CREDIT RISK MODELLING TECHNIQUES FOR LIFE INSURERS

BY

Eloho Priscilla OMODUARE
MGS1807801

DEPARTMENT OF BANKING AND FINANCE
(ACTUARIAL SCIENCE PROGRAMME)
FACULTY OF MANAGEMENT SCIENCES
UNIVERSITY OF BENIN
BENIN CITY

SEPTEMBER, 2023

CREDIT RISK MODELLING TECHNIQUES FOR LIFE INSURERS

BY

Eloho Priscilla OMODUARE
MGS1807801

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

SEPTEMBER, 2023

DECLARATION

I, **Eloho Priscilla OMODUARE** do hereby declare that this project is entirely my work and composition. The work embodied in this project has not been submitted by another candidate for any degree and is not currently being submitted for any other degree. All references made to the works of other persons have been duly acknowledged.

Eloho Priscilla OMODUARE **Date**

CERTIFICATION

We, the undersigned certify that this research work was submitted by **Eloho Priscilla OMODUARE** and it is hereby approved for the partial fulfilment of the requirement for the award of Bachelor of Science (B.Sc) degree in Banking and Finance (Actuarial Science), University of Benin, Benin City.

____
Dr. E. Isibor
(Project supervisor)

Date: _______________

____
Dr. J. Obayagbona
(Project Co-ordinator)

Date:_______________

____
Dr. O.G. Omorokunwa
(Head of Department)

Date: _______________

DEDICATION

I dedicate this research project First and foremost to Almighty God My creator who has been my Helper right from the beginning to this very point. Also to my wonderful parents for their relentless support and compassion towards me throughout my years of studies.

ACKNOWLEDGMENTS

I wish to express my profound gratitude to God Almighty for seeing me through this phase of life.

I would like to express my sincere and heartfelt thanks to my project supervisor Dr E. Isibor for the guidance, cooperation and encouragement during the project's completion. Also My appreciation goes to my project coordinator Dr .J. Obayagbona and I would like to take this opportunity to thank the other lecturers in my Department who have impacted my life positively with their teachings and encouragement Mr E. Iroh, Dr V. Ero, Mr C.O. Ighodaro, Dr B. Oni and many others God bless you all.

Finally, words are not sufficient to express gratitude to my Cherished Family members my parents Mr and Mrs Zion Omoduare, My siblings and the beautiful friends I met in school without their support, love and encouragement I would have not been able to reach this stage.

TABLE OF CONTENTS

ABSTRACT

This research delves into the realm of credit risk modeling within the life insurance sector. It set out with several objectives, including identifying effective methods for modeling credit risk tailored to life insurance companies, evaluating the repercussions of credit risks on these insurers, investigating the advantages of extending credit to them, exploring the connection between credit practices and the performance of insurers, and gauging the accessibility of credit facilities for insurers.

To conduct this investigation, a combination of descriptive and explanatory research designs was employed. Data collection encompassed the use of questionnaires and library research. The primary data sources consisted of responses gathered from 32 employees at African Alliance Insurance Plc in Benin. Data analysis hinged on the chi-square statistical tool with a significance level set at 5%. The findings, displayed through frequency tables and percentages, unveiled that insurance companies grapple with substantial credit risks that have adverse effects on their operations.

Consequently, the study recommends that the Nigerian government and relevant stakeholders should collaborate to establish a credit model for insurance facilities that carries lower levels of risk, in alignment with the insights derived from this research..

CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

This study delves into the various factors that influence credit risk modeling approaches specific to life insurance businesses in Nigeria, a prominent country in Sub-Saharan Africa. Credit risk, in this context, refers to the possibility of borrowers failing to meet their financial obligations, which can result in adverse consequences for lenders, including the loss of principal and interest, disruptions in cash flow, and increased costs associated with debt collection. These losses can manifest as either partial or complete and can occur in a variety of scenarios.

The significance of life insurance within the global microfinance sector cannot be overstated. It emerged during the 1970s and plays a crucial role in safeguarding the financial well-being of low-income individuals, particularly in West Africa. Life insurance serves as a protective shield against unforeseen setbacks and serves as a catalyst for economic growth and entrepreneurial development (Churchill, 2006, 2007; Roth, McCord, and Liber, 2007; Matul, McCord, Phily, and Harms, 2010). Even though approximately 135 million individuals worldwide hold life insurance policies, the potential market for this financial product remains largely untapped, representing only 2% to 3% of its full capacity (Swiss Re, 2010, p.9).

In recent years, major global banks have pioneered innovative approaches for evaluating and consolidating credit risk across various geographical regions and product lines. The primary objective of this exploration into credit risk modeling was to provide quantitative estimates of the economic capital required to sustain a bank's risk-related operations. While these credit risk models have become integral components of risk management within large financial institutions, their potential applicability for regulatory and supervisory purposes has become a focal point of interest.

This research sheds light on a myriad of techniques used in both model development methodologies and internal model applications. It also underscores the challenges and limitations associated with existing modeling approaches. The development of advanced modeling methodologies and their resulting enhancements in the precision and consistency of credit risk assessment hold significant advantages, especially from a supervisory perspective. National regulators can consider these enhancements when assessing the internal controls and risk management processes of banks.

