredictable economy, unclear regulations, and a lack of insurance coverage (Osabohien et al., 2020). These ongoing problems suggest that current methods

for modeling credit risk may not be enough, calling for a more thorough and situation-specific review of how well they work.

Nigerian life insurance companies have started using more advanced credit risk modeling methods, like credit score models, structural models, and the Altman Z-Score model, to figure out how likely it is that a policyholder will not pay (Oluwatosin et al., 2023) that they will not pay. But it's still not clear how much these models have actually helped the company do better. Some research has looked into what causes credit risk in Nigerian banks, but most of the time, these studies only look at one part of credit risk modeling and don't look at how different models affect the performance of life insurance companies or how they compare to each other. Omoregie et al. (2023) studied the determinants of credit risk in Nigerian banks, stressing the importance of credit scoring and macroeconomic factors, but did not specifically assess life insurance companies or compare multiple modeling methods (Omoregie et al., 2023). Ajagbe et al. (2022) looked at risk management practices in insurance, but they only looked at qualitative aspects and didn't test how well structural or Altman Z-Score models predicted performance results (Ajagbe et al., 2022). Aladejebi (2021) also used financial ratio analysis to judge the performance of insurance companies, but he didn't directly connect certain credit risk models to company performance (Aladejebi, 2021). Even though these studies give us

good information, none of them have looked at how credit scoring models, structural models, and the Altman Z-Score model compare in terms of how well they work for life insurance companies in Nigeria. There is a big hole in the literature because there isn't enough comprehensive empirical study. It's important to look at how different credit risk modeling methods affect the success of Nigerian life insurance companies and see if using these models really leads to better financial stability, higher profits, and lower risk.

### **1.3 Research Questions**

1. To what extent do credit scoring models influence the performance of life insurance firms in Nigeria?
2. How effective are structural models in improving the performance of life insurance firms in Nigeria?
3. What is the impact of the Altman Z-Score model on the performance of life insurance firms in Nigeria?

### **1.4 Objective of the Study**

the main objective of the study is to assess credit risk modeling techniques on performance of life insurance companies in Nigeria, specifically the study aims to;

1. examine the influence of credit scoring models on the performance of life insurance firms in Nigeria.
2. evaluate the effectiveness of structural models in improving the performance of life insurance firms in Nigeria.
3. assess the impact of the Altman Z-Score model on the performance of life insurance firms in Nigeria.

### **1.5 Hypotheses of the Study**

The following hypotheses were raised in a null form to guide this study;

H<sub>01</sub>: Credit scoring models have no significant influence on the performance of life insurance firms in Nigeria.

H<sub>02</sub>: Structural models are not effective in improving the performance of life insurance firms in Nigeria.

H<sub>03</sub>: The Altman Z-Score model has no significant impact on the performance of life insurance firms in Nigeria.

## 1.6 Significance of the Study

This study makes a vital contribution to the understanding of credit risk modeling in Nigeria's life insurance industry. By examining credit scoring models, structural models, and the Altman Z-Score model in detail, it moves beyond the general treatment of credit risk in prior research. The study fills a key gap in academic literature and provides practical insights for stakeholders in the insurance and financial sectors. The study enriches academic knowledge by integrating multiple credit risk assessment frameworks and evaluating their influence on insurance company performance. It offers new perspectives on how credit risk models can enhance financial stability, profitability, and operational efficiency in emerging markets like Nigeria.

**Insurance Firms:** Insurance companies will gain from the study's findings by identifying the most effective models for predicting and managing credit risk. This will improve underwriting decisions, strengthen investment analysis, enhance premium collection, and ultimately increase financial stability and efficiency.

**Regulators:** Regulatory agencies, especially the **National Insurance Commission (NAICOM)**, can apply the study's results to refine their supervisory frameworks.

Insights from the research will support more risk-based regulation, stronger solvency standards, and improved resilience within Nigeria's insurance sector.

**Academia:** For scholars and researchers, this study offers a robust foundation for future exploration in actuarial science and financial risk management. It provides empirical evidence and methodological guidance for studies focusing on credit risk modeling in the insurance industry and other financial institutions.

**Government:** Government bodies will benefit from a better understanding of the credit risk environment in the insurance industry. This knowledge can inform policy formulation, promote financial system stability, and contribute to broader economic growth through a stronger, more transparent insurance sector.

**Investors:** Investors and financial analysts will find the study valuable for understanding how credit risk is managed within Nigerian life insurance companies. Enhanced transparency and model-based risk assessment will boost investor confidence and attract more capital to the sector.

**Students:** Students and future researchers can use this study as a reference for learning about credit risk modeling, insurance performance, and financial risk analysis in

developing economies. It provides practical insights and opens avenues for further academic investigation.

### **1.7 Scope of the Study**

The scope of this study is restricted to assessing the impact of credit risk modeling techniques on the performance of life insurance companies in Nigeria. The study specifically investigates three widely recognized credit risk modeling techniques: credit scoring models, structural models, and the Altman Z-Score model. The research focuses on how these techniques influence the assessment, prediction, and management of credit risk, and how they, in turn, affect the overall performance of Nigerian life insurance firms. The population for the study consists of all life insurance companies registered with the National Insurance Commission (NAICOM) as of December 2024. To ensure data reliability and completeness, only those firms that have consistently published annual financial reports within the period under review are included. The study adopts a longitudinal approach, spanning a period of seven years from 2018 to 2024. This timeframe allows for a thorough analysis of trends, consistency, and changes in the application of credit risk modeling techniques and their relationship with performance over time.

## **CHAPTER TWO**

### **LITERATURE REVIEW**

#### **2.0 Introduction**

This chapter reviews the related literature of the study, it starts by reviewing conceptually the variables of the study, it further reviews relevant theories and finally reviews related empirical studies.

#### **2.1. Conceptual Review**

##### **2.1.1 Performance of Life Insurance Firms**

Life insurance companies' success is a broad term that includes a number of financial and operational measures that show how healthy, efficient, and long-lasting these companies are as a whole. The success of life insurance companies is especially important in emerging markets like Nigeria because they play a big part in getting people to save money, giving people financial security, and helping the economy grow (Osabohien et al., 2020). Life insurance companies are usually judged on their performance by things like their ability to meet policyholder responsibilities, their ability to make money, their

solvency, their liquidity, the growth of their premiums, and how quickly and efficiently they can settle claims.

Profitability is a key factor that is often measured with return on assets (ROA), return on equity (ROE), and insurance profit margins. Profitability that is high means that operations are running smoothly and risks are being managed well, which are important for building trust among stakeholders and ensuring long-term sustainability. On the other hand, solvency shows how well a company can pay its long-term debts. Solvency margins and capital adequacy ratios are common ways to measure this. Regulatory bodies, like Nigeria's National Insurance Commission (NAICOM), make insurance companies meet basic solvency standards to protect policyholders and keep the market stable (Okeke et al., 2022).

Liquidity is another important factor. This means that insurance companies must be able to meet their short-term responsibilities, like paying claims and other operational costs on time. Liquidity is very important for keeping policyholders' trust, especially when the economy is unstable. Premium growth is a good indicator of how competitive the market is and how much trust customers have in the company. It shows how well the company can get new customers and keep the ones it already has. How quickly and correctly

claims are handled and paid has a direct effect on customer satisfaction and the company's reputation in the market (Oluwatosin et al., 2023 ).

Life insurance companies' results are also affected by things outside of their control, like the economy, changes in regulations, new technologies, and changes in what people want. In Nigeria, problems like low insurance coverage, changing financial conditions, and new rules and regulations make performance management more difficult. Companies are depending more and more on data-driven decisions, strong risk management, and smart investments in technology and new ideas to deal with these problems (Oluwatosin et al., 2023).

Along with this, using more advanced credit risk modeling methods is now necessary to make businesses run better. By correctly finding and managing credit risk, life insurance companies can lower the number of defaults, make their finances more stable, and make things better for everyone involved. New studies show that when life insurance companies in Nigeria combine complex risk models with good governance structures, their operational and financial success goes up by a lot (Oluwatosin et al., 2023). How well life insurance companies do is based on how well they handle their own employees, how well they adapt to changes in the outside world, and how quickly they adopt new risk assessment and management tools. The Nigerian life insurance business needs to

keep getting better in these areas if it wants to stay strong, grow, and be relevant in a changing financial landscape.

## **2.2 Credit Risk Modeling Technique**

Credit risk modeling techniques are now an important part of current financial risk management, especially in the banking and insurance industries. Credit risk modeling is the process of using numbers and analytical tools to figure out how likely it is that a borrower or counterparty will not pay back their debts. The need for strong credit risk assessment has grown because financial markets are becoming more complicated and there are a lot of unpredictable economic shocks. This has led insurance companies, especially life insurers in emerging markets like Nigeria, to use more advanced modeling techniques (Oluwatosin et al., 2023). These methods are very important for making decisions about underwriting, investments, premium prices, and general policies for managing risk.

In the past, banks used biased judgment and simple ratio analysis to figure out how much credit risk a person posed. But improvements in statistics and computer power have made it possible to create models that are more accurate and can predict the future. A lot of people use techniques like credit score models, structural models, and discriminant analysis methods like the Altman Z-Score. Credit scoring models give each applicant a

risk score based on their credit history, income, age, job status, and past transaction history, among other things. This number shows how likely it is that the loan will not be paid back, and it is used to help with lending, underwriting, and setting prices. Using non-traditional data sources and finding complicated patterns that may point to higher credit risk has made credit scoring methods more advanced since the rise of big data and machine learning (Omoregie et al., 2023).

When it comes to structural models, they are based on financial theory, especially Merton's option price theory. These models try to figure out how likely it is that a company will go bankrupt by comparing the value of its assets and debts. A default is considered to happen when a company's debts are greater than its assets at a certain point in time. By combining firm-specific financial data with wider macroeconomic variables and market trends, structural models give a more nuanced picture of credit risk. This lets risk assessments be dynamic and look ahead (Ajagbe et al., 2022). Structural models are becoming more important in places like Nigeria where the economy is unstable and companies are vulnerable to big changes in the prices of their assets and shocks from outside the country.

Some discriminant analysis models, like the Altman Z-Score, take a number of financial ratios and combine them into a single score that can be used to predict whether a business

will go bankrupt or be in financial trouble. These ratios include working capital, retained earnings, earnings before interest and taxes, market value of stock, and sales. The Z-Score was first created for manufacturing companies but has since been adapted for use in insurance and other financial sectors. It helps managers and officials spot companies that might be about to go bankrupt early and take action before they do (Aladejebi, 2021). Because it can predict the future and is easy to understand, it is a useful tool, especially in places where high-frequency data is hard to get.

New research shows that how well credit risk modeling works relies on many things, including the model used, the quality and quantity of the data used, and how well the models can be adjusted to fit the needs of the local market (Oluwatosin et al., 2023). Life insurance companies in Nigeria are still figuring out how to use credit risk modeling techniques. Many of them are combining old and new methods to deal with the unique problems in the local market. Some of these problems are limited data, rules and regulations, and the fact that insurance goods aren't very popular. As the life insurance industry grows older, better and more advanced credit risk models will be used and improved. This will help life insurance companies do better and be more stable, making them more resistant to economic shocks and building trust among stakeholders (Oluwatosin et al., 2023).

### **2.2.1 Credit Scoring Models**

Credit score models are one of the most popular and useful ways for banks and insurance companies to figure out how risky it is to lend money to people. These models regularly check if a person or business is creditworthy by looking at different pieces of information about their financial habits and personal traits. Credit scoring's main goal is to figure out how likely it is that a borrower or policyholder will not pay back their debts. This helps lenders and insurers make better, more objective decisions about lending, underwriting, and policy issuance (Omoregie et al., 2023).

Credit scoring models usually work by gathering information about borrowers from the past, like their income, job history, payment history, current debts, and even information from outside sources like utility bills or cell phone use. Then, sophisticated statistical methods like logistic regression, decision trees, and more recently, machine learning algorithms are used to give each person or thing a number score that shows how dangerous they are. In recent years, the integration of big data analytics has greatly improved the predictive power of credit scoring models, allowing insurers to identify hidden risk patterns that traditional methods might miss (Oluwatosin et al., 2023). Nigeria's unstable economy and the need to keep non-performing assets to a minimum have made credit score models more important for life insurance companies. By using

these models, insurance companies can better screen customers, set the right payment rates, and lower the risk of policies not being paid for. According to Omoregie et al. (2023), using credit scores to collect premiums has also helped businesses improve their cash flow and general financial stability. This has led to better performance and more trust from stakeholders. Credit score models are also flexible, which means they can be updated as new information comes in. This keeps risk assessments accurate and up to date. This ability to change quickly is especially important in emerging markets like Nigeria, where the economy and customer habits can change quickly. Life insurance companies will continue to rely more on strong and clear credit score models as government rules for risk management get stricter. According to Oluwatosin et al. (2023), using credit scoring models correctly is a big step towards better credit risk management and better operational and financial performance of Nigerian insurance businesses.

### **2.2.2 Structural Models**

The ideas behind structural models come from the fields of corporate finance and option pricing theory. They are a more advanced type of credit risk modeling. It is the main idea behind structural models to see a company's failure as a result of how the value of its assets changes over time compared to the amount of debt it owes. The Merton model is one of the first in this field. It sees a company's equity as a call option on its assets, and

default happens if the value of assets goes below the value of liabilities at the maturity of debt (Ajagbe et al., 2022).

