CREDIT RISK MODELLING TECHNIGUES FOR LIFE INSURERS

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A PROJECT WORK SUBMITTED TO THE DEPARTMENT OF ACTUARIAL SCIENCE AND INSURANCE IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF BACHELOR OF SCIENCE (B.SC) HONOURS DEGREE IN ACTUARIAL SCIENCE, UNIVERSITY OF BENIN, BENIN CITY.

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DECLARATION

I, Ovie David EKPAIYO, do hereby declare that this project is entirely my work and composition. The work embodied in this project has not been submitted in candidature for any degree and is not concurrently being submitted for any other degree. All references made to works of other persons have been duly acknowledged.

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Ovie David EKPAIYO	**DATE**

CERTIFICATION

This is to certify that this project work was submitted by **Ovie David EKPAIYO**, to the Department of Actuarial Science and Insurance, Faculty of Management Sciences, University of Benin, Benin City, in partial fulfillment of the requirements for the award of a Bachelor of Science (B.Sc) Degree in Actuarial Science.

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DEDICATION

This project work is dedicated to God Almighty for His unfailing hands that held me throughout, unmerited grace and unflinching love. I also dedicate this project work to my parents Mr. & Mrs. EKPAIYO and my siblings.

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ABSTRACT

The research looks at how Nigerian life insurance policies are affected by the credit risk modeling approach. From 1995 to 2023, time series quarterly data were obtained from the World Bank Financial Development Database and the CBN statistics bulletin. The multiple regression methods known as Ordinary Least Square (OLS) and General Least Square (GLS) were used. Among other things, the results show that Nigeria's renew life policy is significantly impacted by the human development index. In Nigeria, government spending on health has a big impact on the renew life policy. Nigeria's renew life policy is significantly impacted by life expectancy. Nigeria's renew life policy is not significantly impacted by the rate of inflation. Nigeria's renew life policy is not significantly impacted by the exchange rate. The research comes to the conclusion that life expectancy, government health spending, and the human development index are important factors that influence Nigeria's renew life strategy.

CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

The importance of credit risk approach modeling is difficult to overestimate or underestimate. Credit risk, as defined by Abiola and Olausi (2014), is the likelihood that the debtor will not be able to repay the loan when it matures. Credit risk models, according to Abdulrahim (2013), are mathematical instruments used to evaluate the loss distribution and potential default probability of loan portfolio values. This research will look at the factors influencing the credit risk modeling methods used by life insurers in Nigeria, the most developed nation in sub-Saharan Africa. The risk of loan default caused by a borrower's incapacity to make required payments is known as credit risk. Risks for last-resort lenders include higher collection costs, interrupted cash flows, and lost principle and interest. The loss may be total or partial, depending on the circumstances (Abdou, Muslem & Ismal, 2014).

In the financial industry, risk modeling is done in a very different way depending on the mix of risks that a particular financial organization faces. Unfortunately, studies show that many financial institutions struggle to control the range of risks and variables that might affect them (Lambert & Cooper, 2000). When it comes to credit risk, this is especially crucial since financial institutions could struggle to understand the risks associated with a single loan or investment as well as the total credit risk levels in their portfolios (Alshatti, 2015). This is a crucial problem as poor credit risk assessment practices may negatively impact a financial institution's financial performance and perhaps lead to liquidity issues (Epure & Lafuente, 2015). Similar situations have occurred in other businesses, when a company's financial situation has become perilous due to a lack of knowledge about the various risks connected to loans and investments, as well as the overall credit risk in the portfolios.

Life insurance may be available to those with low incomes. According to LIMRA's 2020 Insurance Barometer Study, 54% of individuals globally own life insurance of some kind. Over 135 million people worldwide already have life insurance policies, and growth rates in some emerging nations may reach as high as 10% per year (Yang, 2012). However, Yang (2012) claims that just 2% to 3% of the potential market is represented by these life insurance contracts. Life insurance is being discussed more and more as a formalized risk management strategy to fight global poverty and as a major driver of economic growth and entrepreneurial development in low-income countries like West Africa because it shields low-income groups from the vulnerability of losses and shocks (Churchill, Phillips & Reinhard, 2011).

Some of the world's leading banks have developed intricate systems to evaluate and aggregate credit risk across product lines and geographical areas throughout the last ten years. Interest in credit risk models was first sparked by the need for more accurate mathematical estimates of the amount of economic capital needed to finance a bank's risk-taking operations. As credit risk models' outputs have become more prominent in the risk management operations of major financial institutions, there has also been an increase in interest in the question of whether they are suitable for supervisory and regulatory reasons (Adeusi, Akeke, Adebisi & Oladunjoye, 2013). According to Aizenman, Jinjarak, Lee, and Park (2016), this research demonstrated the variety of approaches used in the model-building process as well as the internal uses of the models' productivity.

Additionally, this study will highlight a number of shortcomings and restrictions with current modeling approaches. The development of modeling tools and the ensuing improvements to the precision and comprehensiveness of credit risk assessment are especially desired from a supervisory standpoint (Waemustafa & Sukri, 2015). These changes in risk management may be discovered by supervisors conducting federal inspections of banks' internal controls and risk management procedures (Weill, 2011). From a regulatory perspective, banks will be less likely to participate in regulatory capital arbitrage if models are able to adapt to shifts in the economy and improvements in financial products. According to Yegon, Cheruiyot, Sang, and Cheruiyot (2014), a model-based approach may also provide credit risk assessments that more accurately reflect the makeup of each bank's portfolio and align capital needs with the perceived riskiness of underlying assets. Before permitting the use of portfolio modeling methodologies in the formal phase of setting regulatory capital requirements, regulators must make sure that the models are not only conceptually sound, empirically tested, and produce comparable capital requirements across the institution, but also that they are well integrated with the day-to-day credit risk management of financial institutions.

1.2 Statement of the Research Problem

There are many misconceptions about Nigeria's credit risk for life insurers, including its definition, the most effective modeling techniques, how it benefits life insurers, and—above all—how it affects the country's socioeconomic development. the misunderstanding between the financial institution and the insurers themselves on how to reduce the cost of financing life insurance (World Bank, 2016). Giving them credit has also been a concern since the majority of insurers believe such credit has not been justified. Because financial organizations face high operational financial risks, credit risk approach modeling is especially important in the financial industry (Bouteille & Coogan-Pushner, 2012). This study only examines credit risk processes since many scholars and researchers believe that they are the primary factor affecting the stability of financial institutions (Gill & Willey, 2011; Carling & Bloomfield, 2007). Additionally, they imply that poor credit risk modeling might lead to significant losses and perhaps bankruptcy.

Notably, a few of financial institutions continue to see credit risk management as an auxiliary responsibility (Abiola & Olausi, 2014). This makes it more difficult for financial institutions to evaluate, quantify, and reduce credit risk.

The financial crisis, which was brought on by a growing awareness of the significance of errors in credit risk approach modeling, resulted in credit losses for almost all of the nation's leading financial services companies (Blundell-Wignall & Atkinson, 2008). It demonstrates the importance of this study's investigation of the relationship between life insurance coverage and credit risk modeling techniques. to add to the corpus of existing information and provide further light on the function of credit risk modeling in insurance companies in Nigeria.

1.3 Research Questions

1. What is the relationship between the human development index and Nigeria's policy laps ratio?
2. How does Nigeria's policy laps ratio relate to life expectancy?
3. How do government spending on health and Nigeria's policy laps ratio relate to each other?

1.4 Objectives of the Study

The main goal of this study was to investigate how Nigeria's policy laps ratio was affected by the credit risk modeling approach. The particular objectives of the study are to:

1. Ascertain the relationship between Nigeria's policy laps ratio and the human development index.
2. Examine the relationship between life expectancy and Nigeria's policy laps ratio.
3. Analyze the effect of government health spending on Nigeria's policy laps ratio.

1.5 Research Hypotheses

The following hypotheses are presented in their null form in order to examine the connection between the study's variables:

Ho1: The human development index has no discernible impact on Nigeria's policy laps ratio; Ho2: The policy laps ratio has no discernible effect on life expectancy; and Ho3: There is no discernible relationship between government health spending and Nigeria's policy laps ratio.

1.6 Scope of the Study

This research examines how policy laps in the Nigerian insurance market are impacted by credit risk modeling. It takes place from 1995 until 2023. The study's findings are thus limited to the region it examined. Since the primary industry's primary responsibility is to safeguard all other sectors from danger, the insurance industry is taken into consideration. They are one of the prosperous companies in Nigeria's financial services industry.

1.7 Significance of the Study

For insurance companies to control the credit risks related to life insurers, this research would be essential. This study's explanation of the connection between loans and profitability might also be helpful to Nigerians. The assessment of the most effective credit risk modeling techniques for life insurers will be advantageous to the government and insurance stakeholders. This study will be essential for insurers to determine the most effective way to pay back their loans or credits. Thus, the goal of the research is to examine how credit risk modeling approaches affect and cause problems for life insurers in Nigeria. The findings will serve as a basis for lawmakers and opinion leaders to draft and enact laws that address the credit risk modeling issues affecting the nation's life insurance market. Once again, this research endeavor will serve as a roadmap for other studies.