Concerning regulatory aspects, the flexibility of models in responding to dynamic economic conditions and the evolution of financial products can potentially reduce the motivation for banks to engage in regulatory capital arbitrage. Furthermore, a model-based approach has the potential to align capital requirements more effectively with the perceived risks associated with underlying assets, resulting in credit risk estimates that better reflect the composition of each bank's portfolio. However, before the formal implementation of a portfolio modeling approach to establish regulatory capital requirements, regulators must ensure that these models are seamlessly integrated into the day-to-day credit risk management practices of banks, exhibit conceptual soundness, undergo empirical validation, and generate comparable capital requirements that can be applied across different financial institutions.

1.2 Statement of the Research Problem

This study delves into the various factors that influence credit risk modeling approaches specific to life insurance businesses in Nigeria, a prominent country in Sub-Saharan Africa. Credit risk, in this context, refers to the possibility of borrowers failing to meet their financial obligations, which can result in adverse consequences for lenders, including the loss of principal and interest, disruptions in cash flow, and increased costs associated with debt collection. These losses can manifest as either partial or complete and can occur in a variety of scenarios.

The significance of life insurance within the global microfinance sector cannot be overstated. It emerged during the 1970s and plays a crucial role in safeguarding the financial well-being of low-income individuals, particularly in West Africa. Life insurance serves as a protective shield against unforeseen setbacks and serves as a catalyst for economic growth and entrepreneurial development (Churchill, 2006, 2007; Roth, McCord, and Liber, 2007; Matul, McCord, Phily, and Harms, 2010). Even though approximately 135 million individuals worldwide hold life insurance policies, the potential market for this financial product remains largely untapped, representing only 2% to 3% of its full capacity (Swiss Re, 2010, p.9).

In recent years, major global banks have pioneered innovative approaches for evaluating and consolidating credit risk across various geographical regions and product lines. The primary objective of this exploration into credit risk modeling was to provide quantitative estimates of the economic capital required to sustain a bank's risk-related operations. While these credit risk models have become integral components of risk management within large financial institutions, their potential applicability for regulatory and supervisory purposes has become a focal point of interest.

This research sheds light on a myriad of techniques used in both model development methodologies and internal model applications. It also underscores the challenges and limitations associated with existing modeling approaches. The development of advanced modeling methodologies and their resulting enhancements in the precision and consistency of credit risk assessment hold significant advantages, especially from a supervisory perspective. National regulators can consider these enhancements when assessing the internal controls and risk management processes of banks.

Concerning regulatory aspects, the flexibility of models in responding to dynamic economic conditions and the evolution of financial products can potentially reduce the motivation for banks to engage in regulatory capital arbitrage. Furthermore, a model-based approach has the potential to align capital requirements more effectively with the perceived risks associated with underlying assets, resulting in credit risk estimates that better reflect the composition of each bank's portfolio. However, before the formal implementation of a portfolio modeling approach to establish regulatory capital requirements, regulators must ensure that these models are seamlessly integrated into the day-to-day credit risk management practices of banks, exhibit conceptual soundness, undergo empirical validation, and generate comparable capital requirements that can be applied across different financial institutions.

1.3 Objectives of the Study

The following are the aims and objectives of the study

i. To know the best techniques of credit risk modeling for life insurers.
ii. To examine the impact of credit risks on life insurers.
iii. To examine the benefits of credit to life insurer.
iv. To examine the relationship between credit and performance of insurers.
v. To know if credit facilities are readily made available to insurers.

1.4 Significance of the Study

This research holds significant relevance for insurance companies in effectively managing credit risks pertaining to life insurers. It also serves to enlighten Nigerians about the crucial role of credit in enhancing profitability. Additionally, the study offers valuable insights to the government and stakeholders in the insurance sector regarding the most effective methods for modeling credit risk in the context of life insurance. Furthermore, insurers can benefit from this research by gaining a deeper understanding of optimal approaches to repaying loans and credits.

1.5 Scope and Limitation of the Study

This research is an examination of credit risk modeling techniques tailored for life insurance companies, with a focus on the Nigerian insurance sector as a case study.

Limitation of the study

Two significant constraints that may affect the research process are:

1. Financial Constraint: Inadequate funding can present significant challenges to researchers, limiting their capacity to access pertinent materials, literature, or information essential for their study. It can also have a detrimental effect on the data collection phase, particularly when financial resources are necessary for tasks such as internet access, questionnaire printing, or conducting interviews.

2. Time Constraint: The researcher is likely to face time constraints as they need to balance this research with other academic commitments. This could reduce the amount of time available for dedicating to the research work, potentially affecting the thoroughness and depth of the study.

1.6 Research Questions

i. What are the most effective credit risk modeling techniques for life insurance companies?
ii. How do credit risks affect insurance companies, and what is the extent of their impact?
iii. What advantages does extending credit offer to life insurance companies, and how does it contribute to their performance?
iv. How does the provision of credit relate to the overall performance of insurers, and what are the key factors influencing this relationship?
v. Are credit facilities readily made available to insurers?