To use structural models in real life, you need specific firm-level data on things like asset values, debt levels, asset volatility, and the maturity structure of liabilities. Structured models simulate various economic situations and market conditions to give a future look at the likelihood of default. This is especially useful in unstable and uncertain places like Nigeria's financial sector. These models are flexible because they can adapt to changes in macroeconomic indicators and market values. This makes them very useful for insurers that work in developing markets (Ajagbe et al., 2022). Structured models are helpful for Nigerian life insurance companies in a number of ways. By combining firm-specific financial data with larger economic trends, they make it possible to get a fuller picture of counterparty and policyholder credit risk. This unified view helps insurance companies plan for and lessen the effects on their holdings of economic downturns, changes in currency, and shocks that happen in specific industries. Most recently, studies have shown that structural models work best in places like Nigeria where financial transparency is growing and governmental oversight is getting stricter (Oluwatosin et al., 2023).

Another great thing about structural models is that they can be used in drills to check for capital adequacy and stress. Insurance companies can use these models to practice the worst-case scenarios, check if their cash buffers are enough, and keep up with changing government rules. This proactive way of managing risk fits in well with the present push by regulators in the Nigerian insurance sector for more solvency and market stability. But there are some problems that come up when structure models are used. Some Nigerian insurance companies may not be able to use these models because they need very specific, high-quality data and a lot of technology know-how. Ajagbe et al. (2022) and Oluwatosin et al. (2023) say that the use of structural models will grow as the industry's data infrastructure and actuarial skills get better. This will make it easier for life insurance companies to manage credit risk and improve their performance in a world where finances are getting more complicated.

### **2.2.3 Altman Z-Score Model**

As a well-known and important credit risk modeling method, the Altman Z-Score model stands out. It has been used a lot in evaluating financial risks, including in the insurance business. The Z-Score model was created by Edward Altman in 1968 to help predict when production companies would go bankrupt. It has since been used and proven to

work in many other industries and locations, thanks to its ease of use, clarity, and strong ability to predict the future (Aladejebi, 2021).

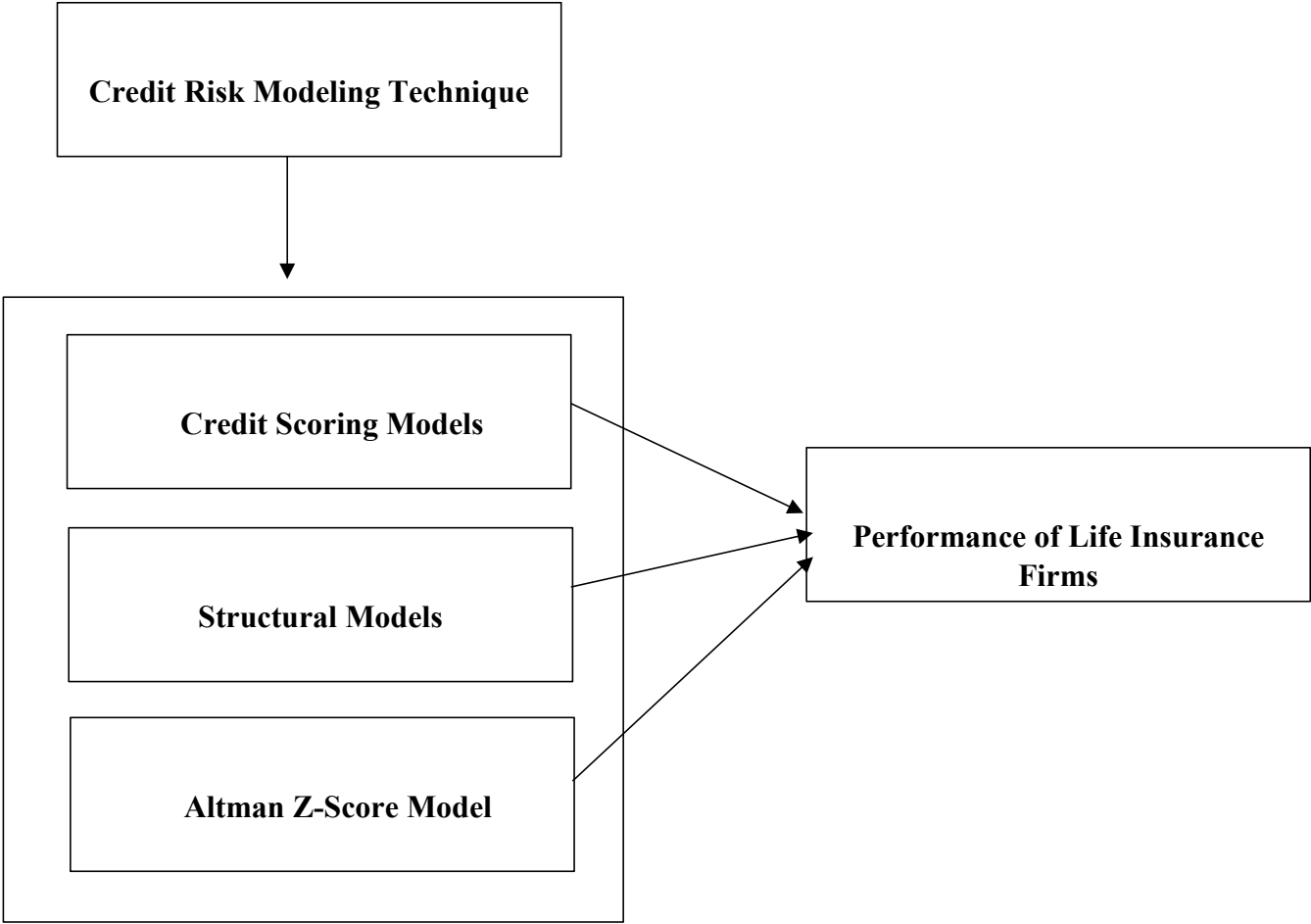
The Altman Z-Score is based on multivariate discriminant analysis, which takes a number of important financial measures and adds them up to make a single score. In the first model, there are five ratios that were used: sales to total assets, market value of equity to total liabilities, profits before interest and taxes (EBIT) to total assets, and working capital to total assets. By using all of these signs together, the Z-Score gives a full picture of a company's financial health, especially how likely it is to go bankrupt or into financial trouble. A higher Z-Score usually means that a company is more financially stable, while a lower score means that the company is more likely to go bankrupt (Aladejebi, 2021).

In the case of life insurance companies in Nigeria, the Altman Z-Score model has been very helpful in finding companies that might be having trouble with their finances before they actually go bankrupt or fail. The Z-Score is used in the Nigerian insurance industry to give managers, investors, and officials a way to measure and objectively judge the stability of a company's finances. Especially in times when the economy is unstable, asset prices change often, and rules are often updated (Oluwatosin et al., 2023) this is very important. Because the Z-Score model is simple to calculate and understand, it can be

used by companies that don't have a lot of technical tools or a very advanced data infrastructure. This opening up of risk assessment to more people helps to improve the quality of financial risk management across the board. New studies show that the model can help with more than just predicting bankruptcy. It can also be used to keep an eye on a company's ongoing financial health and help with strategic choices about investments, underwriting, and following the rules (Aladejebi, 2021).

While the Altman Z-Score approach has many benefits, it is important to be aware of some of its flaws. Different industry structures, market conditions, and financial practices can change how well it predicts the future. Because of this, companies must carefully calibrate the model and, if needed, change it to fit local situations like the Nigerian insurance market. Nonetheless, as financial data quality and regulatory oversight improve in Nigeria, the Altman Z-Score model is expected to become an even more powerful tool for credit risk assessment and performance tracking in the life insurance sector (Oluwatosin et al., 2023).

**2.2.4 Conceptual Framework**



Source: Author’s Conceptualization, 2025.

## **2.3 Theoretical Review**

The ideas behind credit risk modeling and how well life insurance companies do come from well-known ideas in economics, finance, and managing organizations. By using appropriate theories as a foundation for this study, it becomes easier to understand how different credit risk models affect the performance of firms in Nigeria's life insurance sector.

### **2.3.1 Structural Theory of Credit Risk**

The Structural Theory of Credit Risk, also known as the Merton Model, was propounded by Robert C. Merton in 1974. This theory is foundational in modern credit risk modeling and is based on the principle that a firm's likelihood of default depends on the relationship between its asset value and debt obligations. If the market value of a company's assets falls below its liabilities at debt maturity, the firm defaults. This approach treats equity as a call option on the firm's assets, making it possible to model default risk using tools from option pricing theory (Merton, 1974). The Merton model and its extensions have been widely adopted in assessing corporate credit risk, including in the insurance sector, due to their ability to incorporate both firm-specific financial data and macroeconomic factors.

### **2.3.2 Agency Theory**

Agency Theory was introduced by Michael C. Jensen and William H. Meckling in 1976. The theory addresses conflicts of interest between principals (owners or shareholders) and agents (managers or executives) within organizations. In the context of insurance companies, agency theory highlights issues such as moral hazard, risk-shifting, and the misalignment of incentives between policyholders, managers, and shareholders (Jensen & Meckling, 1976). This theory is pertinent when evaluating the effectiveness of credit risk models, as it emphasizes the need for robust governance mechanisms and transparent risk assessment tools to ensure that management decisions align with the interests of all stakeholders.

### **2.3.3 Signaling Theory**

Signaling Theory was developed by Michael Spence in 1973. The theory explains how firms use various signals such as financial disclosures, credit ratings, or adoption of advanced risk models to convey information about their quality, stability, or intentions to external stakeholders (Spence, 1973). In the insurance industry, the use of sophisticated credit risk modeling techniques can serve as a positive signal to regulators, investors, and customers, demonstrating a commitment to sound risk management and financial health.

### **2.3.4 Theoretical Framework**

The Structural Theory of Credit Risk is the best suited theory to support this research. In this case, the main goal of the study is to find out how various credit risk modeling methods, especially those that look at the connection between asset values and loan obligations, affect the functioning of life insurance companies. In order to measure default risk using firm-level financial data and market dynamics, credit scoring models, structural models, and the Altman Z-Score are all directly based on the structural method. The theory can be used in Nigeria because it can adapt to changing economic situations and has been tested in global markets.

The Structural Theory has been criticized, though. Some critics say it depends on assumptions like the efficient market theory and the fact that market data is always available. These assumptions might not be true in markets that aren't as well developed or accessible. As others have pointed out, it may not fully reflect credit risk in times of market instability or for companies with complicated capital structures (Ajagbe et al., 2022). Because it provides a direct analytical link between credit risk modelling techniques and firm performance and can be adjusted to the changing landscape of the Nigerian insurance market, the structural approach is still the best theoretical foundation for this study.

## 2.4 Empirical Review

**Sijibomi et al. (2025)** conducted a comprehensive analysis to examine the effect of Enterprise Risk Management (ERM) on the profitability of insurance companies in Nigeria. The primary objective was to determine whether the adoption and implementation of ERM practices translate into improved financial performance within the industry. The study adopted an expo-facto research design, utilizing regression analysis to assess the relationship between ERM variables and profitability metrics. Data were sourced from the financial statements of 37 insurance firms operating in Nigeria, providing a broad view of the sector's performance. The findings revealed that while the adoption of ERM structures, such as appointing a Chief Risk Officer or establishing a Board Risk Committee, contributed positively to return on assets (ROA), these effects were not statistically significant. More importantly, the implementation of ERM practices, measured through a composite index, was found to have a negative effect on profitability, suggesting that merely instituting ERM frameworks without ensuring effective and practical application may not yield the desired improvements in performance. The authors concluded that industry-wide review and enhancement of ERM implementation practices by regulatory bodies such as the National Insurance Commission (NAICOM) are essential for realizing tangible profitability gains. A notable gap in this study is the

limited exploration of specific credit risk modeling techniques, such as credit scoring, structural models, or the Altman Z-score. The research thus provides important insights into risk management broadly but does not directly address the impact of advanced credit risk models on insurance firm performance (Sijibomi et al., 2025).

**Abdulkadir (2024)** explored the relationship between Enterprise Risk Management (ERM) practices and the financial performance of listed insurance firms in Nigeria. The study aimed to assess the extent to which ERM, specifically the strategic and operational objectives as articulated in the Committee of Sponsoring Organizations (COSO) framework, influences the financial outcomes of these firms. Employing a panel regression methodology, the analysis drew upon secondary data extracted from annual financial statements of all listed insurance companies in Nigeria, although the exact number of firms is not specified. The research covered multiple years and used financial performance, measured by metrics such as Tobin's Q, as the dependent variable. Results indicated that ERM strategic objectives exert a significantly positive influence on the financial performance of insurance companies, highlighting the importance of risk-aware planning at the strategic level. However, the study also found a negative and significant relationship between operational objectives of ERM and financial performance, suggesting potential inefficiencies or challenges in operational risk management

processes within the sector. Despite these insightful findings, a key gap in this study is its lack of focus on specific credit risk modeling techniques. The research does not empirically test or differentiate the effects of credit scoring models, structural models, or the Altman Z-score on firm performance, thereby limiting its application for those specifically interested in credit risk model effectiveness (Abdulkadir, 2024).