1.8 Limitation of the Study

This analysis of credit risk modeling techniques for life insurers uses the Nigerian insurance industry as a case study. For life insurance, it aims to provide the public and government with a framework for evaluating the effect, identifying, and preventing credit risk modeling issues, as well as handling them when they do occur. Despite the fact that credit risk modeling is linked to a number of issues, this research will solely examine the approaches used by life insurers with the Nigerian Insurance Corporation.

1.9 Organization of the Study

The structure or framework of the research inquiry consists of five chapters. The study's background, problem statement, goals, research questions, research hypotheses, relevance, scope, and definitions of relevant terms are all presented in Chapter 1. An outline of the body of existing literature on the subject is provided in the next chapter, chapter 2. This section will examine the effects, financing, competitive strategy, and issues of credit risk modeling methodologies for life insurers operating in the Nigerian market. The third chapter of this study will look more closely at the research method or approach that was used. The demographic under investigation, sample size, data gathering procedure, analysis, and research technique are all covered. Chapter 4 will include the data analysis and conclusions from the field survey conducted for the project, which concentrated on credit risk modeling techniques for Nigerian life insurers. A thorough explanation of the study question, its conclusion, and recommendations based on the results will round off chapter five.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

The main goal of this chapter is to examine important studies on credit risk modeling. We'll look at credit risk models, risk neutral valuation, and the concept of credit risk. Both theoretical and empirical literature are considered in this field.

2.2 Conceptual Framework

From the perspective of the banking industry, financial institutions face a number of risks. Fekri Ali and Shawtari (2015) define these risks as exposure, investment, operational, strategic, credit, and market risks. According to Bouteille and Coogan-Pushner (2012), each of these threats has unique problems, and recognizing and evaluating them may differ significantly from conventional risk management. According to Bouteille and Coogan-Pushner (2012), credit risk is the potential for financial loss as a result of a counterparty's incapacity, reluctance, or tardiness in fulfilling a financial commitment (Dionne, 2013). World War II saw the beginning of credit risk research, which is crucial since any significant borrower failure might cause a catastrophe for both individual banks and whole financial institutions (Waemustafa & Sukri, 2015). According to Livshits (2015), this is especially relevant in light of the rise in personal bankruptcies, the cyclical nature of consumer credit, and the growing influence of new information technologies.

It is acknowledged that there are two primary causes of credit risk losses (Saunders & Cornett, 2014; Bekhet & Eletter, 2014). The incapacity of obligors to fulfill their financial commitments is one of the reasons a thorough risk assessment is necessary (Gill, 2011). According to Chen (2016), a risk assessment that uses real business characteristics to evaluate the likelihood of credit loss is considered successful. Businesses often borrow money to finance their expansion goals, but their cash flows may not be sufficient to reimburse the lender (Laeven & Levine, 2009). Organizations whose revenues are less than their operational and financial expenses may also be linked to the most prevalent sources of credit risk (Boahene, 2012). However, nonpayment by an obligor as a result of business disputes about the legitimacy of a contract is one of the less frequent reasons for credit risk losses (Alsaeed, 2005). In any case, credit risk management is strategically important to financial institutions because it helps bank managers identify circumstances that may lead to a loss of capital. However, managers themselves are a significant source of risk, as shown by Dias' (2015) agency-driven study of the growth and decline of the CDS market. Bank-specific behaviors like poor lending practices, ignorance about borrowers, lax credit assessment, and insufficient credit regulations may also impact the institution's risk level, even though credit risk is based on a creditor's ability and willingness to pay (Waemustafa & Sukri, 2015). The next section discusses the specific actions that financial institutions may take to control their level of credit risk.

2.2.1 Credit Risk Models

In the previous part, we discussed the outcome variables that are included in the corpus of modern credit risk research models. It would make more sense to use their modeling method to evaluate the articles. The three fundamental categories of structural models, portfolio reduced-form models, and individual-level reduced-form models are presented in this section. According to these models, defaults happen when intensity-based latent variables fall below a threshold value, and incomplete accounting and market data limit thorough observation of latent variables (Allen, 2004). To create this kind of model, both structural modeling and reduced-form modeling frameworks are used. However, we categorized this model type as a subset of portfolio reduced form models, which we call the factor model, in order to conduct an effective evaluation.

2.2.2 The Method of Risk-Neutral Appraisal

The DCCF technique is simple to understand and use, even if it does not exactly follow contemporary finance theory. In general, the same discount rates apply to all loans made to businesses with the same internal risk rating (EDF). Therefore, as long as the business has not defaulted as of the planning horizon, the predicted LGDs of the loans have no effect on the future values of its liabilities. Senior and subordinated loans to the same company would have the same future discount price, regardless of differences in the anticipated recovery in the case of a future collapse. Moreover, finance theory states that an asset's value is determined by how closely its return resembles the market's. Even if two businesses are not equally vulnerable to other systemic issues or the economic cycle, DCCF lends to them at the same discount rates.

To overcome these obstacles, the RNV technique uses a structural model of business value and insolvency that is based on Robert Merton's work. This idea states that a company goes into default when the value of its underlying assets drops below what is required to settle its debt. Instead of discounting contractual payments, the RNV technique does so for contingent payments. If a payment is legally due on date t and the company hasn't fallen behind by then, for instance, the lender will only collect the agreed-upon amount. The lender will get 1-LGD, or a portion of the loan's face value, if the borrower defaults on day t; if the borrower defaults before that day, the lender will not receive any compensation. Thus, a loan may be seen as a group of derivative contracts, contingent on the underlying value of the borrower's assets. The loan's value is the total of the present values of various derivative contracts. The discount rate applied to the contingent cash flows of the contracts is calculated using the risk-neutral pricing measure and the risk-free term structure of interest rates.

The risk-neutral pricing measure may be thought of as an adjustment to the probability of borrower default at each horizon to account for the market risk premium associated with the borrower's default risk. The amount of adjustment needed depends on the expected return and the volatility of the borrower's asset value. If the Capital Asset Pricing estimate (CAPM) framework is used to estimate the asset return, the expected return may be described in terms of the market expected return and the firm's relationship to the market. Thus, in accordance with conventional finance theory, the pricing of loans under RNV examines not just the borrower's EDF and LGD but also the link between borrower risk and systemic risk.

2.2.3 The alleged advantages of credit risk models

When evaluating banks' credit risks, geographic regions and product categories are often taken into account. Credit risk models provide firms with a framework for effectively analyzing this risk by integrating data on foreign exposures and evaluating both the absolute and marginal contributions to risk. These model attributes may enhance a bank's overall capacity to recognize, evaluate, and control risk. Since credit risk models provide estimates of credit risk (such as unexpected loss) that take into consideration the makeup of each individual portfolio, they could be a more accurate representation of concentration risk than non-portfolio approaches. By definition, company lines, credit quality, market conditions, and the overall state of the economy may all affect and have an influence on models. Consequently, the modeling approach may provide a more knowledgeable and flexible risk management tool.

Additionally, models may offer: (a) an incentive to improve systems and data collection efforts; (b) a better comprehension of how to establish limits and reserves; (c) more accurate pricing based on performance and risk, which may result in more transparent decision-making; and (d) a more solid basis for economic capital allocation. From the perspective of a supervisor, the advancement of modeling techniques and the resulting improvements in the uniformity and rigor of risk management procedures pertinent to specific segments of banks' credit portfolios are also highly desired. Compared to the Capital Accord's current methodology, a models-based approach would more accurately match capital needs with the perceived riskiness of underlying assets and portfolio concentrations. As a result, it might provide a more thorough analysis of capital needs for credit risk and more effective capital allocation throughout the financial system. Additionally, banks may be less likely to participate in regulatory capital arbitrage if models are able to adapt to shifts in the economy and advancements in financial products. Although the aforementioned arguments highlight the advantages of the modeling process, a few key issues need to be resolved before a modeling method can be taken into consideration for use in the context of regulatory capital requirements. A description of these difficulties follows.

2.2.4 Management of Credit Risk and Profitability

A bank's credit portfolio management must be robust and effective in order to reduce financial loss and guarantee long-term competitiveness (Bekhet & Eletter, 2014). By focusing on credit risk management, financial institutions may maintain or improve their performance (Bouteille & Coogan-Pushner, 2012). Nevertheless, considering the wide range of performance metrics, it is critical to identify the most objective approaches for evaluating organizational performance in the banking industry. A company's profitability is determined by its capacity to generate a profit relative to its associated expenses over a certain time period, according to Bouteille and Coogan-Pushner (2012). Along with profitability, return on equity (ROE) is acknowledged as one of the most crucial aspects of a financial institution's success (Carbo & Rodriguez, 2007). In low-margin industries like financial services, cutting losses is a crucial profitability metric. The majority of a financial institution's income comes from service fees (Lepetit, 2008). An additional 5% comes from interest a bank receives on its assets (Boahene, 2012). However, interest paid on liabilities is a bank's biggest expense (Abor, 2005).