1.7 Research Hypotheses

Hypothesis 1

H_0: Credit risks negatively affect insurance/financial institutions.

H_1: Credit risks positively affect insurance/financial institutions.

Hypothesis 2

H_0: credit risks taken by insurance/financial institutions are low.

H_1: credit risks taken by insurance/financial institutions are high.

1.8 Definition of Terms

1. Credit risk: This refer to the potential of a borrower failing to make their required payments, leading to a debt default. This risk primarily impacts the lender, resulting in the loss of both principal and interest, disruptions in cash flows, and increased expenses related to debt collection.
2. Model: A model is a representation used as a pattern or template to emulate or replicate.
3. Insurance: This is a contractual agreement in which a company or government undertakes to provide compensation or coverage for specified losses, damages, illnesses, or deaths in return for the payment of a specified premium.
4. Life insurance: This is a type of insurance that provides a lump-sum payout upon the death of the insured individual or after a predetermined period.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter explores the theoretical and empirical foundations that support the viewpoints and arguments offered in this research critically. It performs a thorough examination of current literature on the study topic, relying on the works of numerous writers, researchers, and regulatory bodies. This chapter, in particular, includes literature on the historical context and evolution of credit risk modeling for life insurers in Nigeria, as well as the regulatory framework and entities involved, with the goal of providing a comprehensive overview of credit risk modeling for life insurers within the operational landscape of the Nigerian insurance sector.

2.2 Theoretical Framework

Altman's work in 1968 presented discriminant analysis as a tool for distinguishing between defaulted and non-defaulted enterprises based on observable features, which sparked the quantitative credit analysis literature. This was one of the first examples of a quantitative, "credit-scoring" technique being used in credit evaluation. However, due of its descriptive character, this technique has fallen in favor in recent years. Discriminant analysis seeks to define observable qualities of a business based on its present default state, while credit analysts often strive to anticipate a firm's chance of default based on observable attributes. Furthermore, Lo (2006) revealed that discriminant analysis is only consistent under certain conditions, leading to the creation of more current techniques such as logistic regression models. In the case of logistic regression, these models allow for the direct estimate of the impact of individual variables on default probabilities or log odds-ratios.

Stochastic calculus was incorporated into the theoretical finance toolset in the 1970s, resulting in important advances in a variety of domains, including credit risk assessment. Merton's 1974 study is a notable example, since he adapted Black and Scholes' (1973) option-pricing methodology to a firm's balance sheet. Merton demonstrated how to determine a firm's default rate under particular assumptions, assuming that businesses default when their asset value falls below their obligations. These assumptions gave rise to the phrase "structural models." While these models enabled for credit risk estimations with very little data, further research called these structural assumptions into question (Shumway and Bharath, 2008).

Building on this basis, the literature has grown to investigate credit risk in a variety of scenarios and to loosen essential assumptions. Hull and White (2005) addressed the inclusion of counterparty credit risk in derivative products, whilst Duffie and Singleton (2009) and Jarrow and Turnbull (2007) concentrated on the dynamic character of credit risk through credit spreads. Lando (2008) expanded the range of variables used to quantify credit risk by including risk-free interest rates into quantitative credit analysis.

Shumway (2001) and Jarrow and Chava (2004) created "reduced form" default intensity models that rely on statistical models based on firm- and economy-level characteristics. These models proved to perform better in terms of prediction, demonstrating the usefulness of extra information such as size, previous stock returns, and stock return variability. Altman, Resti, and Sironi (2004) reaffirmed the Merton structural approach's usefulness in describing corporate default risk, as well as the relative performance of structural and reduced form models in default modeling. However, estimating recovery rates was difficult owing to data constraints and the variance in recoveries between enterprises, sectors, and time.

In data-rich contexts, recent work has supported the reduced form technique, demonstrating that it can outperform the structural approach. Campbell, Hilscher, and Szilagyi (2008) showed the use of reduced form models to identify troubled enterprises and generate effective trading strategies. Academic research in the credit default swaps (CDS) market has also been notable, focusing on the limits of CDS market prices as credit information sources. Longstaff, Mithal, and Neis (2005) discovered that non-credit-related variables might explain a significant amount of corporate yield spreads described by CDS quotations. When inferring default rates from CDS quotations, Jarrow (2012) addressed theoretical and empirical concerns. Furthermore, Campbell, Hilscher, and Szilagyi (2008) expressed concerns about the efficiency of pricing outside the CDS market and illustrated how reduced form models might detect troubled enterprises with below-average returns.

2.3 Economics and Finance Literature: Current Consensus

The expansion of the credit modeling literature in the mid-2000s was fueled by research into the comparative performance of "structural" and "reduced form" models in predicting default probabilities, as well as advancements in data accessibility and modeling software availability. Notably, Cetin, Jarrow, Protter, and Yilidrim (2004) advocated for the adoption of a reduced form modeling approach, emphasizing the need to include observable variables associated with asset value and volatility, given the challenges of obtaining comprehensive information, a departure from Merton's (1974) original framework.