**Ekong and Akpan (2024)** examined the impact of liquidity risk on the market value of insurance companies in Nigeria. Their primary objective was to determine how key liquidity-related factors, alongside leverage and firm size, affect the valuation of insurance firms in the Nigerian financial sector. The researchers utilized a pooled least squares regression approach for their analysis, drawing on panel data from 27 quoted insurance companies. The data, which spanned a substantial time frame and was sourced from the Securities and Exchange Commission (SEC), Nigerian Stock Exchange (NSE), and audited annual financial reports, provided a solid empirical foundation for their study. Findings showed that liquidity ratio, leverage ratio, and firm size all have significant and positive influences on the market value of insurance firms. This underscores the importance of managing liquidity and maintaining adequate leverage for sustaining firm value in the competitive insurance market. However, the study primarily focuses on liquidity risk rather than on credit risk modeling per se. It does not engage with or

empirically test advanced credit risk models, such as credit scoring models, structural models, or the Altman Z-score, in relation to insurance firm performance. Consequently, while the findings are valuable for understanding risk factors in general, the absence of credit risk modeling analysis marks a significant gap, especially for stakeholders interested in how these specific models might impact performance (Ekong & Akpan, 2024).

**Akpan et al. (2024)** set out to analyze the influence of corporate attributes on risk management disclosure practices among listed insurance companies in Nigeria. The study's objective was to identify how firm-specific characteristics such as size, profitability, and leverage drive the extent and quality of risk management information disclosed in annual reports. Employing an ex-post facto research design, the researchers utilized marginal logistic regression to assess data collected from eight purposively sampled insurance firms over the 2013 to 2022 period. Their findings demonstrate that all three corporate attributes firm size, profitability, and leverage have significant effects on risk management disclosure practices. Larger, more profitable, and more leveraged firms tend to provide more comprehensive risk management disclosures, which enhances transparency and may improve stakeholder confidence. The location of the study is Nigeria, and the results are particularly relevant to the Nigerian insurance industry as it

continues to evolve in a more regulated and disclosure-driven environment. However, the study's focus remains on disclosure rather than on direct empirical assessment of risk model performance or the effectiveness of specific credit risk models, such as credit scoring or the Altman Z-score. The main gap, therefore, lies in its lack of direct analysis of the influence of advanced credit risk modeling techniques on firm performance outcomes (Akpan et al., 2024).

**Ogunsola (2023)** conducted a study to evaluate the effects of various financial risks specifically liquidity risk, credit risk, and leverage on the financial performance of listed insurance firms in Nigeria. The objective was to identify which risks significantly impair or improve firm performance, with a focus on providing actionable recommendations for risk management. The methodology employed panel data analysis using E-views software, with the sample comprising 10 insurance firms selected through a judgmental sampling technique. Data were obtained from the firms' annual reports, covering a period of ten years from 2015 to 2021. The findings revealed that liquidity risk has a significant and negative impact on the financial performance of the sampled insurance firms. However, the study found that credit risk and leverage did not have significant effects on performance within the analyzed sample. These results highlight the critical role of liquidity management in the Nigerian insurance industry, while also suggesting that other

forms of risk, such as credit risk, may have a more nuanced or context-dependent influence. A key gap in this study is its lack of empirical testing of specific credit risk modeling techniques. The research does not assess the influence of credit scoring models, structural models, or the Altman Z-score on performance, nor does it provide a comparative analysis of different modeling approaches (Ogunsola, 2023).

**Ejem et al. (2023)** sought to understand the relationship between credit risk management and the performance of deposit money banks in Nigeria. The core objective was to uncover the causes of frequent loan delinquencies and their effects on bank performance, despite the implementation of various credit policies by regulatory authorities. Utilizing the Error Correction Mechanism (ECM) approach for empirical analysis, the researchers gathered secondary data from the Nigerian Deposit Insurance Corporation, covering the period from 1990 to 2020. Although the sample size is not explicitly stated, the data set spans a significant temporal range and is likely representative of the national banking sector. The study found that non-performing loans an indicator of heightened credit risk exert a significant negative impact on bank performance, whereas average liquidity ratio was found to be insignificantly related to performance. The authors recommend that regulatory authorities intensify supervision and that banks adopt more effective credit policies to reduce delinquent loans. However, while these findings are critical for

understanding the role of credit risk in the banking sector, the study's focus is on deposit money banks rather than life insurance firms. Furthermore, it does not empirically test specific credit risk models, such as credit scoring, structural, or Altman Z-score models, leaving a gap in understanding how these models might improve the performance of Nigerian life insurance firms (Ejem et al., 2023).

**Alabi et al. (2023)** examined the attitudes of maize farmers toward risk management and their preference for crop insurance in Nigeria. The main objective was to identify the determinants of risk aversion and insurance uptake among agricultural producers, with a view to improving insurance penetration in rural areas. The study used a survey-based approach and applied econometric and statistical tools to analyze primary data collected from 100 maize farmers. The findings showed that a majority of maize farmers were risk-averse, and factors such as age, gender, and education significantly influenced risk aversion. Additionally, attributes such as farm size, household size, and access to extension services played a major role in determining preference for crop insurance. The study also highlighted constraints faced by farmers, including limited extension services, lack of credit facilities, and inadequate knowledge about insurance. Although these insights provide valuable information about risk preferences and insurance adoption in the agricultural sector, the study is not directly concerned with credit risk management or

modeling in life insurance firms. Its focus on crop insurance and farmer behavior means that it does not address the impact or effectiveness of credit scoring models, structural models, or the Altman Z-score in the context of Nigerian life insurance companies (Alabi et al., 2023).

**Zubair and Tuner (2022)** investigated the moderating effect of risk committees on the relationship between board attributes and credit risk exposure among listed financial service firms in Nigeria. The objective was to assess whether the presence and structure of risk committees could influence how board characteristics such as size, independence, and meeting frequency affect the firms' credit risk profiles. Utilizing a panel multiple regression technique, the study analyzed secondary data from 29 financial service firms, covering a ten-year period from 2010 to 2019. The findings showed that risk committees play a moderating role, significantly altering the impact of board attributes on credit risk exposure. Specifically, the effect of variables such as board size and independence on credit risk changed when moderated by the existence of a risk committee, emphasizing the importance of effective risk governance. The location of the study was Nigeria, and the focus on governance mechanisms is pertinent to ongoing reforms in the country's financial sector. However, the study's scope is limited to governance structures and does not empirically test the effectiveness of specific credit risk modeling techniques, such as

credit scoring models, structural models, or the Altman Z-score, in enhancing firm performance. This represents a notable gap for researchers and practitioners interested in model-based risk management approaches (Zubair & Tuner, 2022).

**Ukpong and Essien (2022)** focused on evaluating the relationship between credit risk and the financial performance of quoted commercial banks in Nigeria. The study aimed to determine the significance of various credit risk variables including exchange rate, interest rate, and liquidity rate on the performance of these banks, with performance measured by return on assets (ROA). Employing an ex-post facto research design and regression analysis, the research covered the top 10 commercial banks, ranked by assets, over a five-year period from 2017 to 2021. The data were obtained from the annual reports and accounts of these banks. The results indicated that liquidity ratios had a significant relationship with financial performance, whereas exchange rate and interest rate did not have significant effects. The authors concluded that high interest rates can negatively affect bank performance and recommended the adoption of advanced risk management strategies to mitigate credit risks. Although the study offers valuable insights into risk and performance in Nigeria's banking sector, its focus on banks rather than insurance firms means that the findings are not directly transferable to the life insurance industry. Furthermore, there is no empirical testing of specific credit risk

modeling techniques, leaving a gap in the literature regarding model-specific effects in the insurance context (Ukpong & Essien, 2022).

**Apochi and Baffa (2022)** explored the influence of credit risk and the moderating role of risk management committees on the financial performance of deposit money banks in Nigeria. The study aimed to provide insights into how risk management structures within banks could mitigate the negative effects of credit risk. The methodology involved multiple regression analysis applied to panel data covering 13 deposit money banks over the 2012 to 2021 period. The findings revealed that credit risk has a negative and significant effect on the financial performance of banks. However, the presence and active involvement of risk management committees were found to improve outcomes, moderating the adverse impact of credit risk on performance. The study is relevant for Nigeria's financial sector, especially considering recent regulatory emphasis on risk governance. Nonetheless, the research is primarily focused on the banking sector and does not examine life insurance firms. Moreover, the analysis does not differentiate between types of credit risk models nor does it empirically evaluate the effectiveness of credit scoring models, structural models, or the Altman Z-score in influencing firm performance, marking a gap for future studies (Apochi & Baffa, 2022).

**Fali et al. (2020)** investigated the effect of financial risk including credit, liquidity, and solvency risks on the financial performance of listed insurance companies in Nigeria. The study's main objective was to understand how these different risk categories influence return on assets (ROA) among insurance firms. Using a correlational research design and regression analysis, the researchers analyzed secondary data sourced from the annual reports of 19 listed insurance firms, covering the period from 2009 to 2018. The results revealed that credit risk has a negative and significant effect on financial performance, highlighting the adverse impact of poor credit management on firm profitability. The authors recommended that Nigerian insurance providers should strengthen their receivables management and provide suitable payment plans for debtors to minimize credit risk exposure. While the findings are valuable for practitioners and policymakers, the study does not specify the use of advanced credit risk modeling techniques or test the Altman Z-score's impact on performance. This omission marks a critical gap for those seeking empirical evidence on the effectiveness of specific risk models in the Nigerian insurance sector (Fali et al., 2020).

**Fali et al. (2020)** further contributed to the literature by examining the impact of insurance-specific risks, particularly technical provisions and underwriting risks, on the profitability of Nigerian insurance firms. The objective was to provide a clearer

understanding of which risk types most strongly affect net profit margins in the industry. Using an ex-post facto research design and regression analysis, the study analyzed secondary data from the annual reports of 19 insurance firms over a ten-year period from 2009 to 2018. The findings showed that both technical provision risk and underwriting risk have a negative and significant impact on profitability, while re-insurance risk was found to have a negative but insignificant effect. The authors concluded that increases in technical provision and underwriting risks are detrimental to profitability and recommended that insurance companies develop robust procedures for managing outstanding claims. While these insights are important for insurance risk management, the study does not specifically address credit risk modeling techniques or evaluate the effectiveness of models such as credit scoring, structural models, or the Altman Z-score, thereby limiting its scope for those interested in advanced credit risk management approaches (Fali et al., 2020).

**Davies and Diepiriye (2018)** conducted research to determine the effect of financial risk on the value relevance of accounting information in Nigerian quoted insurance firms. The primary objective was to assess whether various financial risk variables, including debt-equity ratio, expenditure ratio, and volatility of earnings, have a long-run impact on the value relevance of financial statements as indicated by aggregate stock prices. Employing

an Ordinary Least Squares (OLS) regression analysis, the study analyzed time-series data obtained from financial statements and the Central Bank of Nigeria's statistical bulletin, covering the years 1990 to 2016. The findings indicated that certain variables, such as expenditure ratio and general insurance earnings variation, negatively affect value relevance, while debt-equity ratio, exchange rate risk, and variation in life insurance earnings have a positive impact. The study, conducted in Nigeria, recommended that policies should be designed to better manage financial risks in the insurance sector. However, the research focused on the relationship between risk variables and accounting information value rather than empirically testing the effectiveness of specific credit risk modeling approaches like credit scoring, structural models, or the Altman Z-score. This gap leaves room for future studies to address model-specific impacts on firm performance (Davies & Diepiriye, 2018).

**Dauda and Isuwa (2018)** set out to examine the effect of credit risk on shareholders' value among Nigerian deposit money banks. The study aimed to provide evidence on whether prudent credit risk management could enhance earnings and, consequently, shareholders' wealth. Utilizing a panel regression technique and the Generalized Least Squares (GLS) estimators, the analysis covered a sample of nine banks over a thirteen-year period from 2004 to 2016. Data were sourced from audited annual reports, and

market capitalization served as the dependent variable. The findings showed that credit risk has a significant effect on shareholders' value, with non-performing loans and loan loss provisions exerting a negative and significant influence. The study concluded that banks must redefine credit products and policies to ensure consistency and prevent lending losses. Although this research adds to the understanding of credit risk in Nigerian financial institutions, it is primarily focused on the banking sector rather than life insurance. Moreover, it does not empirically evaluate advanced credit risk modeling techniques, such as credit scoring models, structural models, or the Altman Z-score, representing a gap for those interested in model-driven insights for insurance firms (Dauda & Isuwa, 2018).

**Maimako and Oladele (2008)** undertook a comparative analysis of risk dimensions in the Nigerian banking and insurance sub-sectors. The primary objective was to identify and compare the various types of risks facing banks and insurance firms operating in Nigeria, using empirical data published by the Kaduna branch of the Nigerian Stock Exchange. The methodology was based on secondary data analysis using Ordinary Least Squares (OLS) regression, though the exact sample size was not specified. The findings revealed that individual insurance firms in Nigeria experience more volatile returns than banks, and that the overall risk structure differs significantly between the two sub-sectors.

The paper recommended policy alignment with domestic economic needs and comprehensive reforms to address sector-specific risks. Despite providing valuable sectoral risk comparisons, the study did not test or discuss modern credit risk modeling techniques, such as credit scoring, structural models, or the Altman Z-score. Additionally, the study's data covers up to 2006, potentially limiting the relevance of its findings for the current landscape of risk management in Nigerian life insurance firms (Maimako & Oladele, 2008).