Despite not being included as one of the costs of banks by Laeven and Levine (2009), credit risk poses a serious threat to a financial organization's ability to operate or even to survive. Fathi (2012) and Gheeraer (2014) assert that credit risks have the potential to cause significant losses and ultimately insolvency. Despite the fact that credit risk poses a significant danger to an organization's performance and existence, many scholars and researchers maintain that it is manageable (Gill, 2011; Olamide, 2015; Kurawa & Garba, 2014). By understanding its fundamental origins, credit risk may be anticipated and effectively managed (Hassan, 2009). However, it's important to remember that credit risk is a result of human behavior and unforeseen events that may result in dangerous situations. Because of this, it is not always possible to properly assess risks and implement strategies to reduce or completely eradicate financial losses (Kane, 2010). Return on equity is another performance metric often used by commercial banks to evaluate organizational success (Carbo & Rodriguez, 2007). Return on equity, or ROE, is the ratio of a bank's net income returned to shareholder equity. This statistic makes it simple to assess a financial organization's performance by revealing how much profit it generates from the capital invested by its shareholders (Bekhet & Eletter, 2014). The company cannot operate efficiently with a high enough ROE if management owns an excessive amount of equity capital. However, having a large quantity of borrowed money is likewise considered unfavorable (Kolapo, 2012). Ahmad and Ariff (2007) contend that debt may increase risk if it is unable to withstand monetary losses. Accordingly, a bank's ability to control credit risk and hold onto a sizable amount of equity capital may be crucial to its long-term survival in a highly competitive market (Bouteille & Coogan-Pushner, 2012). However, banks are inherently contradictory since they tend to be less profitable when they have a larger capitalization (Goddard, 2010).

Return on assets (ROA) is one profitability metric that is often used in the financial literature nowadays (Greuning & Bratanovic, 2003; Fathi, 2012). This figure illustrates a financial institution's profitability relative to its total assets (Bonin, 2005). ROA makes it simple to gauge how well a business's management uses its assets to generate revenue. When compared to its available capital, a financial services company with a higher ROA has made more money (Sundarajan, 2007). Alkhatib and Harsheh (2012) used ROA as the primary performance metric to examine the financial performance of five Islamic banks. They discovered a strong positive correlation between the size and ROA of the financial institutions. However, it has also been said that organizational structure is one of the main factors influencing ROA in the banking industry (Singh, 2015). Due to their sometimes convoluted and bureaucratic organizational structure, major banks find it difficult to use an efficient credit risk assessment approach (Ramachandran & Gavoury, 2011). This theory holds that organizational size and structure have a significant impact on the banking sector's capacity to effectively manage credit risk.

2.2.5 Evaluation of Credit Risk

Credit risk may be analyzed using three different theories: portfolio theory, information theory, and arbitrage pricing theory (Gakure, 2012). The first, portfolio theory, has already been effectively integrated into the banking industry's risk assessment process (Abor, 2005). Many firms use value-based risk models to manage their exposures to interest and market risk (Mutua, 2015). It is not often acknowledged that portfolio theory may be used to identify and evaluate credit risk, despite the fact that credit risk is thought to be the most detrimental to financial institutions' performance and profitability (Idode, 2014). The current research uses profitability as the primary indicator of organizational success in the financial sector to evaluate how credit risk management strategy affects the performance of commercial banks in the United Arab Emirates and the United Kingdom. The limits of profitability are one crucial metric to understand. According to Thakor (2015), estimates of banker skill levels fluctuate with the economic cycle, indicating that structural issues, not agency, influence profitability.

The banking industry has already examined credit risk on an asset-by-asset basis (Jones & Perignon, 2013). Although each company uses a different strategy, this method usually involves regularly assessing the quality of credit exposures using a credit risk rating (Ramona, 2011). This approach might help risk managers identify patterns in their portfolio or changes in an individual's credit standing more quickly (Bouteille & Coogan-Pushner, 2012). Using this information, managers make the appropriate decisions to improve credit monitoring and make it more thorough and effective (Abiola & Olausi, 2014). The asset-to-asset approach still plays a little part in assessing and managing credit risk, despite the fact that many scholars believe it to be the most important element. The main complaint is that when using the asset-to-asset strategy, risk managers do not fully understand portfolio credit risk (Boahene, 2012). Furthermore, this approach makes estimating unforeseen losses challenging. Quantitative evaluations must be included in this approach to increase the effectiveness and efficiency of the credit risk assessment process (Margrabe, 2007).

Ross's (1976) theory of arbitrage pricing offers an intriguing method for examining credit risk. via departing from the risk vs return argument, the researcher took full use of the concept of pricing via arbitrage (Gakure, 2012). This idea states that managers should calculate the covariance of returns between each pair of a company's assets in order to assess the advantages of diversity (Kauko, 2012; Ross, 1976). Although practitioners may encounter difficulties when using this method, the idea advises managers to investigate a range of factors that might affect the assets being examined (Bouteille & Coogan-Pushner, 2012).

Morris (2001) got around this problem and reached the same conclusions by evaluating the correlation between each asset and a wide market index. However, it is important to remember that this process is far slower than Ross's (1976) approach. Furthermore, hazards are difficult to understand, quantify, or even control. Morris's (2001) approach is not very successful in reality as it is hard to account for every potential risk. Furthermore, according to Shawtari (2015), market indices are average values that may vary significantly based on the circumstances of each person.

According to information theory, financial institutions should screen borrowers to identify credit issues and take proactive measures to reduce these risks (Derban, 2005). Obtaining reliable information on potential borrowers is a key factor in assessing how effective appropriate screening is (Gill, 2011). It's important to remember that integrating quantitative and qualitative approaches may help practitioners evaluate credit risk more successfully. By using these strategies, financial institution managers may reduce processing expenses and subjective assessments (Greuning & Bratanovic, 2003). Furthermore, to identify factors that raise the probability of default and weed out troublesome loan applicants, quantitative models of credit risk assessment may be used (Tabari & Emami, 2013). Gill (2011) asserts that a significant barrier to the use of qualitative models is their subjective character. It is difficult to accurately evaluate credit risk using just qualitative evaluation techniques due to the complexity of financial linkages (Morris, 2001). Risk managers should evaluate market volatility, competitor activity, regulatory requirements, and complex demands when assessing a bank's exposure to credit risk (Greuning & Bratanovic, 2003). Financial institutions must effectively identify, access, and manage their risks by combining qualitative methods with quantitative analytical tools.

The fundamental theoretical foundation for the investigation and analysis is information theory. The majority of the credit risk assessment strategies and methods discussed in this research use statistical inference to find important connections for decision-making, which supports this approach (Shawtari, 2015). Other strategies, such stress testing and branch manager inspections, however, rely on an assessor's comprehension of a specific credit circumstance (Tabari & Emami, 2013). Recently, credit risk modeling in the insurance industry has received special attention from scholars and academics (Misman, 2015). Due to their importance to regulatory bodies and financial institution management, the factors that affect credit risk have attracted a lot of research (Olamide, 2015). Studies on credit risk management in the banking industry fall into two main categories. According to the first group, the main factors influencing credit risk include a variety of attributes, such as capital, loan quality, loan growth, and management size and quality (Abor, 2005). Macroeconomic variables, including GDP, interest rates, and unemployment, make up the second category of variables that affect the credit risk of financial firms. Notably, the majority of earlier research on credit risk in the banking industry used either macroeconomic or bank-specific variables to explain bank performance (Psillaki, 2010).

By attempting to determine the factors that influence credit risk in Greece's banking system by taking into account both internal and external variables, Louzis (2012) got over the aforementioned constraint in their empirical investigation. Credit risk is substantially explained by macroeconomic factors such as GDP, interest rates, and unemployment rates, claims Louzis (2012). Internal factors such bank size, loan quality, loan growth, and capital and management quality, however, did not seem to have any discernible impact, according to the study. In contrast to Louzis (2012), Misman (2015) focused on Islamic financial institutions and argued that both internal and external factors affect Islamic banks' credit risk. More specifically, the researchers argued that the quality of funding provided by Malaysian banks was the most important internal factor influencing their credit risks (Misman 2015). These results indicate that Islamic banks must increase their loss provisions in response to any decline in the quality of their funding, which raises their credit risk (Hussain & Al-Ajmi, 2012). However, further study is required in this area since little is currently understood about how credit risk assessment functions in Islamic financial organizations.

2.3 Review of Modeling

In the financial literature, technique assessments are becoming more and more common. McLean (1998) illustrates how credit risk assessment methods evolved from subjective to quantitative between 1977 and 1997. Kao (1999) describes many tactics, including market implied models, Altman Z-scores, statistical models, default-based and transition-matrix-based structural and reduced form models, and others. Smith (1998) states that Jarrow provides a thorough explanation of credit derivatives and pricing strategies. In order to evaluate structural and alternative implementations of reduced form models, Van

Deventer (2005) adopts a multiple model approach. He analyzes structural, reduced form, and hybrid models using the Receiver Operating Characteristic Accuracy Ratio. Five major ways to measuring credit risk are examined by Lleo (2009): huge portfolio models, structural models, intensity models, credit migration, and actuarial approaches. Here, we also examine a number of quantitative methods. Le Roux, Shinnawl, and Rubin (2003) compared structural credit models, particularly the Merton (1974) model, with traditional factor-based models. They also draw attention to the controversial link between credits and the fundamental distinction between a portfolio of credits and individual credits. Horan (2002) states that Das, Fong, and Geng conclude that the likelihood of extreme occurrences would be exaggerated if the correlation of defaults—and hence the skewness and kurtosis of the loss distribution—were disregarded. Leland concludes that the structural models in issue underpredict yield spreads and defaults (Sullivan, 2005). Phelps (2006) summarizes Arora, Bohn, and Zhu's consideration of the Merton model, Vasicek-Kealhofer, and a simplified form model by Hull-White. The Merton model performs worse than the other two, the research found. Using a theoretical Merton model, Bernard and Chen (2007) investigate the relationship between an insurance company's various risk management strategies and regulatory requirements. They conclude that low market value liability contracts will disregard risk management strategies. Hui (2008) talks on the challenges of predicting defaults on mortgage-backed securities (MBS) and issues with historical data. In fact, the main rationale for selecting structural models over reduced form models is concerns about the dependability of the data. There are more safety concerns and fewer formalities. According to Boudreault and Gauthier's (2010) multi-name hybrid credit risk model, each company's default is closely related to how its capital structure changes over time, how insurers' assets and liabilities are interconnected across businesses, and any potential ripple effects. Instead of focusing on specific issuers as has been done in the past, Rosen and Saunders (2010) use risk categories to examine the contributions to a portfolio's risk.