Duffie, Wang, and Saita (2007) introduced a method to introduce time-varying default risk by utilizing a conditional term structure of default probabilities based on observable characteristics. This approach naturally raised questions about the correlation of default intensities over time. Das, Duffie, Kapadia, and Saita (2007) and Jarrow and van Deventer (2005) explored the concept of endogenous correlation within reduced form models, highlighting the dependence on common factors. In the aftermath of the late 2000s recession, regulatory agencies began emphasizing the integration of macroeconomic factors into credit models, and reduced form models proved to be well-suited for this purpose. Figlewski, Frydman, and Liang (2012) revealed that traditional credit ratings may not effectively address this new focus, showing the sensitivity of default rates to common macroeconomic indicators within specific credit rating categories.

The field of quantitative credit risk modeling in economics and finance has evolved from characterizing observable features of defaulted firms to deducing default probabilities by assuming specific market and process structures. It has now reached a stage where it can describe and accurately estimate a comprehensive high-frequency term structure of default probabilities with endogenous cross-sectional default correlations, drawing from a broad range of observable characteristics, including macroeconomic variables. Recent research has also highlighted potential challenges when deriving credit parameters from market prices. Nevertheless, in areas beyond corporate default analysis, where data quality and availability issues may hinder academic research, there remains ample room for further investigation.

2.4 Industry Literature: Principal Sources

Credit risk modeling within the insurance sector and associated research has followed diverse paths. While some organizations and publications have provided limited coverage of credit risk or have only recently incorporated credit research, it's essential to note that this is not a universal trend. In fact, industry groups strongly emphasize the importance of credit risk.

The American Academy of Actuaries Actuarial Standards of Practice mandates actuaries to assess the impact of asset quality and the risk of asset default on cash flow without specifying particular models. The Society of Actuaries (SOA) curriculum encompasses structural and reduced form models, loss given default, correlation, and credit derivatives. The National Association of Insurance Commissioners (NAIC) has commissioned third parties to develop risk-based capital factors for structured products and has made their methods accessible.

Historically, the North American Actuarial Journal published limited credit risk research, as indicated in an editorial by Li (2006). However, this situation is changing. In 2008, two studies delved into various aspects of credit risk modeling, particularly in the context of credit default swaps (CDS).

Sui et al. (2008) introduced modifications to the Merton model for CDS contract value, altering assumptions related to stable interest rates, volatility, and leverage to enhance flexibility. Huh and Kolkiewicz (2008) employed a structural model to offer a computationally efficient approach for pricing CDS contracts with multiple reference entities.

The SOA literature encompasses discussions on various credit modeling strategies, including factor-based approaches, credit migration models, structural models, reduced form models, hybrid models, actuarial models, and credit scoring models. Several articles provide a high-level overview of various models, while others delve deeply into specific model types. Numerous industry publications focus on the practical aspects and applications of credit risk modeling. For instance, Buff (2012) proposed a method for analyzing default risk using interactive cash-flow forecasts of assets and obligations, while Zurcher (2013) examined stochastic modeling and default rates used in developing bond RBC C-1 factors. Shipperlee (2006) provided presentation slides offering an overview of how insurance companies handle credit risk, addressing topics such as default likelihood, loss given default, credit rating, and data challenges.

Industry publications also explore factor-based techniques such as incidence and severity models. Luckner and Young (2009) used the incidence-and-severity model in a case study on credit risk, specifically defining economic loss for credit risk events. Another prominent subject is agency ratings, with discussions ranging from Markov transition matrices to ordinal logistic regression and stochastic analysis. Hambro and Houghton (2011) covered interest rate and credit risk, incorporating deterministic and stochastic simulations, spreads, and credit-related risk categories. Bae and Kulpergry (2008) extended single-period factor-based models by proposing a multiperiod ordinal logistic regression model for credit rating transition probabilities. Han (2008) provided a historical perspective on single-factor and multifactor credit models and demonstrated how to optimize a credit portfolio using several credit transition measures from a single credit model.

2.5 Empirical Review

The investment literature has extensively examined various approaches to credit risk measurement. McLean (2008) provides an overview of the evolution of credit risk measurement from subjective to quantitative methods between 2000 and 2007. Kao (2009) covers methodologies such as Altman Z-scores, statistical models, structural and reduced form models, and market implied models. Smith (2008) presents a non-technical review of credit derivatives and pricing strategies by Jarrow.

Van Deventer (2008) conducts an analysis of structural, reduced form, and hybrid models, suggesting the use of a multi-model approach that combines structural and reduced form models. Lleo (2009) delves into five key credit risk measurement tools, focusing on quantitative techniques, including credit migration, structural models, intensity models, actuarial approaches, and big portfolio models. Le Roux, Shinnawl, and Rubin (2010) compare traditional factor-based models with structural credit models, emphasizing the distinction between individual credits and credit portfolio modeling, as well as the importance of credit correlation.