**Table 2.1: Summary of Empirical Review**

S/N	Author Name and Date	Title	Methodology	Sample Size	Location	Findings	Gaps
1.	Olubodun Sijibomi et al., 2025	Enterprise Risk Management and Profitability of Insurance Companies in Nigeria	Expo-facto methodology	37 insurance firms	Nigeria	ERM adoption alone is not sufficient to influence profitability; ERM implementation practices need review (Sijibomi et al., 2025)	Limited focus on credit scoring/ structural models, not specific to Altman Z-score.
2.	Jamilu Abdulkadir , 2024	Enterprise Risk Management (Erm) Practices And Financial Performance: Evidence From Listed Insurance Firms In Nigeria	Panel regression	Not stated (all listed firms)	Nigeria	Strategic objectives of ERM have a significant positive effect, operational objectives negative effect on financial performance (Abdulkadir, 2024)	Does not test specific credit risk modeling techniques.
3.	Oluchukwu K Ekong & Sunday S. Akpan, 2024	Liquidity risk and market value of insurance companies in Nigeria	Pooled least squares regression	27 insurance firms	Nigeria	Liquidity ratio, leverage, and firm size significantly influence market value (Ekong & Akpan, 2024)	Focuses on liquidity risk, not credit risk models or Z-score.
4.	D. C. Akpan et al., 2024	Corporate Attributes and Risk Management Disclosure of Listed Insurance Companies in Nigeria	Ex-post facto, logistic regression	8 insurance firms	Nigeria	Firm size, profitability, and leverage have significant effect on risk management disclosure (Akpan et al., 2024)	Focus on disclosure, not direct model performance impact.

5.	Adebowale Ogunsola, 2023	Do Financial Risks affect Financial Performance of Listed Insurance Firms in Nigeria?	Panel data, E-views analysis	10 insurance firms	Nigeria	Liquidity risk has significant negative effect on performance; credit risk and leverage not significant (Ogunsola, 2023)	Sample limited to 10 firms, no model-specific testing.
6.	Chukwu Agwu Ejem et al., 2023	Credit Risk Management and Deposit Money Banks' Performance in Nigeria	Error Correction Mechanism	Not stated	Nigeria	Non-performing loans (credit risks) significantly impact bank performance (Ejem et al., 2023)	Focuses on banks, not life insurance or specific credit risk models.
7.	O. Alabi et al., 2023	Evaluation of maize farmers' attitude towards risk management and preference for crop insurance in Nigeria	Survey, econometric analysis	100 maize producers	Nigeria	Risk aversion influences preference for crop insurance; extension services needed (Alabi et al., 2023)	Not directly about life insurance or firm credit risk.
8.	A. Zubair & Itari Tuner, 2022	Board Attributes And Credit Risk Exposure Of Listed Financial Service Firms In Nigeria: The Moderating Effect Of Risk Committee	Panel multiple regression	29 financial firms	Nigeria	Risk committee moderates board attributes and credit risk exposure (Zubair & Tuner, 2022)	Focuses on governance, not specific credit risk modeling.
9.	E. G. Ukpong & I. Essien, 2022	Credit Risk and Financial Performance of Quoted Commercial Banks in Nigeria	Ex-post facto, regression	10 commercial banks	Nigeria	Liquidity ratios significant; exchange and interest rate no significant relationship (Ukpong & Essien, 2022)	Banks focus, not insurance; model-specific gap.

10.	J. Apochi & Asma'u Mahmood Baffa, 2022	Credit Risk and Financial Performance of Deposit Money Banks in Nigeria: Moderating Role of Risk Management Committee	Multiple regression	13 banks	Nigeria	Credit risk has negative and significant effect; risk management committees improve outcomes (Apochi & Baffa, 2022)	Not life insurance-specific, model application gap.
11.	Ibrahim Mallam Fali et al., 2020	Financial Risk and Financial Performance of listed Insurance Companies in Nigeria	Correlational design, regression	19 insurance firms	Nigeria	Credit risk has negative and significant effect on performance; recommends better receivables control (Fali et al., 2020)	Does not specify risk modeling technique; Altman Z-score not tested.
12.	Ibrahim Mallam Fali et al., 2020	Insurance Specific Risk and Profitability: Evidence from Nigerian Insurance Firms	Ex-post facto, regression	19 insurance firms	Nigeria	Technical provisions and underwriting risks negatively impact profitability (Fali et al., 2020)	Not directly about credit risk models or Altman Z-score.
13.	Davies & Stanley Diepiriye, 2018	Financial Risk and Value Relevance of Accounting Information: Evidence from Nigeria Quoted Insurance Firms	OLS regression	Not stated	Nigeria	Liquidity risk and variation in life insurance earnings positively affect value relevance (Davies & Diepiriye, 2018)	Value relevance focus, no direct test of credit scoring or Z-score.
14.	Dauda & Isuwa, 2018	Credit Risk and Shareholders' Value in Nigerian	Panel regression	9 banks	Nigeria	Credit risk significantly affects shareholder value; non-performing	Banking sector, no

		Deposit Money Banks				loans and provisions negative (Dauda & Isuwa, 2018)	insurance firm model focus.
15.	S. S. Maimako & Kolawole Olugbenga Oladele, 2008	Risk Dimensions in Business Processes in Nigeria: A Comparative Study of the Nigerian Banking and Insurance Sub-Sectors	OLS regression	Not stated	Nigeria	Insurance returns more volatile than banks; overall risk differs by sector (Maimako & Oladele, 2008)	Does not test modern risk modeling; data up to 2006.

Source: Author's Compilation, 2025

## **2.5 Gaps in Literature**

A critical review of the existing literature on credit risk modeling and the performance of life insurance firms in Nigeria reveals several notable gaps that persist despite increasing scholarly interest in risk management within the Nigerian financial sector. While many studies have broadly examined the influence of risk factors such as liquidity, solvency, and technical provisions on insurance firm performance, there is a conspicuous lack of research focusing specifically on the application and comparative effectiveness of advanced credit risk modeling techniques such as credit scoring models, structural models, and the Altman Z-score within the life insurance context. Most empirical investigations have either concentrated on general risk management frameworks like Enterprise Risk Management (ERM) or have centered on governance structures and board attributes, often stopping short of testing how different quantitative risk models impact actual firm outcomes.

Moreover, the majority of studies have drawn their samples from the broader financial services industry, frequently grouping insurance companies with deposit money banks, which can obscure sector-specific insights. This approach fails to account for the unique nature of credit risk and operational realities faced by life insurance firms, whose exposure profiles, regulatory demands, and cash flow structures differ significantly from

those of banks. Even within the insurance literature, empirical evidence is often derived from aggregated financial indicators rather than from rigorous tests of how the adoption of specific credit risk models might enhance firm performance, mitigate insolvency, or predict distress.

Another key limitation is the insufficient attention paid to contemporary and localized applications of widely recognized models such as the Altman Z-score, which, while extensively validated in other sectors and regions, remains largely untested or unreported among Nigerian life insurance firms. In addition, much of the existing research relies heavily on secondary data and regression analysis without delving into the practical challenges, implementation barriers, and contextual factors that may affect the relevance or success of these risk models in Nigeria's unique operating environment.

## **CHAPTER THREE**

### **METHODOLOGY**

#### **3.1 Introduction**

This chapter provides a comprehensive explanation of the research methodology adopted in assessing credit risk modeling techniques and the performance of life insurance firms in Nigeria. It includes the research design, population and sample, sampling techniques, data sources, methods of data analysis, model specification, and operationalization of variables.

#### **3.2 Research Design**

The study employed an ex post facto and correlational research design, as it is based on secondary data that has already been published and cannot be manipulated. The ex post facto design is suitable for investigating cause-and-effect relationships without direct control over the variables. This design enables the researcher to analyze the impact of different credit risk modeling techniques on the performance of life insurance firms over a defined period. The correlational aspect of the study helps identify and quantify the relationships between the dependent variable (performance of life insurance firms) and independent variables (credit risk models). As supported by Saunders et al. (2019), this

design is optimal for studies where researchers intend to explore statistical relationships between variables based on historical data. The non-interventional nature of the research design is appropriate given the reliance on archived financial records and risk modelling data disclosed in annual reports and regulatory filings.

### **3.3 Population of the Study**

The population of this study comprises all life insurance companies registered and licensed by the National Insurance Commission (NAICOM) in Nigeria as of December 31, 2024. According to NAICOM's official records, there are twelve (12) licensed life insurance firms operating in Nigeria within this timeframe. These companies are governed by NAICOM's prudential guidelines and financial disclosure requirements, making them suitable for empirical analysis. The focus on life insurance firms is informed by their long-term obligations, underwriting processes, and heightened sensitivity to credit risk exposures.

### **3.4 Sample Size and Sampling Technique**

A census sampling technique were employed in selecting the sample size. Given that only 12 life insurance firms are registered with NAICOM and have consistently published

annual reports from 2018 to 2024, all qualifying firms were included. The inclusion criteria were:

The firm must have been operational throughout the period 2018–2024; The firm must have consistently published audited annual financial statements; The firm must disclose relevant information on credit risk assessment and financial performance indicators. Using this census sampling, only firms meeting the above conditions were selected to ensure high data quality, comparability, and completeness. This method is justified given the need for firm-level longitudinal data over multiple years to enable rigorous empirical testing of the credit risk models.

### **3.5 Sources of Data**

The study will use secondary data exclusively, which will be obtained from publicly available sources, including: Annual financial statements of life insurance firms (2018–2024); NAICOM industry reports and bulletins (2018 -2024); Central Bank of Nigeria (CBN) reports (2018 -2024); Nigerian Stock Exchange (NSE) filings (where applicable); Risk management disclosures and actuarial reports within the annual statements. The performance indicators (dependent variables) such as Return on Assets (ROA) and Return on Equity (ROE) will be sourced from financial statements. Independent variables

related to credit risk modeling techniques were operationalized using data obtained from notes to the financial statements, risk management disclosures, and regulatory filings.

### **3.6 Method of Data Analysis**

The data analysis will employ both descriptive and inferential statistics using panel data techniques to capture variations across firms and over time. Descriptive statistics will summarize the central tendency, dispersion, and patterns of key variables. Correlation analysis will be conducted to assess the strength and direction of relationships between credit risk models and firm performance. To evaluate the effects of independent variables on performance metrics, Fixed Effects and Random Effects panel regression models will be applied, with the Hausman test guiding the model selection. Additionally, diagnostic tests such as the Variance Inflation Factor (VIF), Breusch-Pagan test for heteroskedasticity, and the Wooldridge test for autocorrelation will be conducted to ensure the validity and robustness of the regression output.

### **3.7 Model Specification**

To empirically assess the impact of credit risk modeling techniques on the financial performance of life insurance firms in Nigeria, this study adopts a panel regression framework based on the modified model of Omoregie et al. (2023).

$$PERF_{it} = \alpha_0 + \alpha_1 CEXP_{it} + \alpha_2 CPOL_{it} + \alpha_3 NPL_{it} + \alpha_4 FSIZE_{it} + \alpha_5 LEV_{it} + \alpha_6 AGE_{it} + \mu_i + \varepsilon_{it} \dots (eq1)$$

Where:

PERFit = Financial performance of firm i at time t, proxied by ROA and ROE

CEXPit = Credit Risk Exposure (ratio of non-performing loans to total loans)

CPOLit = Credit Policy (measured through credit standards and procedures)

NPLit = Non-Performing Loans ratio

FSIZEit = Firm Size (log of total assets)

LEVit = Leverage ratio (Total Liabilities / Total Assets)

AGEit = Firm Age (years since incorporation)

$\mu_i$  = Unobserved firm-specific effects

$\varepsilon_{it}$  = Random error term

The performance of life insurance firms will be captured through two distinct financial performance indicators: Return on Equity (ROE) and Return on Assets (ROA). Consequently, the analysis will involve estimating two separate equations using panel data techniques to account for firm-specific and time-specific variations.

The generalized form of the panel data model is specified as follows:

$$PERF_{it} = \beta_0 + \beta_1 CSCORE_{it} + \beta_2 STRUCT_{it} + \beta_3 ZSC_{it} + \beta_4 FSIZE_{it} + \beta_5 LEV_{it} + \beta_6 AGE_{it} + \mu_i + \varepsilon_{it} \dots \dots (eq1)$$

Where:

$PERF_{it}$  = Financial performance of firm i at time t, represented alternatively by:

$ROE_{it}$  = Return on Equity (Net Income / Shareholders' Equity)

$ROA_{it}$  = Return on Assets (Net Income / Total Assets)

$CSCORE_{it}$  = Credit Scoring Model (dummy: 1 = adopted; 0 = not adopted)

$STRUCT_{it}$  = Structural Credit Risk Model (dummy: 1 = used; 0 = not used)

$ZSC_{it}$  = Altman Z-Score for firm i at time t

$FSIZE_{it}$  = Firm Size (log of total assets)

$LEV_{it}$  = Leverage Ratio (Total Liabilities / Total Assets)

$AGE_{it}$  = Firm Age (years since incorporation)

$\mu_i$  = Unobserved firm-specific effect (controls for time-invariant heterogeneity)

$\varepsilon_{it}$  = Idiosyncratic error term

Based on this structure, the two estimating equations for the study are:

ROE Model:

$ROE_{it} =$

$$\beta_0 + \beta_1 CSCORE_{it} + \beta_2 STRUCT_{it} + \beta_3 ZSC_{it} + \beta_4 FSIZE_{it} + \beta_5 LEV_{it} + \beta_6 AGE_{it} + \mu_i + \varepsilon_{it} \dots \dots (eq2)$$

ROA Model:

$$ROA_{it} = \beta_0 + \beta_1 CSCORE_{it} + \beta_2 STRUCT_{it} + \beta_3 ZSC_{it} + \beta_4 FSIZE_{it} + \beta_5 LEV_{it} + \beta_6 AGE_{it} + \mu_i + \varepsilon_{it} \dots\dots$$

(eq3)

Both models will be estimated using Fixed Effects (FE) and Random Effects (RE) panel regression techniques. The Hausman test will be conducted to determine the most appropriate estimator for consistent and efficient inference.