Several studies warn against relying too much on models, concluding that if we accept a future disaster based on the assumption that people follow mathematical principles, we are essentially conflating the model with reality. Schoolman (2008) asserts that insurers and Wall Street tend to underestimate risk, especially when it comes to new, innovative securities; Klein (2009) believes that companies and regulators relied too much on third-party credit ratings, which caused the financial crisis (Deventer, 2012); and he warns that specific stresses (especially on correlation assumptions) should be included in model reviews and historical data.

2.4 How Credit Risk Modeling Assessment Techniques Affect Organizational Performance and Profitability

Empirical research has examined the relationship between credit risk assessment methods and organizational profitability. An important paper in this area is Gakure (2012), which attempts to measure how credit risk detection and assessment affect the organizational performance of financial institutions. They found that risk assessment and identification had an effect on the performance of the financial institutions after gathering primary data from 39 management individuals at different levels of commercial banks, including middle- and top-level managers (Gakure, 2012). The results also shown that branch manager inspection, financial statement analysis, standardization, credit scoring, and risk assessment all had a statistically significant influence on the performance of unsecured bank loans (Gakure, 2012). However, it should be critically noted that although the researchers paid minimal attention to risk identification, Gakure (2012) put a major emphasis on alternative risk management stages, such as risk analysis, risk assessment, risk monitoring, and credit approval. These results, however, are somewhat in line with those of Al-Tamimi and Al-Mazrooei (2007), who discovered that the most important techniques for assessing risk in Islamic financial organizations were risk surveys, financial statement analysis, physical inspections by middle management, and bank risk manager inspections.

Similar conclusions are also supported by research by Alshatti (2015), who examined the impact of credit risk management on the financial performance of insurance companies. He discovered a statistically significant relationship between non-performing loans and bank financial performance as assessed by return on equity and return on assets, the two main profitability criteria. Abdelrahim (2013) further supports this by finding that the performance of Nigerian financial institutions was positively impacted by gross and non-performing loans. Nevertheless, Alshatti (2015) failed to discover any link between the capital adequacy ratio, credit interest, and the profitability of Islamic financial institutions. This specific outcome, however, is not the same as that of Kurawa & Garba (2014), who claim that credit risk management, as measured by capital adequacy, has a positive impact on organizational performance in the context of Nigerian financial institutions. Similarly, Berrios (2013) used profitability indicators such as ROE and ROA to analyze data from 200 financial institutions and discovered that the more banks lend their financial assets to borrowers, the more exposed they are to credit risk. Thus, the demand for effective risk management assessment approaches rises during times of financial volatility (Goddard, 2004). At the same time, Lee (2000) thought that by guaranteeing higher provisions or making provisions for loan losses, banks might better manage credit risk. Not all banks, nevertheless, could have the resources needed to do these tasks successfully (Margrabe, 2007). Berrios (2013) limited his study of the connection between credit risk management and bank profitability to the present global financial crisis, when banks were more vulnerable to credit risks (Lambert & Cooper, 2000). Changes in consumer disposable income, currency rates, and governmental tax legislation are the causes of this (Boahene, 2012). Therefore, the findings of Berrios (2013) do not fully apply to modern European and Islamic financial institutions. Other scholars, however, think that the recent changes in oil prices and the geopolitical environment signal the beginning of a new, long-lasting crisis (Margrabe, 2007). Furthermore, there is little probability that the findings may be extrapolated to the UK since Berrios (2013) exclusively examined financial businesses with American headquarters. The design, operations, and banking institutions of the financial systems in the United States and the United Kingdom really differ greatly (Beck, 2012). However, given how quickly internationalization and globalization are taking place, it seems that these differences are changing and losing their significance over time (Booth, 2001). The primary competitive challenges that the US and UK financial systems have had to contend with over the last ten years include heightened competition, financial market innovation, and regulatory changes (Amarjit, 2011). Despite the government's adoption of certain regulatory changes in response to the present economic crisis, the Nigerian financial system is still seen as susceptible to disruption (Rieck & Schuknecht, 2018).

Unlike the previously mentioned publications, Hosna (2009) investigated the connection between credit risk management and profitability in commercial banks in a European country. Similar to Kurawa and Garba (2014) and Alshatti (2015), they utilized ROE as the main profitability measure; however, they omitted ROA because the risks connected to the mentioned assets were not taken into consideration by this approach of evaluating credit risk (Ruziqa, 2013). According to research, banks with active capital usage have higher ROEs (Parramore & Watsham, 1997), and rising ROEs might be a sign of greater risk (Kabir, 2015). Because it demonstrates that financial firms reinvest their revenues to create future profit, the usage of ROE makes logical (Alessandri & Drehmann, 2010). Hosna (2009) asserts that an organization's profitability is impacted by credit risk management. The researchers discovered that a bank's approach to credit risk assessment had a considerable impact on its level of profitability. These findings, however, are not applicable to all banks since their capital adequacy ratio and non-performing ratio do not define ROE (Khediri, 2015). Stated differently, the profitability of financial institutions may be impacted by the substitute for ROE predictors. The fact that Hosna (2009) only used two independent variables to forecast ROE should be noted since this might compromise the reliability and validity of their findings. On the other hand, Samy and Magda (2009) used 15 parameters to determine how capital constraints affected bank performance. According to the study, financial companies are more profitable when they have higher capital requirements. Therefore, by adding more parameters, Hosna (2009) could have improved the regression model's predictive ability. Despite all of the differences between Islamic and conventional banking, Hosna (2009) and Kurawa and Garba (2014) found that credit risk management, as measured by capital adequacy, has a positive effect on a bank's organizational performance. Neither team of researchers, however, was able to identify any specific techniques for assessing credit risk that would affect the primary aspects of bank profitability.

2.5 Allocation of Economic Capital to Credit Risk

2.5.1 Credit loss probability density function

Many large, sophisticated banks use an analytical framework that connects the total amount of economic capital required for credit risk to the probability density function of credit losses (PDF) of their portfolio, which is the main output of a credit risk model, in order to estimate the amount of economic capital required to support their credit risk activities.

In general, a portfolio with a model that has a comparatively long and fat tail is considered hazardous. The amount of credit loss the bank would anticipate experiencing on its credit portfolio during the selected time horizon is shown by the projected credit loss, which is represented by the vertical line on the left. A measure of unexpected credit loss—that is, the amount by which actual losses surpass the predicted loss—is often used by banks to represent the risk of the portfolio. One of the main features of a PDF is that the chance of credit losses surpassing a certain amount X (along the x-axis) is equal to the area under the model to the right of X.

Similar to the value at risk (VAR) techniques used to allocate economic capital against market risks, the necessary economic capital for credit risk is the anticipated amount of economic capital needed to sustain a bank's exposure to credit risk. This is done to ensure that the goal bankruptcy rate is lower than the projected chance of an unanticipated credit loss depleting economic capital (Basle, 2009).

The banks that used a hold-to-maturity approach took into account the following factors: (a) exposures were intended to be held until maturity; (b) there were limited markets to trade the credits; (c) new obligor information could be revealed; (d) default rate data may be published; (e) accounting statements, capital planning, and internal budgeting are prepared; and (f) a one-year modeling horizon was chosen because it reflected the typical timeframes in which: (a) new capital could be raised; (b) loss mitigating action could be taken to remove future risk from the portfolio; (c) new obligor information could be revealed; (d) default rate data may be published; and (f) credits are usually reviewed for renewal.

2.5.2 The paradigm of the default model

According to the DM paradigm, a credit loss only occurs if a borrower fails within the planning horizon, as shown by a standard term loan. The difference between the bank's credit exposure (the amount owing at the time of default) and the present value of future net recoveries (bearer cash payments minus workout expenses) would be the credit loss in the event of a borrower failure.

According to the underlying two-state (default vs. non-default) idea of credit losses, the DM paradigm establishes the present and future values of credit instruments. For example, the current value of a term loan is typically measured by the bank's credit exposure (e.g., book value); however, the (uncertain) future value of the loan would depend on whether or not the borrower defaults during the planning horizon. If the borrower does not default, the future value of the loan would normally be calculated as the bank's credit exposure at the end of the planning horizon, adjusted to add back any principal payments made during that time; if the borrower defaults, the future value of the loan would typically be calculated as one minus its loss rate given default (LGD); the lower the LGD, the higher the recovery rate due to default.