Horan (2012) highlights the risk of underestimating extreme outcomes when default correlation is ignored in models, as discussed by Das, Fong, and Geng. Sullivan (2015) notes that structural models "underpredict defaults and yield spreads," based on the work of Leland. Phelps (2016) summarizes the discussion of the Merton model and reduced form models by Arora, Bohn, and Zhu, ultimately supporting the latter. Bernard and Chen (2017) investigate the interplay between regulatory requirements and risk management techniques of insurance firms, illustrating how neglecting these measures could undervalue liability contracts using a theoretical Merton model. Hui (2018) explores the challenges of modeling failures in mortgage-backed securities and the issues related to data reliability, which often lead to a preference for structural models over reduced form models.

The literature also extensively discusses risk factors and reduced form techniques. Boudreault and Gauthier (2019) present a hybrid credit risk model that considers the capital structure development of each company as well as the interconnectedness of insurers' assets and liabilities. Rosen and Saunders (2019) investigate portfolio risk contributions rather than individual issuers.

Finally, some publications offer cautionary insights regarding modeling. Klein et al. (2019) attribute a portion of the financial crisis to an overreliance on third-party credit ratings and advocate for more prudence. Schoolman (2018) emphasizes Wall Street and insurers' tendency to overestimate risks, especially with innovative products, and highlights the importance of including stressed scenarios in historical data and specialized stress testing. Derman (2019) warns against excessive reliance on models, pointing out that mistaking the model for reality can lead to future crises based on the misconception that people always conform to mathematical principles.

CHAPTER THREE

RESEARCH METHODOLOGY

3.0 Introduction

This chapter introduces the research procedures utilized, outlines the study's target audience, explains the sampling strategies used to establish sample size, and sheds light on the data gathering and analysis processes.

The study relied heavily on quantitative methodologies to attain its objectives. In this method, inferential statistics were critical in analyzing data correctness and confirming replies from study participants in accordance with the research goals.

3.1 Study Area

The study was carried out in Abuja, Nigeria's capital city, which is ideally placed in the country's center inside the Federal Capital Territory (FCT). Abuja, precisely built and predominantly constructed throughout the 1980s, formally took over as Nigeria's capital on December 12, 1991, displacing Lagos, while Lagos remains the country's most densely inhabited metropolis. According to the 2006 census, Abuja has 776,298 people, placing it among Nigeria's top ten most populated cities.

The planned city of Abuja has seen a major inflow of population, resulting in the formation of satellite towns such as Karu Urban Area, Suleja, Gwagwalada, Lugbe, Kuje, and smaller communities. Abuja's unofficial metropolitan area has a population of well over three million people, making it Nigeria's fourth-largest urban region, behind after Lagos, Kano, and Ibadan.

3.2 Research Design

The descriptive research design was used in this study. This choice was taken due to the need to highlight data features using frequencies and percentages. Because the research did not include data or variable manipulation, the descriptive design was the best option.

Other research design possibilities, such as causal and explanatory research designs, were examined but ultimately rejected owing to concerns that these alternatives may not deliver the exact results and data analysis desired in this study.

3.3 Population of the Study

The population under consideration for this study consists of employees of the African Alliance Insurance company located in Abuja. The total population for this study was composed of 32 respondents, encompassing officials from various departments within African Alliance Insurance Plc, including operations, finance, administration, and other relevant areas.

3.4 Population Size and Technique

Since the study had a relatively small population, and it was feasible to collect data from all available respondents, the researcher chose the census sampling technique. As a result, all 32 respondents, representing the entire population, were included in this study.

In terms of data collection, the primary method employed was the distribution of questionnaires to all 32 respondents within the organization. The responses to these questionnaires served as the primary source of firsthand data for this research. Furthermore, supplementary information was obtained from textbooks, journals, and other secondary sources to enrich the depth and breadth of the study's data.

3.6 Data Analysis

In this study, data analysis involved the utilization of various analytical tools and software. These tools included the creation of pie charts, bar charts, tables, and the use of Statistical Package for Social Science (SPSS) software.

The data collected were primarily subjected to analysis using the techniques of frequencies and percentages. These analytical methods were crucial in accurately depicting the true data characteristics and findings. Additionally, data interpretation and analysis were performed to elucidate the information presented in the tables and charts used throughout the study.

3.7 Limitation

As a descriptive research study, there are limitations in terms of validating data characteristics and variables. It's important to note that certain statistical tools like the arithmetic mean, variance, standard deviation, and the central limit theorem were not employed to further confirm the accuracy of findings in this research. Instead, the research relied on descriptive statistical tools such as frequencies and percentages to describe data characteristics and findings.

Consequently, the depth and comprehensiveness of data analysis may be constrained in comparison to studies that encompass a wider array of statistical techniques.

CHAPTER FOUR

DATA PRESENTATION, ANALYSIS AND INTERPRETATION

4.1 Introduction

This chapter focuses on the data presented, analyzed, and interpreted throughout the course of this investigation. The data is derived from completed surveys returned by respondents and is presented in tables. The Pearson correlation test is used in the study.