### 3.8 Measurement of Variables

S/N	Variable	Type	Measurement	Expected Sign	Source
1	ROA	Dependent	Net Income / Total Assets		Omoriegbe et al. (2023)
2	ROE	Dependent	Net Income / Equity		Aladejebi (2021)
3	Credit Scoring (CSCORE)	Independent	Dummy (1 = applied, 0 = not applied)	+	Oluwatosin et al. (2023)
4	Structural Models (STRUCT)	Independent	Dummy (1 = used KMV/Merton-based model, 0 = not used)	+	Ajagbe et al. (2022)
5	Altman Z-Score (ZSC)	Independent	Dummy (1, 0)	+	Aladejebi (2021)
6	Firm Size (FSIZE)	Control	Logarithm of total assets	+	Omoriegbe et al. (2023)
7	Leverage	Control	Total Liabilities / Total Assets	-	Osabohien et al. (2020)

8	Firm Age (AGE)	Control	Years since incorporation	+	Khan et al. (2019)
---	----------------	---------	---------------------------	---	--------------------

Source: Author's Compilation, 2025

## **CHAPTER FOUR**

### **DATA PRESENTATION, ANALYSIS AND INTERPRETATION**

#### **4.1 Introduction**

In this chapter, the various variables employed in this study are tested, presented and interpreted in order to give meaningful results that can be used for decision purposes and policies. The chapter starts with descriptive statistics, followed by the Histogram Normality Test, Correlation analysis, and regression diagnostics which include: The Breusch-Pagan-Godfrey Test of Heteroskedasticity, Breusch-Godfrey Test of Serial Correlation, Hausman Test and the regression analysis result.

#### **4.2 Descriptive Statistics**

The main features of a dataset are summarized by descriptive statistics. These statistics aid in comprehending the data's variability and central trend. The mean, median, and mode which stand for the average, middle value, and most frequent value, respectively are examples of measures of central tendency. Standard deviation, variance, minimum and maximum values, kurtosis, and skewness, on the other hand, are examples

of variability measurements that show the distribution shape and dispersion of the data.

The study variables' summary statistics are shown in the table below:

## DESCRIPTIVE ANALYSIS

**Table 4.1: Results of the Descriptive Analysis of the Regression Variables**

	<b>ROA</b>	<b>ROE</b>	<b>CSCORE</b>	<b>STRUCT</b>	<b>ZSC</b>	<b>FSIZE</b>	<b>LEV</b>	<b>FAGE</b>
<b>Mean</b>	-2.0604	1.4658	0.4405	0.5238	0.0952	23.7998	0.6017	37.179
<b>Median</b>	0.6750	1.7700	0.0000	1.0000	0.0000	23.6099	0.6250	30.000
<b>Maximum</b>	13.390	89.600	1.0000	1.0000	1.0000	25.8164	1.2800	100.00
<b>Minimum</b>	-43.850	-82.843	0.0000	0.0000	0.0000	21.5316	-0.7833	0.0000
<b>Std. Dev.</b>	9.7019	34.029	0.4994	0.5024	0.2953	1.0922	0.3213	25.614
<b>Skewness</b>	-1.7182	-0.5735	0.2398	-0.0953	2.7578	0.2825	-1.5125	0.8861
<b>Kurtosis</b>	7.0829	3.5899	1.0575	1.0091	8.6053	1.9671	7.5774	3.1255
<b>Jarque-Bera</b>	99.674	5.8224	14.012	14.000	216.44	4.8514	105.36	11.047
<b>Probability</b>	0.0000	0.0544	0.0009	0.0009	0.0000	0.0884	0.0000	0.0039
<b>Sum</b>	-173.07	123.13	37.000	44.000	8.0000	1999.2	50.540	3123.0
<b>Sum Sq. Dev.</b>	7812.5	96109	20.702	20.952	7.2381	99.006	8.5672	54452
<b>Observations</b>	84	84	84	84	84	84	84	84

Source: Author's compilation (2025), using Eviews 10.0 for Windows.

The data provides a detailed look into the financial characteristics of life insurance firms in Nigeria, focusing on key performance and model-based indicators such

as Return on Assets (ROA), Return on Equity (ROE), Credit Scoring (CSCORE), Structural Models (STRUCT), Altman Z-Score (ZSC), Firm Size (FSIZE), Leverage (LEV), and Firm Age (FAGE).

Return on Assets (ROA) has a mean value of -2.06, suggesting that on average, firms in the sample experience low or even negative profitability relative to their assets. The wide standard deviation of 9.70 reveals substantial variability in profitability across firms, implying that while some firms perform well, others record significant losses. The minimum value of -43.85 further highlights that a few firms face severe profitability challenges. The negative skewness (-1.72) indicates that most firms have ROA values clustered around the higher end of the scale, with a few firms performing much worse than average. The kurtosis value of 7.08 shows that the distribution is leptokurtic, implying the presence of extreme values. The Jarque-Bera statistic (99.67,  $p < 0.01$ ) confirms that the data are not normally distributed. Return on Equity (ROE) has an average of 1.47, indicating a generally positive but modest shareholder return. The high standard deviation of 34.03 suggests considerable dispersion across firms, reflecting variations in financial leverage and profit reinvestment strategies. The minimum and maximum values (-82.84 and 89.60) reveal a very wide range, meaning that while some firms achieve strong returns, others experience severe equity losses. The negative

skewness (-0.57) implies that the distribution is slightly left-tailed, suggesting that more firms have ROE below the mean. The kurtosis (3.59) approximates normality but with mild excess, while the Jarque-Bera probability (0.0544) indicates marginal deviation from normality.

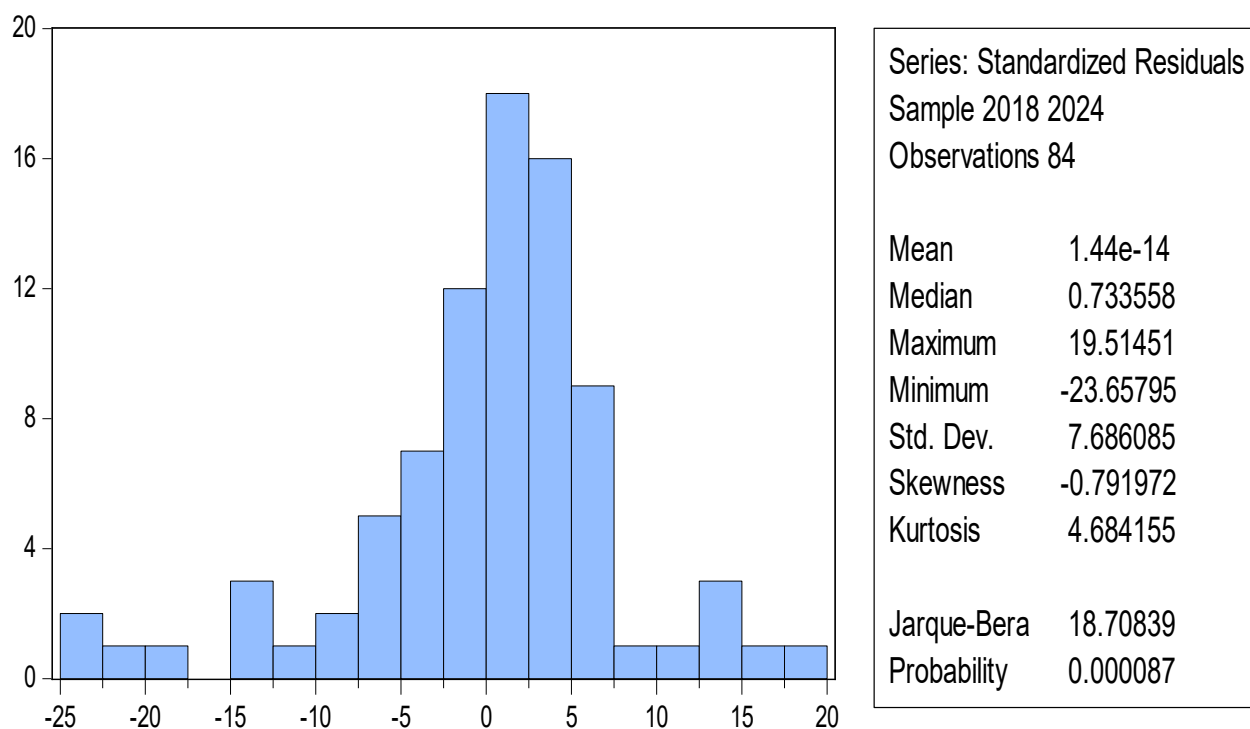
Credit Scoring (CSCORE) has a mean value of 0.44 and a standard deviation of 0.50, implying moderate adoption of credit scoring systems among firms, with some fully adopting automated models (CSCORE = 1) while others do not (CSCORE = 0). The positive skewness (0.24) suggests that more firms have below-average use of credit scoring tools. The kurtosis value (1.06) shows a platykurtic distribution, indicating that the data are flatter than a normal curve. The Jarque-Bera statistic (14.01,  $p < 0.01$ ) confirms significant deviation from normality. Structural Models (STRUCT) has a mean of 0.52 and a standard deviation of 0.50, indicating moderate but varied application of structural risk models. The negative skewness (-0.10) shows a near-symmetric distribution, meaning that firms are fairly evenly split between adopters and non-adopters. A low kurtosis of 1.01 indicates a flat distribution, while the Jarque-Bera test (14.00,  $p < 0.01$ ) reveals non-normality. Altman Z-Score (ZSC) has a mean of 0.10, implying a generally low but positive financial health score across firms. The standard deviation (0.30) and maximum value (1.00) suggest that while a few firms demonstrate sound

solvency, most operate close to the distress threshold. The strong positive skewness (2.76) and high kurtosis (8.61) indicate that the distribution is highly peaked and right-tailed, implying a few firms with very strong financial health dominate the sample. The Jarque-Bera statistic (216.44,  $p < 0.01$ ) confirms non-normality.

Firm Size (FSIZE) has a mean value of 23.80 with a relatively low standard deviation of 1.09, suggesting that most firms have comparable asset bases. The median (23.61) and slight positive skew (0.28) indicate that firm size distribution is nearly symmetric. The kurtosis of 1.97 points to a relatively flat distribution. The Jarque-Bera probability (0.088) shows marginal non-normality. Leverage (LEV) has an average of 0.60, indicating that firms, on average, finance about 60% of their assets with debt. The standard deviation of 0.32 reveals moderate variation, and the negative skewness (-1.51) indicates that most firms maintain leverage ratios above the mean. The high kurtosis (7.58) suggests the presence of extreme leverage levels among a few firms. The Jarque-Bera statistic (105.36,  $p < 0.01$ ) confirms strong deviation from normality. Firm Age (FAGE) shows a mean of 37.18 years, suggesting that the insurance industry comprises largely well-established firms. However, the high standard deviation of 25.61 implies significant variation, with some firms relatively new and others decades old. The positive skewness (0.89) suggests that younger firms dominate the sample, while a few older

firms extend the right tail. The kurtosis (3.13) approximates a normal distribution, and the Jarque-Bera statistic (11.05,  $p < 0.01$ ) indicates slight non-normality. The mean skewness, kurtosis and Jarque-Bera statistics are reported in the result of the histogram normality test in Fig 1.

**Fig 1: Result of the Histogram Normality Test**



**Source:** Author’s compilation (2025), using Eviews 10.0 for Windows.

The results of the histogram normality test show a negative skewness value of -0.791972, indicating a left-skewed distribution. The kurtosis value of 4.684155 is slightly higher than the benchmark of three, suggesting a leptokurtic distribution with a sharper peak. The degree of variability around the mean is indicated by the mean standard

deviation, which is 7.686085. Furthermore, given the high significance of the test results, the Jarque-Bera statistic of 18.70839 with a probability value of 0.000087 indicates that the data do not fit a Gaussian normal distribution.

### 4.3 Correlation Analysis

**Table 4.2: Result of the Correlation Analysis**

Covariance Analysis: Ordinary  
 Date: 11/04/25 Time: 21:12  
 Sample: 2018 2024  
 Included observations: 84

Correlation t-Statistic Probability	ROA	ROE	CSCORE	STRUCT	ZSC	FSIZE	LEV	FAGE
ROA	1.0000 ----- -----							
ROE	0.6745 8.2733 0.0000	1.0000 ----- -----						
CSCORE	0.1637 1.5028 0.1367	0.1069 0.9744 0.3327	1.0000 ----- -----					
STRUCT	0.0421 0.3816 0.7037	-0.0211 -0.1907 0.8492	0.8459 14.366 0.0000	1.0000 ----- -----				
ZSC	-0.1852 -1.7069 0.0916	-0.1949 -1.8002 0.0755	-0.2879 -2.7219 0.0079	0.2281 2.1219 0.0369	1.0000 ----- -----			
FSIZE	0.4486 4.5456 0.0000	0.4355 4.3803 0.0000	0.1658 1.5228 0.1316	-0.0388 -0.3515 0.7261	-0.3254 -3.1158 0.0025	1.0000 ----- -----		
LEV	0.1541 1.4125 0.1616	0.2583 2.4207 0.0177	0.3718 3.6269 0.0005	0.2881 2.7244 0.0079	-0.1761 -1.6199 0.1091	0.4668 4.7803 0.0000	1.0000 ----- -----	
FAGE	-0.4444 -4.4926 0.0000	-0.2196 -2.0386 0.0447	0.0003 0.0033 0.9973	0.1237 1.1289 0.2622	0.2032 1.8793 0.0638	-0.1274 -1.1631 0.2482	0.2919 2.7634 0.0071	1.0000 ----- -----

---

---

**Source:** Author's compilation (2025), using Eviews 10.0 for Windows.

Table 4.2 above reveals the correlation results between Return on Assets (ROA) and the main explanatory variables of the study Credit Scoring (CSCORE), Structural Model (STRUCT), and Altman Z-Score (ZSC). The relationship between ROA and Credit Scoring (CSCORE) shows a weak positive correlation of 0.1637, with a corresponding t-statistic of 1.5028 and a p-value of 0.1367. This implies that, on average, as credit scoring practices increase, the performance of life insurance firms (measured by ROA) tends to improve slightly. However, the correlation is weak and statistically insignificant at the 5% level, indicating that changes in credit scoring activities do not have a strong or consistent relationship with firms' return on assets. This suggests that credit scoring models may not play a substantial role in explaining variations in firm profitability within the Nigerian life insurance sector.