In DM-type credit risk models, a bank imposes or estimates the joint probability distribution with respect to three types of random variables: (1) the bank's associated credit exposure, (2) a zero/one indicator denoting whether the facility defaults during the planning horizon, and (3) the associated LGD in the event of default. It should be highlighted that although the future values of credit instruments are unpredictable, their present values are presumed to be known at the beginning of the planning horizon, when the credit risk model is being used to estimate the portfolio (Deventer, 2012). The combined distribution of these variables across the several facilities that make up the portfolio must also be ascertained by the model-builder.

2.6 Experiment Analysis

According to Munyai (2010), even though the South African president created and signed the National Credit Act into law in 2005, excessive interest rates remained the main issue throughout the 2007–2008 crisis. This resulted in a crippling debt load that eventually led to default. Borrowers find it more difficult to repay as interest rates rise (Wambui, 2013). Because low interest rates encourage banks to take on more risk and enhance their risk appetite, which drives inflation, interest rate variations have an impact on financial stability (González-aguado, 2014). Regardless of a bank's size, inflation has a detrimental impact on its performance, claim Ifeacho and Ngalawa (2014). A successful economy is closely associated with both growth and better bank performance (Kumar & Kavita, 2017). A similar study found that growth has a positive impact on bank profitability (Petria 2015). If the loan growth strategy is poorly evaluated, it has a negative impact on bank profitability (Siaw, 2014). In an attempt to increase their market share, banks often take on more risk (Mishi, 2016). Growth at the price of a comprehensive credit evaluation jeopardizes the capacity to repay loans. Even banks with adequate capital are impacted by this. Dangerous lending is often motivated by the desire to outperform competitors (Dang, 2011). Nonetheless, South African banks function in a fiercely competitive market that drives up prices, supported by a strong legal and regulatory framework (Kumbirai & Webb, 2010). As credit risk increases with loan volume, profitability decreases. Unexpected financial and macroeconomic instability consequences might result from rapid loan expansion that isn't accompanied by economic progress (Peric & Konjusak, 2017). In some situations, banks must acquire more funds in order to carry out their expansion plan. This problem ultimately impacts investment results. When the bank does well and credit limitations are set, shareholder value increases. Musah (2017) asserts that one of the key factors influencing bank profitability is liquidity. Dima (2011) offered more support for this notion by demonstrating a high link between profitability and liquidity, suggesting that cash flow is created by earnings. According to Murerwa (2015), banks often show strong financial performance during periods of high GDP growth and bad financial performance during periods of sluggish GDP development. In prosperous times, there is a higher demand for loans as living standards rise. In South Africa, the banking industry accounts for more than 20% of the country's GDP, where economic expansion stabilizes borrowers' capacity to repay loans (Ifeacho & Ngalawa, 2014). When a bank has enough capital to cover its loans and depositors, it is said to be liquid. A bank seems to be more lucrative when it has enough capital (Dietrich & Wanzenried, 2009). It is a profitable investment as shareholders provide a bank the money it needs to turn a profit. Sufficient financial resources build trust and a solid reputation among all parties involved (Armitage & Marston, 2008). When there are liquidity issues, banks take on less risk. Larger banks with sufficient capital and loan settlement capabilities are more profitable and have more financial stability (Paleckova, 2016; Mahathanaseth & Tauer, 2014). According to Githaiga (2015), capital must be sufficient to cover all risks, including foreseen and unexpected losses. When assessing capital adequacy, which is often advantageous for successful banks with lower borrowing, equity, solvency ratio, and internal capital are important factors to take into account (Klepczarek, 2015). When enough capital is ensured, banks take on more calculated risk, reducing the likelihood of failure. According to some research, credit risk and banks' financial success are positively correlated. Among other studies, Boahene (2012) found a favorable correlation between banks' financial performance and the credit risk indicators of non-performing loans. Additionally, Alshatti (2015) looked at the connection between Jordanian commercial banks' financial performance and credit risk management and discovered a favorable correlation between non-performing loans and bank performance. Alshatti (2015) came to the conclusion that banks' profitability as determined by ROE is unaffected by the capital adequacy ratio. However, it has been shown that leverage has a detrimental effect on banks' profitability.

2.7 Summary

Credit risk is believed to have a major impact on a financial institution's losses (Al Ajlouni and Shawer, 2013). Managers of commercial banks must so concentrate more on controlling credit risk. However, events like the Great Financial Crisis of 2007–2008 demonstrate that credit risk assessment is still a significant and real contribution to financial instability (Berrios, 2013), and some companies continue to see it as an add-on activity (Bouteille & Coogan-Pushner, 2012). One of the main problems with the comparative framework of this study is that interest charging, which is the foundation of conventional banking systems like the UK, is forbidden by Islamic religious law (Ogden, 2003). The performance of unsecured bank loans is statistically significantly impacted by a variety of criteria, including branch manager inspection, financial statement analysis, standardization, credit scoring, and risk assessment (Gakure, 2012; Al-Tamimi & Al-Mazrooei, 2007; Abdelrahim, 2013). Important elements including organizational and board structure, culture, and internal and external audit may also have an influence on how well credit risk assessment techniques work in the banking industry (Forssbaeck, 2011; Iannota, 2007). The research compares credit risk management methods and processes in the United Arab Emirates with the United Kingdom, taking into account all of these issues as well as their fundamental relationship to bank profitability. Nonetheless, this research will fill in some of the gaps in the literature outlined in this chapter: First, there are still a lot of unanswered questions about whether Islamic and conventional banking systems function similarly; Second, there is still a lack of knowledge about how credit risk assessment works in Islamic financial institutions; and Third, there is still a lack of clarity about how risk assessment techniques are applied in both Islamic and conventional commercial banks, as well as how alternative risk assessment techniques affect the profitability of these banking forms.

CHAPTER THREE

METHODOLOGY

3.1 INTRODUCTION

The research design, study population, study sampling techniques, data source and categorization, model specification, data analysis method, and variable operationalization are all covered in depth in this chapter. The nature of the issue and the goal of the inquiry always determine the research methodology used in a given study.

3.2 Research Design

The research technique selected and used for this study was the longitudinal survey, which comprises assessing the current state of a group or unit over a predetermined period of time. This approach was chosen because of the historical nature of our sample data.

3.3 Population and Sample

A non-probabilistic approach strengthens the validity of the study's findings, improves the scientific rigor of the research endeavor, and facilitates information sharing. In order to choose a sample size from the study population, which encompasses the whole Nigerian financial industry, convenience sampling—a deliberate non-probability sampling strategy—is used. The sample period spans twenty-nine (29) years of quarterly observations, from 1995 to 2023.

3.4 Types and Sources of Data

The Security and Exchange Commission statistics bulletin (2023) and the Central Bank of Nigeria statistical bulletin provide secondary data for this study. The data was collected on a quarterly basis over a twenty-nine-year period (1995 to 2023) to provide us enough observations to account for degree of freedom and to demonstrate the impact of the various policies established in the insurance industry. The study will primarily concentrate on time series data for six variables: government health care expenditure, inflation rate, life expectancy, human development index, policy lapse ratio, and currency rate.

3.5 Model Specification

To estimate the economic cost of medical mistakes in Nigeria, we have selected a range of factors related to government spending on health, health investment, and economic growth that may take into consideration the impact of the many transmission channels. The dependent variable is medical mistakes as measured by the number of Nigerian health workers, and the analytical model uses a linear technique to incorporate explanatory time series variables. The relationship between the policy lapse ratio and economic measurement variables is examined using the structural model that follows:

PLR = f(HDI, LE, GEH, EXR, INFR). ………………… (3.1)

Consequently, the model's econometric form is as follows:

$PLR = \beta0 + \beta1HDI + \beta2LE + \beta3GEH+\beta4EXR+ \beta5INFR+U$ -------------------- (3.2)

The Human Development Index, or HDI, uses LE as a proxy for life expectancy. The abbreviation for the exchange rate is EXR, or Spending on Government Health (GEH).

INFR is the shorthand for inflation rate.

The following definitions apply to the variables U, B0, and A Prior Expectation: β1, β2, β3, and $\beta4 > 0$ whereas $\beta5 < 0$.

The currency rate and inflation rate were included as controlled variables as they significantly affect the output of insurance companies.

3.6 Method of Data Analysis

The primary statistical method used in this investigation is the Ordinary Least Square (OLS) methodology. Knowing the value of one or more independent variables helps in estimating the value of the dependent variables. The data will also be examined using a variety of statistical tests, including descriptive statistics, correlation matrices, and the Augmented Dickey Fuller unit root test for variables stationarity. The researcher may determine if two variables are related in any way using OLS, a statistical method chosen for its Best Linear Unbiased Estimator (BLUE) properties. The probability values from the OLS results are used to examine the different hypotheses generated for the study.

By utilizing the E-views 9.0 program to convert the received data stream to high frequency quarterly data from 1995 to 2023, this limitation is resolved. This produces more reliable results and provides more observations, which are crucial for the OLS estimation methodology. The collected data stream consists of a very modest amount of low frequency data (year data from 1995 to 2023), which is insufficient to fully represent the situation in question.

3.6 Measurement of Variables

S/N	Variables	Definition	Type of variables	Measurement
1	PLR	Policy Lapse Ratio in Nigeria	Dependent	Life insurance premium volume to GDP (%)
2	HDI	Human Development Index	Independent	Real human capital index
3	LE	Life Expectancy	Independent	Expectancy life ratio
4	GEH	Government expenditure on Health	Independent	Capital spending on Health
5	EXR	Exchange rate		Proxied by annual real exchange rate
6	INFR	Inflation rate		Proxied by consumer price index

Source: Researcher's Compilation, 2024

CHAPTER FOUR

DATA PRESENTATION AND ANALYSIS

4.1 Introduction

This chapter focuses on the analyses of data collected from CBN statistical bulletin and Word Bank Financial Development database subjected to the model in the previous chapter. The output of the results is attached as appendices.