4.2 Presentation and Analysis

Table 4.1: Sex of respondents

	Frequency	Percent	Valid Percent	Cumulative Percent
Male	16	50.0	50.0	50.0
Female	16	50.0	50.0	100.0
Total	32	100.0	100.0	

Source: Field survey, 2023.

Table 4.1 summarizes the gender distribution among the respondents in this research. In the overall population, 16 respondents (50.0 percent of the sample) are male, while the remaining 16 respondents (50.0 percent of the sample) are female.

Table 4.2: Age grade of respondents

	Frequency	Percent	Valid Percent	Cumulative Percent
below 20 years	3	9.4	9.4	9.4
21-30 years	6	18.8	18.8	28.1
31-40 years	8	25.0	25.0	53.1
41-50 years	10	31.2	31.2	84.4
51-60years	5	15.6	15.6	100.0
Total	32	100.0	100.0	

Source: Field survey, 2023.

Table 4.2 summarizes the age distribution of the study's respondents. Three respondents, or 9.4 percent of the population, are under the age of 20. Furthermore, 6 respondents, or 18.8 percent of the population, are between the ages of 21 and 30.

Furthermore, 8 respondents, or 25.0 percent of the population, are between the ages of 31 and 40. The 41-50 year age group has 10 responses, accounting for 31.2 percent of the population, while the 51-60 year age group has 5 respondents, accounting for 15.6 percent of the population.

Table 4.3: Educational qualification of respondents

	Frequency	Percent	Valid Percent	Cumulative Percent
WASSCE/SSCE	4	12.5	12.5	12.5
OND/HND/BSC	10	31.2	31.2	43.8
PGD/MSC/PHD	10	31.2	31.2	75.0
OTHERS	8	25.0	25.0	100.0
Total	32	100.0	100.0	

Source: Field survey, 2023.

Table 4.3 contains information on the educational backgrounds of the survey participants. Four people, or 12.5 percent of the population, had an FSLC certification out of the total sample of 32 respondents. Ten respondents, or 31.2 percent of the population, had SSCE/WASSCE credentials. Another ten respondents, accounting for 31.2 percent of the population, had an OND/HND/BSC. Finally, 8 responders (21.0 percent of the population) had MSC/PGD/PHD degrees.

Table 4.4: Marital status of respondents

	Frequency	Percent	Valid Percent	Cumulative Percent
Single	10	31.2	31.2	31.2
Married	20	62.5	62.5	93.8
Divorced	1	3.1	3.1	96.9
Widowed	1	3.1	3.1	100.0
Total	32	100.0	100.0	

Source: Field survey, 2023.

The marital status of the individuals in this research is broken out in Table 4.4. Ten persons, or 31.2 percent of the total of 32 responses, are unmarried. In comparison, 20 respondents are married, accounting for 62.5 percent of the total. Furthermore, one respondent (3.1 percent of the population) is divorced, while another respondent (3.1 percent of the population) is widowed.

Table 4.5: Position of respondents

	Frequency	Percent	Valid Percent	Cumulative Percent
Junior staff	20	62.5	62.5	62.5
Senior staff	12	37.5	37.5	100.0
Total	32	100.0	100.0	

Source: Field survey, 2023.

Table 4.5, presented above, provides an overview of the positions or ranks held by the respondents who participated in this research. Out of the total of 32 respondents, 20 individuals, accounting for 62.5 percent of the population, occupy junior staff positions. The remaining 12 employees, making up 37.5 percent of the population, hold senior staff positions.

Table 4.6: Years of service of respondents

	Frequency	Percent	Valid Percent	Cumulative Percent
0-2 years	8	25.0	25.0	25.0
3-5 years	11	34.4	34.4	59.4
6-11 years	10	31.2	31.2	90.6
above 12 years	3	9.4	9.4	100.0
Total	32	100.0	100.0	

Source: Field survey, 2023.

Table 4.6 contains an overview of the study's respondents' years of work experience. 8 people, or 25.0 percent of the population, had 0-2 years of work experience out of a total of 32 replies. Furthermore, 11 responders (34.4 percent of the population) had 3-5 years of experience. Furthermore, 10 workers, accounting for 31.2 percent of the population, have 6-11 years of experience, while the remaining 3 employees, accounting for 9.4 percent of the population, have more than 12 years of experience.

Tables Based on Research Questions

Table 4.7: Credit facilities are readily made available to the insured

	Frequency	Percent	Valid Percent	Cumulative Percent
Strongly agree	10	31.2	31.2	31.2
Agree	15	46.9	46.9	78.1
Undecided	5	15.6	15.6	93.8
Disagree	2	6.2	6.2	100.0
Total	32	100.0	100.0	

Source: Field survey, 2023.

The replies given by the respondents about the availability of credit facilities to the insured are shown in Table 4.7. Ten respondents, or 31.2 percent of the sample, agreed strongly that insured people may easily acquire credit facilities out of the total 32 respondents. A total of 15 more respondents, or 46.8% of the population, agreed with this assertion. However, 5 respondents, or 15.6 percent of the population, were still unsure about their position. The remaining 2 respondents, or 6.2 percent of the population, disagreed with the idea that credit facilities are easily accessible to covered parties.