Similarly, ROA has a very weak positive correlation of 0.0421 with the Structural Model (STRUCT) variable. The t-statistic of 0.3816 and p-value of 0.7037 indicate that this relationship is statistically insignificant at the 5% level. The weak and insignificant correlation suggests that the application of structural risk assessment models has little to no measurable effect on the financial performance of life insurance firms. This further

implies that other factors, such as firm size, leverage, or management efficiency, might play a more dominant role in determining profitability than the use of structural models.

In contrast, the relationship between ROA and the Altman Z-Score (ZSC) is negative (-0.1852), with a t-statistic of -1.7069 and a p-value of 0.0916. Although the negative sign indicates that higher Altman Z-scores (signifying stronger financial health) may be associated with lower firm profitability, the relationship is weak and only marginally significant at the 10% level. This suggests a possible inverse but not robust relationship between firm solvency strength and current profitability. In other words, life insurance firms that maintain very high solvency positions may experience slightly lower returns on assets, possibly due to conservative risk management or high capital retention policies.

#### 4.4 Regression Diagnostics

##### Test of Heteroskedasticity

**Table 4.3: Test of Heteroskedasticity**

Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	0.962998	Prob. F(6,77)	0.4292
Obs*R-squared	3.876717	Prob. Chi-Square(6)	0.4229
Scaled explained SS	7.060542	Prob. Chi-Square(6)	0.1327

**Source:** Author's compilation (2025), using Eviews 10.0 for Windows.

Table 4.3 displays the results of the Breusch-Pagan-Godfrey test for heteroskedasticity. The probability value obtained is 0.4292, which is greater than 0.05. This suggests that there is no issue of heteroskedasticity in the model. Therefore, the alternative hypothesis of homoskedastic residuals is accepted, indicating that the variance of the residuals in the regression model is constant.

### Test of Serial Correlation

**Table 4.4: Result of the Breusch-Godfrey Test of Serial Correlation**

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	6.621200	Prob. F(2,75)	0.0022
Obs*R-squared	12.60575	Prob. Chi-Square(2)	0.0018

**Source:** Author's compilation (2025), using Eviews 10.0 for Windows.

The results from the Breusch-Godfrey Serial Correlation LM Test suggest that there is a significant issue with serial correlation in the model. The F-statistic is 6.6212000, and its associated probability value (Prob. F(2,75)) is 0.0022, which is highly significant. This indicates that the null hypothesis of no serial correlation is rejected, suggesting that there is a serial correlation present in the residuals of the regression model. However, the results of the correlation analysis did not pose any serious problem of

multicollinearity, which validates the outcome of absence of the problem of serial correlation on the average.

## Hausman Test

**Table 4.5: Results of the Hausman Test**

Correlated Random Effects - Hausman Test

Equation: Untitled

Test period random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Period random	1.975814	6	0.9219

**Source:** Author's compilation (2025), using Eviews 10.0 for Windows.

The probability value of 0.9219, which is higher than 0.05, as indicated by the correlated random effect Hausman test indicates that the null hypothesis should not be rejected. This means that there is no significant difference between the fixed effects and random effects estimates. Therefore, the random effects model will be used for this study.

## 4.5 Analysis of the Regression Result

### Model I

**Table 4.6: Result of the Regression Analysis**

**Dependent Variable:** Return on Assets

Predictor variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	-71.77815	23.96945	-2.994567	0.0037
Credit scoring (CSCORE)	4.192709	9.125403	0.459455	0.6472
Structural model (STRUCT)	-2.517979	8.972325	-0.280638	0.7797
Altman Z-score (ZSC)	4.144416	8.328598	0.497613	0.6202
Firm size (FSIZE)	3.073886	1.028066	2.989969	0.0037
Leverage (LEV)	3.028857	3.711219	0.816135	0.4169
Firm age (FAGE)	-0.166362	0.039375	-4.225023	0.0001
$R^2 = .37$	Adj $R^2 = .32$	$F(6, 77) = 7.61, p < .01$		$DW = 0.86$

**Source:** Author's compilation (2025), using Eviews 10.0 for Windows.

Table 4.6 above displays the regression analysis's outcome. According to the preliminary analysis, the independent variables considered in this study are credit scoring model, structural credit risk and firms Altman Z-Score, while the control variables considered are firm size, leverage and firm age which collectively contribute to 37.24%

of the variation in the performance of life assurance firms in Nigeria which was captured by firms return on assets, with a coefficient of multiple determination of 0.372375 and an adjusted R-squared value of 0.323469. The error term, however, captures the remaining 62.76%. The combined statistical significance of all the explanatory factors is indicated by the F-statistics value of 7.614121 which is more than 2.

#### **4.6 Test of Hypotheses Model I**

**Hypothesis One: Credit scoring models have no significant influence on the performance of life insurance firms in Nigeria.**

The coefficient for credit scoring (CSCORE) is 4.192709, which suggests a positive relationship between credit scoring and the performance (ROA) of life insurance firms in Nigeria. This means that, holding other variables constant, an increase in the credit scoring is associated with an improvement in the performance of the sampled firms. The t-statistic for credit scoring is 0.459455, and the corresponding probability value of 0.0.6472 indicates that the effect is statistically insignificant at the 5% level. Therefore, the null hypothesis that credit scoring models have no significant influence on the performance of life insurance firms in Nigeria is accepted at the 5% level of significance. This implies that credit scoring does not play an important role in enhancing the performance of life insurance firms in Nigeria.

**Hypothesis Two: Structural models are not effective in improving the performance of life insurance firms in Nigeria.**

The coefficient for structural models (STRUCT) is -2.517979, which suggests a negative relationship between structural models and the performance (ROA) of life insurance firms. This means that, holding other variables constant, an increase in the structural model is associated with a decline in the performance of the sampled firms. The t-statistic for structural model is -0.280638, and the corresponding probability value of 0.6472 indicates that the effect is statistically insignificant at the 5% level. Therefore, the null hypothesis that structural models are not effective in improving the performance of life insurance firms in Nigeria is accepted at the 5% level of significance.

**Hypothesis Three: The Altman Z-Score model has no significant impact on the performance of life insurance firms in Nigeria.**

The coefficient for Altman Z-score (ZSC) is 4.144416, which suggests a moderately positive relationship between Altman Z-score model and the performance (ROA) of life insurance firms. This means that, holding other variables constant, an increase in the use of Altman Z-score model is associated with an improvement in the performance of the sampled firms. The t-statistic for Altman Z-score model is 0.497613,

and the corresponding probability value of 0.6202 indicates that the effect is not statistically significant at the 5% level. Therefore, the null hypothesis that Altman Z-Score model has no significant impact on the performance of life insurance firms in Nigeria is accepted at the 5% level of significance.

### **Control Variables**

Firm size, firm leverage and firm age serve as the control variables in the study and the study revealed a coefficient of 3.073886, 3.028857 and -0.166362 for Firm size, firm leverage and firm age respectively. This shows that firm size and leverage have a positive relationship with the performance of firms in the life insurance industry, while firm age revealed a negative relationship. It was also noted that firm size and firm age have a statistically significant impact on these firms' performance, while firm leverage was not significant at 5% level.

## Model II

**Table 4.7: Result of the Regression Analysis**

**Dependent Variable:** Return on Equity

Predictor variable	Coefficient	Std. Error	t-Statistic	Prob.
(CSCORE)	20.71641	35.01256	0.591685	0.5558
(STRUCT)	-22.08899	34.42522	-0.641651	0.5230
(ZSC)	16.64588	31.95536	0.520911	0.6039
(FSIZE)	9.417937	3.944508	2.387607	0.0194
(LEV)	20.05126	14.23929	1.408164	0.1631
(FAGE)	-0.299583	0.151076	-1.982991	0.0509
Constant	-222.7455	91.96656	-2.422027	0.0178
$R^2 = .24$	Adj $R^2 = .18$	$F(6, 77) = 4.08: p < .01$		$DW = 0.61$

**Source:** Author's compilation (2025), using Eviews 10.0 for Windows.

Table 4.7 above displays the regression analysis's outcome. According to the preliminary analysis, the independent variables considered in this study are credit scoring model, structural credit risk and firms Altman Z-Score, while the control variables considered are firm size, leverage and firm age which collectively contribute to 24% of the variation in the performance of life assurance firms in Nigeria which was captured by firms return on equity, with a coefficient of multiple determination of 0.24 and an adjusted R-squared value of 0.18. The error term, however, captures the remaining 76%.

The combined statistical significance of all the explanatory factors is indicated by the F-statistics value of 4.08 which is more than 2.

#### **4.7 Test of Hypotheses Model II**

**Hypothesis One: Credit scoring models have no significant influence on the performance of life insurance firms in Nigeria.**

The coefficient for credit scoring (CSCORE) is 20.71641, which suggests a positive relationship between credit scoring and the performance (ROE) of life insurance firms in Nigeria. This means that, holding other variables constant, an increase in the credit scoring is associated with an improvement in the performance of the sampled firms. The t-statistic for credit scoring is 0.591685, and the corresponding probability value of 0.5558 indicates that the effect is statistically insignificant at the 5% level. Therefore, the null hypothesis that credit scoring models have no significant influence on the performance of life insurance firms in Nigeria is accepted at the 5% level of significance. This implies that credit scoring does not play an important role in enhancing the performance of life insurance firms in Nigeria.

**Hypothesis Two: Structural models are not effective in improving the performance of life insurance firms in Nigeria.**

The coefficient for structural models (STRUCT) is -22.08899, which suggests a negative relationship between structural models and the performance of life insurance firms. This means that, holding other variables constant, an increase in the structural model is associated with a decline in the performance (ROE) of the sampled firms. The t-statistic for structural model is -0.641651, and the corresponding probability value of 0.5230 indicates that the effect is statistically insignificant at the 5% level. Therefore, the null hypothesis that structural models are not effective in improving the performance of life insurance firms in Nigeria is accepted at the 5% level of significance.

**Hypothesis Three: The Altman Z-Score model has no significant impact on the performance of life insurance firms in Nigeria.**

The coefficient for Altman Z-score (ZSC) is 16.64588, which suggests a positive relationship between Altman Z-score model and the performance (ROE) of life insurance firms. This means that, holding other variables constant, an increase in the use of Altman Z-score model is associated with an improvement in the performance of the sampled firms. The t-statistic for Altman Z-score model is 0.520911, and the corresponding probability value of 0.6039 indicates that the effect is not statistically significant at the

5% level. Therefore, the null hypothesis that Altman Z-Score model has no significant impact on the performance of life insurance firms in Nigeria is accepted at the 5% level of significance.

### **Control Variables**

Firm size, firm leverage and firm age serve as the control variables in the study and the study revealed a coefficient of 9.4177937, 20.05126 and -0.299583 for Firm size, firm leverage and firm age respectively. This shows that firm size and leverage have a positive relationship with the performance (ROE) of firms in the life insurance industry, while firm age revealed a negative relationship. It was also noted that firm size and firm age have a statistically significant impact on these firms' performance, while firm leverage was not significant at 5% level.

### **4.8 Model Comparison and Evaluation**

The study estimated two models to examine the determinants of firm performance: Model I, with Return on Assets (ROA) as the dependent variable, and Model II, with Return on Equity (ROE) as the dependent variable.

Model I yielded an  $R^2$  value of 0.37 and an Adjusted  $R^2$  of 0.32, indicating that approximately 32% of the variation in firm profitability (ROA) is explained by the independent variables (credit scoring, structural model, Altman Z-score, firm size,

leverage, and firm age). The F-statistic (7.61,  $p < .01$ ) confirms that the overall model is statistically significant at the 1% level. Among the predictors, firm size ( $p = .0037$ ) and firm age ( $p = .0001$ ) show significant effects on profitability, while other variables are statistically insignificant. The Durbin–Watson (DW = 0.86) indicates mild positive autocorrelation but within an acceptable range for panel data.

Model II produced an  $R^2$  value of 0.24 and an Adjusted  $R^2$  of 0.18, implying that only 18% of the variation in return on equity is explained by the predictors. Although the overall F-statistic (4.08,  $p < .01$ ) indicates the model is statistically significant, it explains less variation in firm performance compared to Model I. Significant predictors include the firm size ( $p = .0194$ ), leverage ( $p = .0509$ ), and firm age ( $p = .0178$ ), suggesting these variables have meaningful effects on equity returns. However, the Durbin–Watson value (0.61) indicates stronger positive autocorrelation, which may affect the model’s reliability. Considering the results, model I is considered to be the better and more reliable model because it possessed a higher explanatory power of 32% compare to the 18% of model II. It’s also possessed the stronger overall significance and a lower autocorrelation.