4.2 Data Analysis

Table 4.1: Summary Statistics

	LIP	HDI	GEH	LE	INFR	EXR
Mean	0.095034	0.401517	11.59276	49.36241	18.23345	93.57897
Median	0.096594	0.475672	14.01875	48.81000	11.91000	115.4367
Maximum	0.153750	0.532125	23.16469	54.71344	76.76000	198.5791
Minimum	0.033844	0.214500	-2.390625	45.83938	0.220000	10.82750
Std. Dev.	0.027192	0.129917	7.567106	3.183986	17.53370	57.05680
Skewness	0.119195	-0.427569	-0.247250	0.316344	2.142246	-0.196666
Kurtosis	2.932482	1.313256	1.578606	1.567426	6.482040	1.533765
Jarque-Bera	0.296710	17.28578	10.94697	11.85406	147.3271	11.13868
Probability	0.862125	0.000176	0.004197	0.002666	0.000000	0.003813

Source: Researcher's Computation using E-views 9.0 (2024)

As shown by the Jarque-Bera statistic values and their related probability values that are significant at the 5% level of significance, respectively, Table 4.1 showed that all of the variables taken into consideration (except from LIP) in the model are not normally distributed. There is a considerable difference between the lowest and greatest values of the variables over the study period, and the mean to median ratio is around one. The positive values of Skewness show that the LIP, LE INFR, and EXR variables have a long tail to the right. Others, as shown by their matching negative values, have a lengthy tail to the left. Lastly, the associated Kurtosis values larger than 3.0 indicate that only the INFR variable has peak distribution features.

Table 4.2 Correlation Matrix

Correlation t-Statistic Probability	LIP	HDI	GEH	LE	INFR	EXR
LIP	1.000000 ----- -----					
HDI	0.116994 1.257797 0.2110	1.000000 ----- -----				
GEH	0.364773* 4.182935 0.0001	0.277512 3.084161 0.0026	1.000000 ----- -----			
LE	0.158819 1.717517 0.0886	0.695379 21.46849 0.0000	-0.018791 -0.200672 0.8413	1.000000 ----- -----		
INFR	-0.077755 -0.832714 0.4067	-0.527435 -6.628404 0.0000	-0.477185 -5.797594 0.0000	-0.433161 -5.131271 0.0000	1.000000 ----- -----	
EXR	0.278072* 3.090902 0.0025	0.539625 6.843546 0.0000	0.647185 17.02520 0.0000	0.293217 3.274640 0.0014	-0.499519 -6.156507 0.0000	1.000000 ----- -----

Source: Researcher's Computation using E-views 9.0 (2024)

The degree and direction of the association between the independent and dependent variables taken into account in the model are shown in Table 4.2. According to their separate positive correlation coefficients of r = 0.11, 0.37, 0.16, and 0.28, almost all of the variables show a weakly positive link with LIP. This indicates that within the reviewed time, a rise in these factors raises LIP. With a negative correlation value of r = -

0.08, INFR is the only one that has a very modest negative connection with LIP. This demonstrates that throughout the scope under examination, a rise in INFR lowers LIP.

Table 4.3: Test of Stationarity

Variables	ADF Statistic	Order	Remark
LIP	-5.237635*	I(2)	Stationary
HDI	-6.367505*		
GEH	5.962159*		
LE	-11.08932*		
INFR	-11.64632*		
EXR	-6.128773*		
Critical Value			
1%	-4.046925	Second Diff	
5%	-3.452764	Second Diff	
10%	-3.151911	Second Diff	
** = 1% Significance Level*			

Source: E-views 9.0 computation by the researcher (2024)

Unstable time series variables often provide erroneous regression results. This justifies determining the stationarity status of the variables under consideration using ADF statistics. The variables were not stationary at the levels and first difference. All of the variables became stationary and integrated of the same order I(2) after the second difference of the variables was calculated. The variables are thus suitable for use in further regression estimate.

Table 4.4: Outcomes of OLS and GLS Regression Analysis

OLS Estimation				**GLS Estimation**		
Variable	**Coefficient**	**t-Statistic**	**Prob.**	**Coefficient**	**t-Statistic**	**Prob.**
C	-0.453177	-5.645975	0.0000	-0.408995	-2.961019	0.0038
HDI(-2)	-0.238302*	-5.013264	0.0000	-0.290149*	-3.692798	0.0004
GEH(-2)	0.004172*	6.376887	0.0000	0.003348*	3.359307	0.0011
LE(-2)	0.012165*	6.459337	0.0000	0.011748*	3.634986	0.0004
INFR(-2)	0.000515*	3.356567	0.0011	2.29E-05	0.155816	0.8765
EXR(-2)	-0.000157	-1.841437	0.0683	2.03E-05	0.140652	0.8884
AR(1)				1.387711	16.83793	0.0000
AR(2)				-0.557203	-6.817164	0.0000
R-squared	0.356291			0.890498		

Adjusted R-squared	0.326489			0.883128		
F-statistic	11.95552*			120.8223		
Prob(F-statistic)	0.000000			0.000000		
Durbin-Watson stat	0.274654			2.255306		
Dependent Variable = LIP						
** = 1% Significance Level*						

Source: Researcher's Computation using E-views 9.0 (2024)

Table 4.4 displays the outcomes of the ols and GLS regressions. With a modified coefficient of determination of around 0.33, the OLS result shows that, after adjusting for degree of freedom, all of the explanatory variables together account for about 33% of systematic fluctuations in LIP. The F-statistic value of 11.95, which is significant at the 5% confidence level, confirms that there is a strong connection between the explained variable and all of the explanatory variables combined, despite the data suggesting otherwise. However, the output's serial correlation has reduced the model's predictive strength, making this conclusion potentially misleading for policy recommendations. The Durbin-Watson statistic value of 0.2747, which cannot be approximately converted to 2.0, serves as an example of this. The Cochrane-Orcutt Autoregressive (AR) order 2 was used to correct for the serial correlation seen in the OLS. After 12 iterations with 112 data included, convergence was achieved; table 4.4 shows the GLS result. With a modified coefficient of determination of around 0.88, the GLS result shows that, after adjusting for degree of freedom, all explanatory variables account for 88% of the overall systematic variation in LIP. The F-statistic value of 120.82, which is significant at the 5% confidence level, shows a substantial correlation between the explained variable and all of the explanatory variables combined. This demonstrates the significant difference between zero and one of the parameter estimates. Three variables (LE, GEH, and HDI) seem to have passed their significant test based on matching probability values of less than 0.05. Only 12% of the overall dynamic changes in LIP could not be explained by the model, which included the perturb term—other factors that affect LIP but were excluded since they are beyond the purview of this investigation. With a 5% degree of confidence, this indicates that the previously mentioned variables were more responsible for LIP throughout the research period. For the two control variables that are part of the model, the opposite is true. There is no serial association, according to the Durbin Watson statistics value of 2.255, which is almost equivalent to 2.0. As a result, policy ideas may be generated using the model without re-specification.

4.3 Hypotheses Testing

The GLS result's probability values were used to assess the study's underlying assumptions. The alternative hypothesis is accepted if the probability value is less than

0.05; else, the null hypothesis is accepted. This serves as the deciding rule for the section. Hypothesis 1 (Ho1): Nigeria's renew life strategy is not clearly impacted by the human development index.

At 0.0004, the HDI probability value is less than 0.05. The alternative hypothesis is acknowledged. This implies that throughout the period under review, LE had a significant impact on Nigeria's renew life policy.

Hypothesis Two (Ho2): Nigeria's renew life policy is not significantly impacted by life expectancy.

At 0.0004, the likelihood value of LE is less than 0.05. The alternative theory is selected. This demonstrates how HDI had a significant impact on Nigeria's renew life policy throughout the course of the inquiry.

Hypothesis Three (Ho3): There is no significant correlation between Nigeria's renew life policy and government health expenditures.

At 0.0011, the probability value for GEH is less than 0.05. The alternate interpretation is therefore accepted. This demonstrates how GEH had a significant impact on Nigeria's renew life policy throughout the relevant period.

4.4 Discussion of Findings

The GLS coefficient values for each explanatory variable in table 4.4 indicate the degree of association between the components and renew life policy (PLR). The only documents that were incorrectly signed and did not meet A priori assumptions were HDI and INFR. First, Nigeria's renew life policy (PLR) is severely harmed by HDI. This indicates that there is a 29% significant decline in PLR for every 1% change in HDI. This presents a serious policy conundrum since the Nigerian government's HDI plan has failed to meet its goal of increasing covered life insurance in the nation; as a result, more effective policies are still needed in this area. This conclusion is consistent with earlier research findings by Misman (2015) and Gakure (2012).