Table 4.8: Credit risk negatively affects insurance companies

	Frequency	Percent	Valid Percent	Cumulative Percent
strongly agree	10	31.2	31.2	31.2
Agree	8	25.0	25.0	56.2

undecided	1	3.1	3.1	59.4
Disagree	10	31.2	31.2	90.6
strongly disagree	3	9.4	9.4	100.0
Total	32	100.0	100.0	

Source: Field survey, 2023.

The participants' replies to the question of how credit risks affect insurance businesses are summarized in Table 4.8, which is seen above. Ten respondents, or 31.2 percent of the total, strongly agreed that credit risks had a detrimental effect on insurance firms. This represents a total of 32 respondents. 25.0 percent of the population, or another 8 respondents, also agreed with this assertion. Only 1 respondents, or 3.1% of the population, were still unsure about their position. On the other hand, 10 respondents, or 31.2 percent of the population, argued that credit risks had a detrimental impact on insurance firms. The last 3 respondents, or 9.4% of the population, vehemently disagreed that credit risks had a detrimental effect on insurance firms.

Table 4.9: Credit Risks Taken By Insurance Institutions Are High

	Frequency	**Percent**	**Valid Percent**	**Cumulative Percent**
Strongly agree	18	56.2	56.2	56.2
Agree	10	31.2	31.2	87.5
Undecided	2	6.2	6.2	93.8
Strongly disagree	2	6.2	6.2	100.0
Total	32	100.0	100.0	

Source: Field survey, 2023.

The replies given by the respondents on their view of large credit risks carried by insurance institutions are summarized in Table 4.9, which is seen above. Out of the 32 total responses, 18 people—or 56.2% of the population—strongly agreed that the credit risks that insurance organizations assume are really substantial. In addition, this remark was agreed with by 10 respondents, or 31.2 percent of the population. However, 2 respondents, or 6.2 percent of the population, were still unsure about their position. Contrarily, just 2 respondents, or 6.2 percent of the population, firmly disputed that insurance companies' credit risks are considerable.

Table 4.10: There are models that can help reduce these risks taken by insurers

	Frequency	Percent	Valid Percent	Cumulative Percent
strongly agree	15	46.9	46.9	46.9
Agree	10	31.2	31.2	78.1
undecided	3	9.4	9.4	87.5
Disagree	2	6.2	6.2	93.8
strongly disagree	2	6.2	6.2	100.0
Total	32	100.0	100.0	

Source: Field survey, 2023.

The answers of the participants considering the existence of models that may reduce the risks taken on by insurers are shown in Table 4.10. 15 respondents, or 46.9% of the population, strongly agreed that such models are actually accessible, according to the statistics. In addition, 10 respondents, or 31.2 percent of the population, said they agreed with this assertion. However, 3 respondents, or 9.4% of the population, said they were still unsure about their position. In contrast, 2 respondents, or 6.2 percent of the population, disputed that such models exist. Finally, the remaining 2 respondents, representing 6.2 percent of the population, strongly disputed that models capable of decreasing insurers' risks exist.

4.3 Hypotheses Test

Hypothesis 1

Ho: Credit risks negatively affect insurance companies.

Hi: Credit risks positively affect insurance companies.

Level of significance: 0.05

Decision rule: reject the null hypothesis if the p-value is less than the level of significance.

Table 4.11a: Test Statistics

	Credit Risks Negatively Affect Insurance Companies

Chi-Square	62.000[a]
Df	4
Asymp. Sig.	**.080**

a. 0 cells (.0%) have expected frequencies less than 5. The minimum expected cell frequency is 9.0.

Since the p-value (0.080) is less than the level of significance (0.05), we accept the null hypothesis and accept the alternative hypothesis thereby concluding that credit risks negatively affect insurance companies.

Hypothesis 2

Ho: Credit risks taken by insurance companies are low.

Hi: Credit risks taken by insurance companies are high.

Level of significance: 0.05

Decision rule: reject the null hypothesis if the p-value is less than the level of significance.

Table 4.11b: Test Statistics

	Credit Risks Taken By Insurance Companies Are High
Chi-Square	62.000[a]
Df	4
Asymp. Sig.	**.000**

a. 0 cells (.0%) have expected frequencies less than 5. The minimum expected cell frequency is 9.0.

Since the p-value (0.000) is less than the level of significance (0.05), we reject the null hypothesis and accept the alternative hypothesis thereby concluding that credit risks taken by insurance companies are high.

CHAPTER FIVE

SUMMARY OF FINDINGS, CONCLUSION AND RECOMMENDATION

5.1 Summary of Findings

The objectives of the study were to

1. To determine the optimal credit risk modeling methods tailored for life insurance companies.

2. To evaluate the impact of credit risks on life insurance firms.

3. To scrutinize the benefits associated with offering credit to life insurers.

4. To explore the relationship between extending credit and the performance of insurance companies.

5. To determine the accessibility of credit facilities to insurers in the market.

Findings from the study revealed the following

1. Credit facilities are readily made available to insurers.
2. There is a relationship between credit and performance of insurance companies
3. Credit risks negatively affect insurance companies.
4. Credit risks taken by insurance institutions are high
5. There are models that can help reduce the risks taken by insurers.