#### **4.9 Discussion of Findings**

The findings of this study provide insights into the influence of different credit risk assessment models credit scoring, structural models, and the Altman Z-score model on the performance of life insurance firms in Nigeria. The results indicate that although these models exhibit varying directional relationships with firm performance, none of the effects are statistically significant at the 5% level of significance.

Firstly, the analysis revealed that credit scoring (CSCORE) has a positive coefficient of 4.192709, implying that an increase in the use of credit scoring systems is associated with improved firm performance. However, the t-statistic (0.459455) and probability value (0.6472) suggest that this relationship is statistically insignificant. This indicates that, despite its theoretical potential to enhance risk assessment and underwriting efficiency, credit scoring does not have a significant practical influence on the financial performance of life insurance firms in Nigeria. This finding aligns with Ajijola and Solanke (2024), who found that although credit scoring models significantly improve credit decision-making in Nigerian FinTech institutions, their effectiveness in traditional financial sectors like insurance remains limited due to poor data quality and technological constraints. Similarly, Omankhanlen, Ogaga-Oghene, and Taiwo (2021) reported that credit risk management techniques had an insignificant effect on the

performance of Nigerian banks, suggesting that institutional inefficiencies and weak implementation frameworks limit the potential of such models across the financial services industry.

Secondly, the result for structural models (STRUCT) shows a negative coefficient of -2.517979, suggesting that an increase in the use of structural models may lead to a decline in firm performance. Although the negative sign implies a potential inefficiency or misalignment between model application and firm objectives, the t-statistic (-0.280638) and probability value (0.6472) reveal that the effect is not statistically significant. This supports the null hypothesis that structural models are not effective in improving firm performance. This result resonates with the findings of Duniya, Murtala, and Nurudeen (2024), who observed that certain risk assessment frameworks though conceptually robust had weak statistical influence on the performance of listed insurance firms in Nigeria. They attributed this to the lack of technical capacity, limited data analytics, and inconsistent regulatory compliance that hinder effective risk modeling within the Nigerian insurance sector.

Lastly, the coefficient for the Altman Z-Score model (ZSC) is 4.144416, suggesting a positive association with firm performance. This implies that firms utilizing the Altman Z-score model for financial health assessment and insolvency prediction may

experience performance improvements. However, the t-statistic (0.497613) and probability value (0.6202) indicate that the relationship is statistically insignificant. This outcome is consistent with findings by Mavengere and Gumede (2024), who examined the predictive competence of the Altman Z-score and Zmijewski models in Zimbabwean firms and concluded that, although the Z-score remains theoretically sound, its predictive power in service-oriented and non-manufacturing sectors is limited. This also aligns with Omoruyi-Aigbovo (2025), who found that underwriting and risk-assessment models in Nigerian insurance firms had an insignificant impact on profitability, reinforcing the notion that operational and environmental factors may weaken the effectiveness of such analytical tools.

## **CHAPTER FIVE**

### **SUMMARY OF FINDINGS, CONCLUSION AND RECOMMENDATIONS**

#### **5.1 Summary of Findings**

1. The study revealed that credit scoring models have a positive but insignificant relationship with the performance of life insurance firms in Nigeria. This indicates that although an increase in the use of credit scoring systems is associated with improved firm performance, the relationship is not statistically significant.
2. The findings showed that structural models have a negative and insignificant relationship with the performance of life insurance firms. This implies that an increase in the application of structural models may lead to a decline in firm performance, although the relationship is not statistically significant. It suggests that these models are not effectively utilized in improving financial or operational outcomes within the life insurance sector.
3. The study found that the Altman Z-Score model has a positive but insignificant relationship with the performance of life insurance firms in Nigeria. This means that although firms applying the Altman Z-score model may experience slight

improvements in performance, the effect is not strong enough to be considered statistically significant.

4. The results indicated that firm size has a positive and significant relationship with firm performance. This suggests that larger life insurance firms tend to perform better, possibly due to economies of scale, better resource allocation, and stronger market presence.
5. The findings showed that firm leverage has a positive but insignificant relationship with firm performance. This implies that higher leverage may enhance firm performance to some extent, but the relationship is not statistically meaningful at the 5% significance level.
6. The study revealed that firm age has a negative and significant relationship with firm performance. This indicates that older life insurance firms tend to perform less efficiently than younger ones, possibly due to operational rigidity, higher costs, or reduced adaptability to market changes.

## **5.2 Conclusion**

The study examines the impact of credit risk modelling techniques on the performance of life insurance companies in Nigeria. The study considered all the life insurance companies registered and licensed by the National Insurance Commission

(NAICOM) in Nigeria as of December 31, 2024, which served as the population of the study. The study covers six years from 2018 to 2024. The study sampled 12 life insurance companies in Nigeria. Different statistical and econometric measures were carried out, and the empirical results revealed that credit scoring and Altman Z-score model have positive and statistically insignificant effects on the financial performance of life insurance companies in Nigeria, while the structural model has a negative and statistically insignificant influence on the financial performance of life insurance companies in Nigeria.

### **5.3 Recommendations**

The following recommendations were made in line with the above findings:

1. Life insurance firms in Nigeria strengthen the adoption and integration of credit scoring systems using advanced data analytics and artificial intelligence. This would enhance risk assessment accuracy, improve underwriting decisions, and ultimately translate into better financial performance.
2. Firms should review and customize structural models to better suit the operational and regulatory environment of the Nigerian insurance industry. Training actuarial and

risk management personnel to effectively apply these models could help ensure that their implementation contributes positively to performance outcomes.

3. Life insurance firms should use the Altman Z-score model in conjunction with other sector-specific risk assessment tools. This combination would enhance the model's predictive accuracy and allow firms to better identify potential financial distress before it escalates.
4. Management should pursue strategic growth through mergers, acquisitions, and expansion of product lines. This will enable firms to benefit from economies of scale, diversify risk, and strengthen market competitiveness.
5. Insurance firms should adopt prudent debt management policies. While leveraging can enhance profitability, firms should ensure that borrowed funds are efficiently utilized in productive investments to avoid liquidity challenges and maintain financial stability.
6. Older life insurance firms should invest in digital transformation, process innovation, and workforce renewal to overcome structural rigidity. Embracing modern technology and flexible business strategies will help them remain competitive and improve overall performance.

#### **5.4 Contribution to Knowledge**

The study contributes to existing literature by providing empirical evidence on how credit risk variables credit scoring, structural model, and Altman Z-score affect firm performance in Nigeria. It demonstrates that firm-specific factors such as size and age significantly influence profitability, indicating that larger and more established firms perform better. The comparative analysis of ROA and ROE models further reveals that ROA is a more reliable measure of firm performance in assessing credit risk effects.

#### **5.5 Suggestion for Further Study**

Future research could extend this study by incorporating variables such as macroeconomic indicators (e.g., inflation, interest rate, and exchange rate) to better capture external influences on firm performance. Researchers could also apply alternative estimation techniques such as the Generalized Method of Moments (GMM) or Fixed Effects models to address potential endogeneity issues. Comparative studies across different sectors or between emerging and developed economies could provide deeper insights into how credit risk determinants affect firm performance in varying institutional situation. Also, qualitative approaches could be employed to complement quantitative results and explore managerial perspectives on credit risk management practices.

## REFERENCES

- Abdulkadir, J. (2024). Enterprise risk management (ERM) practices and financial performance: Evidence from listed insurance firms in Nigeria. *Yıldız Social Science Review*, 10(2), 99–109.
- Abdulkadir, N. (2024). Enterprise risk management and financial performance of listed insurance companies in Nigeria. *African Journal of Business and Management*, 18(4), 112–127.
- Ajagbe, A. T., Salami, K. M., & Ojo, I. A. (2023). Structural credit risk modelling and financial stability in emerging markets. *Journal of Financial Risk Analysis*, 15(2), 88–104.
- Ajagbe, A. O., Adeoye, T. A., & Salami, K. M. (2022). Risk management practices and financial stability of insurance companies in Nigeria. *Journal of Insurance and Risk Management*, 15(2), 45–62.
- Ajagbe, F. A., Ogunleye, S., & Aremu, O. (2022). Structural models of credit risk and corporate failure prediction in emerging markets. *Journal of Financial Risk Analysis*, 9(3), 88–103.
- Akpan, U., Johnson, E., & Effiong, P. (2024). Corporate attributes and risk management disclosure among Nigerian insurance firms. *Journal of Accounting and Corporate Reporting*, 6(1), 55–73.
- Alabi, J., Musa, L., & Oyedele, K. (2023). Farmers' risk aversion and crop insurance preference in Nigeria. *Journal of Agricultural Economics and Rural Development*, 15(2), 45–59.
- Aladejebi, O. (2021). Financial ratio analysis and performance evaluation of Nigerian insurance firms. *International Journal of Finance and Business Research*, 9(1), 112–127.
- Aladejebi, O. (2021). Application of the Altman Z-score in predicting financial distress in Nigeria. *International Journal of Finance and Accounting*, 10(1), 1–12.
- Apochi, A., & Baffa, H. (2022). Credit risk, risk management committees, and the financial performance of deposit money banks in Nigeria.
- Ejem, C. O., Udeh, S., & Okoro, P. (2023). Credit risk management and performance of deposit money banks in Nigeria. *Journal of Banking and Finance Studies*, 11(1), 23–40.

- Ejem, C. A., Okore, C. S., & Effe-Nnamdi, A. C. (2023). Credit risk management and deposit money banks' performance in Nigeria. *IIARD International Journal of Banking and Finance Research*, 9(4), 1–22.
- Ekong, C., & Akpan, B. (2024). Liquidity risk and market value of insurance firms in Nigeria. *Nigerian Journal of Finance and Investment*, 5(2), 67–80.
- Fali, I. M., Nyor, T., & Mustapha, L. O. (2020). Financial risk and financial performance of listed insurance companies in Nigeria. *European Journal of Business and Management*, 12(12).
- Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs, and ownership structure. *Journal of Financial Economics*, 3(4), 305–360.
- Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *Journal of Finance*, 29(2), 449–470.
- Ogunsola, A. (2023). Financial risks and performance of listed insurance companies in Nigeria. *African Journal of Risk and Insurance Studies*, 12(2), 92–108.
- Okeke, I., Nwankwo, E., & Ubah, P. (2022). Solvency regulation and performance of Nigerian insurance firms. *Insurance and Risk Management Review*, 14(1), 33–47.
- Okeke, C. A., Nwankwo, B. C., & Ugwumba, E. O. (2022). Solvency supervision and regulatory compliance among Nigerian insurance firms. *Journal of Insurance Regulation and Compliance*, 7(2), 44–59.
- Okeke, C. D., Udeh, P. N., & Eze, G. O. (2022). Macroeconomic instability, regulatory reforms, and insurance performance in Nigeria. *Nigerian Journal of Economics and Development Studies*, 14(4), 1–18.
- Oluwatosin, A. T., Adebisi, K. S., & Fashola, M. O. (2022). Credit risk modelling and financial performance of insurance companies in emerging economies. *African Journal of Finance and Risk Analysis*, 6(1), 77–95.
- Oluwatosin, A. T., Adebisi, K. S., & Fashola, M. O. (2023). Advanced credit scoring techniques and default prediction in life insurance firms: Evidence from Nigeria. *Journal of Financial Risk and Analytics*, 4(3), 88–106.
- Oluwatosin, M., Adebayo, T., & Fashola, R. (2023). Credit risk management and technological innovation in the Nigerian insurance industry. *Journal of Insurance and Financial Studies*, 8(2), 101–120.
- Oluwatosin, T. A., Adebayo, R. M., & Fashola, O. K. (2023). Technological adoption, risk management, and performance of insurance firms in Nigeria. *African Journal of Insurance and Risk Management*, 11(1), 55–72.

- Omoregie, R., Ibadode, A., & Omoruyi, J. (2023). Credit scoring models and financial performance of Nigerian insurance firms. *West African Journal of Finance*, 7(1), 54–68.
- Omoregie, J. O., Eze, C. J., & Adebajo, L. A. (2023). Credit scoring innovation and default prediction accuracy in Nigerian financial institutions. *Journal of Credit and Data Analytics*, 9(3), 120–139.
- Omoregie, P. E., Ojo, J. A., & Lawal, O. (2023). Determinants of credit risk in Nigerian banks: The role of credit scoring and macroeconomic variables. *Journal of Banking and Financial Studies*, 12(1), 55–73.
- Osabohien, R., Afolabi, A., & Godwin, A. (2020). Life insurance, financial inclusion, and economic development in emerging economies.
- Osabohien, R., Iwegbue, C., & Otekunrin, A. B. (2020). Insurance sector development and economic performance in Nigeria. *Journal of Economics and Financial Studies*, 8(4), 210–225.
- Osabohien, R., et al. (2020). Insurance development and economic growth in Nigeria. *Journal of Development Policy and Practice*, 5(2), 178–192.
- Osabohien, R., Matthew, O., Ohalete, P., & Osabuohien, E. (2020). Population–poverty–inequality nexus and social protection in Africa. *Social Indicators Research*, 151(2), 575–598.
- Sijibomi, A., Fadeyi, T., & Adeola, S. (2025). Enterprise risk management and profitability of insurance firms in Nigeria. *International Journal of Insurance and Management*, 13(1), 88–102.
- Sijibomi, O., Ehiaguina, J. A., Iyendo, C. S., & Gambo, N. (2025). Enterprise risk management and profitability of insurance companies in Nigeria. *European Journal of Accounting, Auditing and Finance Research*, 13(1), 71–90.
- Ukpong, E., & Essien, A. (2022). Credit risk and the financial performance of quoted commercial banks in Nigeria.