Second, GEH significantly strengthens Nigeria's renew life policy (PLR). This implies that there is a 0.03% significant increase in PLR for every 1% change in GEH. This suggests that the GEH initiative of the Nigerian government is headed in the right direction and has achieved its goal of increasing the number of life insurance policies in the nation. This conclusion is consistent with research by Kurawa and Garba (2014) and Alshatti (2015). Third, throughout the required time period, LE significantly increases PLR in Nigeria. This implies that PLR has changed significantly in Nigeria as a result of government initiatives to advance it. Because there is a 1.1% increase in PLR for every percentage change in LE. This outcome is in line with the literature's results of Hosna (2009).

According to the substantial F-statistic and t-statistic values from the aforementioned study, HDI, GEH, and LE significantly contributed to PLR in Nigeria both individually and in combination. Furthermore, as they could account for almost 88% of the total dynamic variation in PLR during the study period, HDI, GEH, and LE—the model's core explanatory variables—are significant PLR drivers. Nevertheless, the model's inclusion of INFR and EXR had no appreciable impact on PLR. This indicates that over the studied time, PLR in Nigeria was not significantly impacted by changes in these attributes.

CHAPTER FIVE

5.1 Introduction

The primary objective of this chapter is to provide a summary of the study's findings and offer relevant recommendations.

5.2 Summary of Findings

The study examines the impact of the credit risk modeling technique on life insurance policies in Nigeria. Time series quarterly data were sourced from the CBN statistics bulletin and the World Bank Financial Development Database between 1995 and 2023. Ordinary Least Square (OLS) and General Least Square (GLS), two multiple regression techniques, were used. The findings indicate, among other things, that:

1. The human development index has a major impact on Nigeria's renew life strategy.
2. In Nigeria, the renew life policy is significantly impacted by government health expenditures.
3. Life expectancy has a big influence on Nigeria's renew life policy.
4. Inflation has little effect on Nigeria's renew life strategy.
5. Exchange rates have little effect on Nigeria's renew life policy.

5.3 Conclusion

The study examines the impact of the credit risk modeling technique on life insurance policies in Nigeria. Based on the findings, this study concludes that the human development index, life expectancy, and government health expenditure are significant determinants of Nigeria's renew life policy.

5.4 Recommendations

The following suggestions are derived from the study's findings:

1. The government should increase the organization's financing flow and ensure that regulatory agencies have enough control to ensure that HDI's influence on renew life policy stays notable and positive.
2. Because the renew life program has a significant and positive effect, the government should increase its efforts and commitment to health expenditures in order to support its further development.
3. In addition to providing infrastructure and employment possibilities, the government should adequately support the community health sector in order to increase life expectancy and further Nigeria's renew life plan.
4. An efficient macroeconomic policy mix must be adjusted to the inflation rate and exchange rate to keep them within a manageable threshold if the variables are to

substantially contribute to the renewal of life insurance in the Nigerian insurance business.

5. Regulatory organizations like NAICOM must make every effort to educate the public about the benefits of renewing a life insurance policy in order to encourage and increase voluntary participation.

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APPENDIX I

Data for Regression

obs	LIP	HDI	GEH	LE	INFR	EXR
1995Q1	0.036563	0.214500	-2.390625	45.86375	48.80000	14.44469
1995Q2	0.045938	0.215500	-0.434375	45.86125	48.80000	16.55281
1995Q3	0.054688	0.216500	1.178125	45.85875	48.80000	18.35406
1995Q4	0.062813	0.217500	2.446875	45.85625	48.80000	19.84844
1996Q1	0.070313	0.218500	3.371875	45.85375	61.26000	21.03594
1996Q2	0.077188	0.219500	3.953125	45.85125	61.26000	21.91656
1996Q3	0.083438	0.220500	4.190625	45.84875	61.26000	22.49031
1996Q4	0.089063	0.221500	4.084375	45.84625	61.26000	22.75719
1997Q1	0.090937	0.222344	2.306250	45.84063	76.76000	21.92500
1997Q2	0.096562	0.223406	2.043750	45.83938	76.76000	21.89500
1997Q3	0.102812	0.224531	1.968750	45.83938	76.76000	21.87500
1997Q4	0.109687	0.225719	2.081250	45.84063	76.76000	21.86500
1998Q1	0.135000	0.226969	3.084375	45.84313	51.59000	21.89000
1998Q2	0.136000	0.228281	3.290625	45.84688	51.59000	21.89000
1998Q3	0.130500	0.229656	3.403125	45.85188	51.59000	21.89000
1998Q4	0.118500	0.231094	3.421875	45.85813	51.59000	21.89000
1999Q1	0.073281	0.233219	2.925000	45.86719	14.32000	21.89000
1999Q2	0.058969	0.234531	2.925000	45.87531	14.32000	21.89000
1999Q3	0.048844	0.235656	3.000000	45.88406	14.32000	21.89000
1999Q4	0.042906	0.236594	3.150000	45.89344	14.32000	21.89000

2000Q1	0.050531	0.236094	3.578125	45.90031	10.21000	21.89000
2000Q2	0.049219	0.237156	3.796875	45.91219	10.21000	21.89000
2000Q3	0.048344	0.238531	4.009375	45.92594	10.21000	21.89000
2000Q4	0.047906	0.240219	4.215625	45.94156	10.21000	21.89000
2001Q1	0.033844	0.243625	2.665625	45.95750	11.91000	10.82750
2001Q2	0.039906	0.245375	3.559375	45.97750	11.91000	15.25250
2001Q3	0.052031	0.246875	5.146875	46.00000	11.91000	24.10250
2001Q4	0.070219	0.248125	7.428125	46.02500	11.91000	37.37750
2002Q1	0.132594	0.248813	13.44688	46.04938	0.220000	75.73062
2002Q2	0.147656	0.249688	15.89813	46.08063	0.220000	89.59437
2002Q3	0.153531	0.250437	17.82563	46.11563	0.220000	99.62187
2002Q4	0.150219	0.251063	19.22938	46.15438	0.220000	105.8131
2003Q1	0.100531	0.250625	19.40938	46.19531	14.52000	98.51344
2003Q2	0.093719	0.251375	20.04563	46.24219	14.52000	100.8941
2003Q3	0.092594	0.252375	20.43813	46.29344	14.52000	103.3003
2003Q4	0.097156	0.253625	20.58688	46.34906	14.52000	105.7322
2004Q1	0.129750	0.255906	20.49031	46.40594	16.50000	108.3788
2004Q2	0.136750	0.257344	20.15219	46.47156	16.50000	110.7863
2004Q3	0.140500	0.258719	19.57094	46.54281	16.50000	113.1438
2004Q4	0.141000	0.260031	18.74656	46.61969	16.50000	115.4513
2005Q1	0.136531	0.233781	16.75250	46.70531	12.19000	117.6838
2005Q2	0.131219	0.245969	15.81250	46.79219	12.19000	119.9013
2005Q3	0.123344	0.269094	15.00000	46.88344	12.19000	122.0788
2005Q4	0.112906	0.303156	14.31500	46.97906	12.19000	124.2163

2006Q1	0.081625	0.400656	12.60281	47.07750	23.79000	126.8778
2006Q2	0.073375	0.435594	12.63469	47.18250	23.79000	128.7097
2006Q3	0.069875	0.460469	13.25594	47.29250	23.79000	130.2759
2006Q4	0.071125	0.475281	14.46656	47.40750	23.79000	131.5766
2007Q1	0.095406	0.457375	19.26344	47.53219	10.01000	132.8053
2007Q2	0.098844	0.461125	20.45406	47.65531	10.01000	133.4972
2007Q3	0.099719	0.463875	21.03531	47.78156	10.01000	133.8459
2007Q4	0.098031	0.465625	21.00719	47.91094	10.01000	133.8516
2008Q1	0.086125	0.462781	18.36344	48.04656	11.60000	132.9922
2008Q2	0.082375	0.463969	17.91906	48.18094	11.60000	132.5203
2008Q3	0.079125	0.465594	17.66781	48.31719	11.60000	131.9141
2008Q4	0.076375	0.467656	17.60969	48.45531	11.60000	131.1734
2009Q1	0.072875	0.472188	17.66969	48.60000	8.500000	129.8563
2009Q2	0.071625	0.474312	18.02781	48.74000	8.500000	129.0238
2009Q3	0.071375	0.476062	18.60906	48.88000	8.500000	128.2338
2009Q4	0.072125	0.477437	19.41344	49.02000	8.500000	127.4863
2010Q1	0.069969	0.477188	21.65344	49.16313	6.600000	127.5813
2010Q2	0.074281	0.478313	22.41906	49.30188	6.600000	126.5988
2010Q3	0.081156	0.479563	22.92281	49.43938	6.600000	125.3388
2010Q4	0.090594	0.480938	23.16469	49.57562	6.600000	123.8013
2011Q1	0.113063	0.482906	23.10719	49.71219	15.10000	115.4222
2011Q2	0.123438	0.484344	22.84031	49.84531	15.10000	115.9553
2011Q3	0.132187	0.485719	22.32656	49.97656	15.10000	118.8366
2011Q4	0.139312	0.487031	21.56594	50.10594	15.10000	124.0659