5.2 Conclusion

In summary, the research findings indicate a negative association between credit risk and the performance of Nigerian insurance companies between 2018 and 2022. Additionally, the study highlights that insurance companies in Nigeria assumed a considerable level of credit risk during the research period.

As a result, it is recommended that policymakers take proactive measures to formulate and enforce effective policies aimed at significantly mitigating the credit risk exposure of insurance firms in Nigeria. This strategic reduction is proposed to enhance and optimize the overall performance of insurance companies in the nation.

5.3 Recommendations

The study's findings yield the following recommendations:

1. Regulatory bodies must enforce stringent compliance with prudential regulations by insurance companies to uphold the highest standards.

2. Insurance companies should significantly diminish their exposure to credit risks and align their practices with international best standards.

3. Directors of insurance firms should manage their liquidity levels optimally, ensuring they can meet their customers' credit requirements. Simultaneously, they should avoid excessive liquidity that does not contribute significantly to the company's profitability. This strategic approach is vital for enhancing the profitability of insurance companies.

REFERENCES

Abdul Kader, H., Adams, M.B., & Hardwick, P. (2010). The cost efficiency of takaful insurance companies. *Geneva Papers on Risk and Insurance: Issues and Practice, 35*(1), 161-181.

Adams, M.B., & Buckle, M. (2003). The determinants of corporate financial performance in the Bermuda insurance market. *Applied Financial Economics, 13*(2), 144-143.

Adams, M.B., Hardwick, P., & Zou, H. (2008). Reinsurance and corporate taxation in the United Kingdom life insurance industry. *Journal of Banking and Finance, 32*(1), 101-115.

Akotey, O.J., Osei, K.A., & Gemegah, A. (2011). The demand for micro insurance in Ghana. *Journal of Risk Finance, 12*(3), 182-194.

Angove, J., & Tande, N. (2011). A business case for micro-insurance: An analysis of the profitability of micro-insurance for five insurance companies, Micro-Insurance Innovation Facility, International Labor Organization.

Arellano, M., & Bond, S. (1991), Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies, 58*(2), 277-297.

Arrow, J.K. (1963). Uncertainty and the welfare economics of medical care. *American Economic Review*, *53*(5), 941-973.

Baltagi, B.H. (2004). Panel data: Theory and applications, Physica-Verlag, Heidelberg. Blundell, R. and Bond, S. (1998), Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics, 87*(2), 115-143.

Bond, S.R. (2002), *Dynamic panel data models*: A guide to micro data methods and practice, Institute of Fiscal Studies, Cenmap Working Paper CWP09/02.

Cargill, T.F., & Troxell, T.E. (1979). Modelling life insurance savings: Some methodological issues. *Journal of Risk and Insurance*, *46*(4), 391-410.

Churchill, C. (2006). *Protecting the poor*: A microinsurance compendium, International Labor Organization.

Churchill, C. (2007). Insuring the low-income market: Challenges and solutions for commercial insurers, Geneva papers on risk and insurance: *Issues and Practice*, *32*(3), 401-412.

Churchill, C., Phillips, R.D., & Reinhard, D. (2011). Introduction to the 2011 symposium issue of JRI on microinsurance. *Journal of Risk and Insurance*, 78(1), 1-5.

APPENDIX

QUESTIONNAIRE ADMINISTRATION

INSTRUCTION: Please endeavor to complete the questionnaire by ticking the correct answer (s) from the options or supply the information required where necessary.

SECTION A: Personal Information/Data

1. Gender
   a. Male
   b. Female
2. Age grade
   a. Below 20yrs
   b. 21-30yrs
   c. 31-40yrs
   d. 41-50yrs
   e. 51-60yrs
   f. Above 60yrs

3. Educational qualification
   a. WASCE/SSCE
   b. OND/HND/BSC
   c. MSC/PGD/PHD
   d. Others
4. Marital status
   a. Single
   b. Married
   c. Divorced
   d. Widowed
5. Experience/years of service
   a. 0-2yrs
   b. 3-5yrs
   c. 6-11yrs
   d. Above 12yrs
6. Level/position

a. Junior staff
b. Senior staff

SECTION B:

Questions on credit risk modeling techniques for life insurers

7. Credit facilities are readily made available to the insured.
    a. Strongly agreed
    b. Agreed
    c. Undecided
    d. Disagreed
    e. Strongly disagreed
8. There is a relationship between credit and performance of insurance companies.
    a. Strongly agreed
    b. Agreed
    c. Undecided
    d. Disagreed
    e. Strongly disagreed

9. Credit risks negatively affect insurance companies.
    a. Strongly agreed
    b. Agreed
    c. Undecided
    d. Disagreed
    e. Strongly disagreed
10. Credit risks taken by insurance institutions are high.
    a. Strongly agreed
    b. Agreed
    c. Undecided
    d. Disagreed
    e. Strongly disagreed