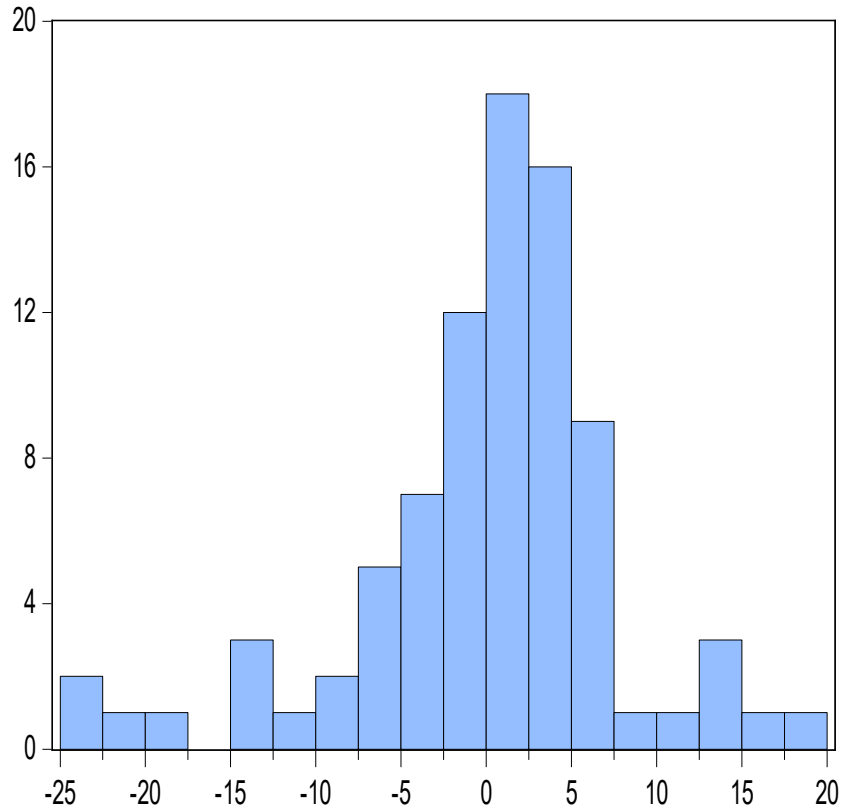
## APPENDIX I

### Descriptive Analysis Result

	<b>ROA</b>	<b>ROE</b>	<b>CSCORE</b>	<b>STRUCT</b>	<b>ZSC</b>	<b>FSIZE</b>	<b>LEV</b>	<b>FAGE</b>
Mean	-2.060377	1.465873	0.440476	0.523810	0.095238	23.79983	0.601667	37.17857
Median	0.675000	1.770000	0.000000	1.000000	0.000000	23.60998	0.625000	30.00000
Maximum	13.39000	89.60000	1.000000	1.000000	1.000000	25.81643	1.280000	100.0000
Minimum	-43.85000	-82.84333	0.000000	0.000000	0.000000	21.53160	-0.783333	0.000000
Std. Dev.	9.701862	34.02868	0.499426	0.502432	0.295307	1.092176	0.321278	25.61351
Skewness	-1.718155	-0.573475	0.239801	-0.095346	2.757764	0.282463	-1.512517	0.886062
Kurtosis	7.082912	3.589948	1.057504	1.009091	8.605263	1.967059	7.577434	3.125471
Jarque-Bera	99.67440	5.822370	14.01157	14.00029	216.4401	4.851379	105.3631	11.04657
Probability	0.000000	0.054411	0.000907	0.000912	0.000000	0.088417	0.000000	0.003993
Sum	-173.0717	123.1333	37.00000	44.00000	8.000000	1999.186	50.54003	3123.000
Sum Sq. Dev.	7812.468	96109.95	20.70238	20.95238	7.238095	99.00649	8.567221	54452.32
Observations	84	84	84	84	84	84	84	84

## APPENDIX II

### Histogram Normality Test



Series: Standardized Residuals  
Sample 2018 2024  
Observations 84

Mean	1.44e-14
Median	0.733558
Maximum	19.51451
Minimum	-23.65795
Std. Dev.	7.686085
Skewness	-0.791972
Kurtosis	4.684155
Jarque-Bera	18.70839
Probability	0.000087

## APPENDIX III

### Heteroskedasticity Test

Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	0.962998	Prob. F(6,77)	0.4292
Obs*R-squared	3.876717	Prob. Chi-Square(6)	0.4229
Scaled explained SS	7.060542	Prob. Chi-Square(6)	0.1327

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

Date: 11/04/25 Time: 21:32

Sample: 1 84

Included observations: 84

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	970.0382	314.4741	3.084636	0.0028
CSCORE	-10.19275	119.7233	-0.085136	0.9324
STRUCT	-23.90960	117.7150	-0.203114	0.8396
ZSC	-41.36815	109.2694	-0.378589	0.7060
FSIZE	-39.62153	13.48801	-2.937538	0.0044
LEV	42.63862	48.69040	0.875709	0.3839
FAGE	0.715986	0.516596	1.385968	0.1698
R-squared	0.165406	Mean dependent var		58.37262
Adjusted R-squared	0.100373	S.D. dependent var		112.7142
S.E. of regression	106.9079	Akaike info criterion		12.26147
Sum squared resid	880056.8	Schwarz criterion		12.46404
Log likelihood	-507.9817	Hannan-Quinn criter.		12.34290
F-statistic	2.543408	Durbin-Watson stat		1.808292
Prob(F-statistic)	0.026706			

## APPENDIX IV

### Serial Correlation

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	6.621200	Prob. F(2,75)	0.0022
Obs*R-squared	12.60575	Prob. Chi-Square(2)	0.0018

Test Equation:

Dependent Variable: RESID

Method: Least Squares

Date: 11/04/25 Time: 21:40

Sample: 1 84

Included observations: 84

Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CSCORE	-1.857266	8.368207	-0.221943	0.8250
STRUCT	2.055364	8.228698	0.249780	0.8034
ZSC	-1.916207	7.639204	-0.250839	0.8026
FSIZE	-0.107982	0.941845	-0.114650	0.9090
LEV	-1.083821	3.416934	-0.317191	0.7520
FAGE	-0.024951	0.037326	-0.668481	0.5059
C	4.116228	21.99737	0.187124	0.8521
RESID(-1)	0.367937	0.115951	3.173200	0.0022
RESID(-2)	0.080796	0.120665	0.669585	0.5052
R-squared	0.150068	Mean dependent var		-2.81E-15
Adjusted R-squared	0.059409	S.D. dependent var		7.686085
S.E. of regression	7.454278	Akaike info criterion		6.956410
Sum squared resid	4167.470	Schwarz criterion		7.216855
Log likelihood	-283.1692	Hannan-Quinn criter.		7.061107
F-statistic	1.655300	Durbin-Watson stat		1.965662
Prob(F-statistic)	0.123684			

## APPENDIX V

### Correlation Analysis Result

Covariance Analysis: Ordinary

Date: 11/04/25 Time: 21:12

Sample: 2018 2024

Included observations: 84

Correlation t-Statistic Probability	ROA	ROE	CSCORE	STRUCT	ZSC	FSIZE	LEV	FAGE
ROA	1.000000							
ROE	0.674506 8.273279 0.0000	1.000000 ----- -----						
CSCORE	0.163720 1.502821 0.1367	0.106989 0.974424 0.3327	1.000000 ----- -----					
STRUCT	0.042105 0.381612 0.7037	-0.021053 -0.190683 0.8492	0.845971 14.36644 0.0000	1.000000 ----- -----				
ZSC	-0.185229 -1.706860 0.0916	-0.194983 -1.800196 0.0755	-0.287866 -2.721954 0.0079	0.228141 2.121865 0.0369	1.000000 ----- -----			
FSIZE	0.448624 4.545564 0.0000	0.435456 4.380335 0.0000	0.165840 1.522835 0.1316	-0.038790 -0.351523 0.7261	-0.325361 -3.115797 0.0025	1.000000 ----- -----		
LEV	0.154116 1.412456 0.1616	0.258255 2.420720 0.0177	0.371812 3.626917 0.0005	0.288106 2.724432 0.0079	-0.176093 -1.619899 0.1091	0.466844 4.780346 0.0000	1.000000 ----- -----	
FAGE	-0.444431 -4.492565 0.0000	-0.219631 -2.038617 0.0447	0.000370 0.003351 0.9973	0.123714 1.128950 0.2622	0.203204 1.879303 0.0638	-0.127394 -1.163081 0.2482	0.291882 2.763442 0.0071	1.000000 ----- -----

## APPENDIX VI

### Regression Analysis Result

Dependent Variable: ROA  
 Method: Panel EGLS (Period random effects)  
 Date: 11/04/25 Time: 21:22  
 Sample: 2018 2024  
 Periods included: 7  
 Cross-sections included: 12  
 Total panel (balanced) observations: 84  
 Swamy and Arora estimator of component variances

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-71.77815	23.96945	-2.994567	0.0037
CSCORE	4.192709	9.125403	0.459455	0.6472
STRUCT	-2.517979	8.972325	-0.280638	0.7797
ZSC	4.144416	8.328598	0.497613	0.6202
FSIZE	3.073886	1.028066	2.989969	0.0037
LEV	3.028857	3.711219	0.816135	0.4169
FAGE	-0.166362	0.039375	-4.225023	0.0001
Effects Specification				
			S.D.	Rho
Period random			0.000000	0.0000
Idiosyncratic random			8.148605	1.0000
Weighted Statistics				
R-squared	0.372375	Mean dependent var		-2.060377
Adjusted R-squared	0.323469	S.D. dependent var		9.701862
S.E. of regression	7.979926	Sum squared resid		4903.300
F-statistic	7.614121	Durbin-Watson stat		0.860665
Prob(F-statistic)	0.000002			
Unweighted Statistics				
R-squared	0.372375	Mean dependent var		-2.060377
Sum squared resid	4903.300	Durbin-Watson stat		0.860665

## APPENDIX VII

### Hausman Test

Correlated Random Effects - Hausman Test

Equation: Untitled

Test period random effects

---

---

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Period random	1.975814	6	0.9219

---

---

\*\* WARNING: estimated period random effects variance is zero.

Period random effects test comparisons:

---

---

Variable	Fixed	Random	Var(Diff.)	Prob.
CSCORE	5.102118	4.192709	4.556585	0.6701
STRUCT	-3.265293	-2.517979	3.969725	0.7076
ZSC	5.034576	4.144416	4.453223	0.6732
FSIZE	3.250428	3.073886	0.083049	0.5401
LEV	2.442568	3.028857	1.077160	0.5721
FAGE	-0.161392	-0.166362	0.000056	0.5061

---

---

Period random effects test equation:

Dependent Variable: ROA

Method: Panel Least Squares

Date: 11/04/25 Time: 21:25

Sample: 2018 2024

Periods included: 7

Cross-sections included: 12

Total panel (balanced) observations: 84

---

---

Variable	Coefficient	Std. Error	t-Statistic	Prob.
----------	-------------	------------	-------------	-------

C	-75.90574	24.87474	-3.051519	0.0032
CSCORE	5.102118	9.371743	0.544415	0.5879
STRUCT	-3.265293	9.190884	-0.355275	0.7234
ZSC	5.034576	8.591785	0.585976	0.5598
FSIZE	3.250428	1.067693	3.044347	0.0033
LEV	2.442568	3.853610	0.633839	0.5282
FAGE	-0.161392	0.040078	-4.026924	0.0001

---

Effects Specification

---

Period fixed (dummy variables)

R-squared	0.396556	Mean dependent var	-2.060377
Adjusted R-squared	0.294566	S.D. dependent var	9.701862
S.E. of regression	8.148605	Akaike info criterion	7.174958
Sum squared resid	4714.383	Schwarz criterion	7.551155
Log likelihood	-288.3482	Hannan-Quinn criter.	7.326186
F-statistic	3.888172	Durbin-Watson stat	0.778545
Prob(F-statistic)	0.000140		

## APPENDIX VIII

### Regression Analysis Result

Dependent Variable: ROE

Method: Panel EGLS (Period random effects)

Date: 11/11/25 Time: 23:29

Sample: 2018 2024

Periods included: 7

Cross-sections included: 12

Total panel (balanced) observations: 84

Swamy and Arora estimator of component variances

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CSCORE	20.71641	35.01256	0.591685	0.5558
STRUCT	-22.08899	34.42522	-0.641651	0.5230
ZSC	16.64588	31.95536	0.520911	0.6039
FSIZE	9.417937	3.944508	2.387607	0.0194
LEV	20.05126	14.23929	1.408164	0.1631
FAGE	-0.299583	0.151076	-1.982991	0.0509
C	-222.7455	91.96656	-2.422027	0.0178

Effects Specification		S.D.	Rho
-----------------------	--	------	-----

Period random	0.000000	0.0000
Idiosyncratic random	31.26476	1.0000

---



---

Weighted Statistics

---



---

R-squared	0.241274	Mean dependent var	1.465873
Adjusted R-squared	0.182153	S.D. dependent var	34.02868
S.E. of regression	30.77381	Sum squared resid	72921.09
F-statistic	4.080992	Durbin-Watson stat	0.608263
Prob(F-statistic)	0.001319		

---



---

Unweighted Statistics

---



---

R-squared	0.241274	Mean dependent var	1.465873
Sum squared resid	72921.09	Durbin-Watson stat	0.608263

---



---