2012Q1	0.153250	0.489844	20.04125	50.23344	12.00000	142.0278
2012Q2	0.153750	0.490406	18.99375	50.35906	12.00000	147.7997
2012Q3	0.149250	0.490281	17.90625	50.48281	12.00000	151.7659
2012Q4	0.139750	0.489469	16.77875	50.60469	12.00000	153.9266
2013Q1	0.104313	0.483750	14.65500	50.72469	11.80000	149.2956
2013Q2	0.093188	0.483250	13.83000	50.84281	11.80000	149.8394
2013Q3	0.085438	0.483750	13.34750	50.95906	11.80000	150.5719
2013Q4	0.081063	0.485250	13.20750	51.07344	11.80000	151.4931
2014Q1	0.087563	0.489000	14.11781	51.18281	10.30000	153.4453
2014Q2	0.086938	0.492000	14.37969	51.29469	10.30000	154.4072
2014Q3	0.086688	0.495500	14.70094	51.40594	10.30000	155.2209
2014Q4	0.086813	0.499500	15.08156	51.51656	10.30000	155.8866
2015Q1	0.087469	0.506969	16.24656	51.62500	12.00000	156.5213
2015Q2	0.088281	0.510781	16.45594	51.73500	12.00000	156.8438
2015Q3	0.089406	0.513906	16.43469	51.84500	12.00000	156.9713
2015Q4	0.090844	0.516344	16.18281	51.95500	12.00000	156.9038
2016Q1	0.094625	0.516688	14.97844	52.06500	8.480000	155.5538
2016Q2	0.095875	0.518313	14.55406	52.17500	8.480000	155.5313
2016Q3	0.096625	0.519813	14.18781	52.28500	8.480000	155.7488
2016Q4	0.096875	0.521188	13.87969	52.39500	8.480000	156.2063
2017Q1	0.094594	0.522438	13.13594	52.50500	8.060000	152.6444
2017Q2	0.094656	0.523563	13.14156	52.61500	8.060000	155.2856
2017Q3	0.095031	0.524563	13.40281	52.72500	8.060000	159.8706
2017Q4	0.095719	0.525438	13.91969	52.83500	8.060000	166.3994

2018Q1	0.097969	0.525875	16.35625	52.94656	9.020000	197.0234
2018Q2	0.098781	0.526625	16.71875	53.05594	9.020000	198.5791
2018Q3	0.099406	0.527375	16.67125	53.16469	9.020000	193.2178
2018Q4	0.099844	0.528125	16.21375	53.27281	9.020000	180.9397
2019Q1	0.099781	0.529031	15.73062	53.38188	15.70000	145.8478
2019Q2	0.099969	0.529719	14.29937	53.48812	15.70000	126.0947
2019Q3	0.100094	0.530344	12.30437	53.59313	15.70000	105.7834
2019Q4	0.100156	0.530906	9.745625	53.69688	15.70000	84.91406
2020Q1	0.100000	0.531875	3.254375	53.80094	10.93000	50.61625
2020Q2	0.100000	0.532125	0.915625	53.90156	10.93000	33.77875
2020Q3	0.100000	0.532125	-0.639375	54.00031	10.93000	21.53125
2020Q4	0.100000	0.531875	-1.410625	54.09719	10.93000	13.87375
2021Q1	0.100000	0.530281	-0.076250	54.19063	11.88000	14.62188
2021Q2	0.100000	0.529969	0.191250	54.28437	11.88000	14.61813
2021Q3	0.100000	0.529844	0.713750	54.37687	11.88000	17.67813
2021Q4	0.100000	0.529906	1.491250	54.46812	11.88000	23.80188
2022Q1	0.100000	0.530781	4.239375	54.66906	12.84000	49.58000
2022Q2	0.100000	0.530969	4.840625	54.71344	12.84000	55.19500
2022Q3	0.100000	0.531094	5.010625	54.71219	12.84000	57.23750
2022Q4	0.100000	0.531156	4.749375	54.66531	12.84000	55.70750
2023Q1	0.100000	0.531156	4.056875	54.57281	11.88000	50.60500
2023Q2	0.100000	0.531094	2.933125	54.43469	11.88000	41.93000
2023Q3	0.100000	0.530969	1.378125	54.25094	11.88000	29.68250
2023Q4	0.100000	0.530781	-0.608125	54.02156	11.88000	13.86250

APPENDIX II

Dependent Variable: LIP(-2)
Method: Least Squares
Date: 07/18/24 Time: 07:52
Sample (adjusted): 1995Q1 2023Q4
Included observations: 112 after adjustments
Convergence achieved after 12 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.408995	0.138127	-2.961019	0.0038
HDI(-2)	-0.290149	0.078571	-3.692798	0.0004
GEH(-2)	0.003348	0.000997	3.359307	0.0011
LE(-2)	0.011748	0.003232	3.634986	0.0004
INFR(-2)	2.29E-05	0.000147	0.155816	0.8765
EXR(-2)	2.03E-05	0.000145	0.140652	0.8884
AR(1)	1.387711	0.082416	16.83793	0.0000
AR(2)	-0.557203	0.081735	-6.817164	0.0000

R-squared	0.890498	Mean dependent var	0.096643
Adjusted R-squared	0.883128	S.D. dependent var	0.026209
S.E. of regression	0.008960	Akaike info criterion	-6.523376
Sum squared resid	0.008349	Schwarz criterion	-6.329198
Log likelihood	373.3091	Hannan-Quinn criter.	-6.444592
F-statistic	120.8223	Durbin-Watson stat	2.255306
Prob(F-statistic)	0.000000		

Inverted AR Roots	.69-.28i	.69+.28i

Dependent Variable: LIP(-2)

Method: Least Squares

Date: 07/18/24 Time: 07:53

Sample (adjusted): 1995Q3 2023Q4

Included observations: 114 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.453177	0.080266	-5.645975	0.0000
HDI(-2)	-0.238302	0.047534	-5.013264	0.0000
GEH(-2)	0.004172	0.000654	6.376887	0.0000
LE(-2)	0.012165	0.001883	6.459337	0.0000
INFR(-2)	0.000515	0.000154	3.356567	0.0011
EXR(-2)	-0.000157	8.51E-05	-1.841437	0.0683

R-squared	0.356291	Mean dependent var	0.095978
Adjusted R-squared	0.326489	S.D. dependent var	0.026457
S.E. of regression	0.021713	Akaike info criterion	-4.770611
Sum squared resid	0.050917	Schwarz criterion	-4.626600
Log likelihood	277.9248	Hannan-Quinn criter.	-4.712165
F-statistic	11.95552	Durbin-Watson stat	0.274654
Prob(F-statistic)	0.000000		

	LIP	HDI	GEH	LE	INFR	EXR
Mean	0.095034	0.401517	11.59276	49.36241	18.23345	93.57897
Median	0.096594	0.475672	14.01875	48.81000	11.91000	115.4367
Maximum	0.153750	0.532125	23.16469	54.71344	76.76000	198.5791
Minimum	0.033844	0.214500	-2.390625	45.83938	0.220000	10.82750
Std. Dev.	0.027192	0.129917	7.567106	3.183986	17.53370	57.05680
Skewness	0.119195	-0.427569	-0.247250	0.316344	2.142246	-0.196666
Kurtosis	2.932482	1.313256	1.578606	1.567426	6.482040	1.533765
Jarque-Bera	0.296710	17.28578	10.94697	11.85406	147.3271	11.13868
Probability	0.862125	0.000176	0.004197	0.002666	0.000000	0.003813
Sum	11.02400	46.57600	1344.760	5726.040	2115.080	10855.16
Sum Sq. Dev.	0.085031	1.941020	6585.026	1165.843	35354.52	374380.0
Observations	116	116	116	116	116	116

Covariance Analysis: Ordinary

Date: 07/18/24   Time: 07:54

Sample: 1995Q1 2023Q4

Included observations: 116

Correlation t-Statistic Probability	LIP	HDI	GEH	LE	INFR	EXR
LIP	1.000000					

HDI	0.116994	1.000000				
	1.257797	-----				
	0.2110	-----				
GEH	0.364773	0.277512	1.000000			
	4.182935	3.084161	-----			
	0.0001	0.0026	-----			
LE	0.158819	0.895379	-0.018791	1.000000		
	1.717517	21.46849	-0.200672	-----		
	0.0886	0.0000	0.8413	-----		
INFR	-0.077755	-0.527435	-0.477185	-0.433161	1.000000	
	-0.832714	-6.628404	-5.797594	-5.131271	-----	
	0.4067	0.0000	0.0000	0.0000	-----	
EXR	0.278072	0.539625	0.847185	0.293217	-0.499519	1.000000
	3.090902	6.843546	17.02520	3.274640	-6.156507	-----
	0.0025	0.0000	0.0000	0.0014	0.0000	-----

Null Hypothesis: D(LIP,2) has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 11 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.237635	0.0002
Test critical values:	1% level	-4.050509	
	5% level	-3.454471	
	10% level	-3.152909	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(HDI,2) has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 7 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.367505	0.0000
Test critical values:	1% level	-4.046925	
	5% level	-3.452764	
	10% level	-3.151911	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(GEH,2) has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 11 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.904025	0.0000
Test critical values:	1% level	-4.050509	
	5% level	-3.454471	
	10% level	-3.152909	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LE,2) has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.08932	0.0000
Test critical values:	1% level	-4.041280	
	5% level	-3.450073	
	10% level	-3.150336	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(INFR,2) has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 2 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.64632	0.0000
Test critical values:	1% level	-4.042819	
	5% level	-3.450807	
	10% level	-3.150766	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(EXR,2) has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 11 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.128773	0.0000
Test critical values:	1% level	-4.050509	
	5% level	-3.454471	
	10% level	-3.152909	

*MacKinnon (1996) one-sided p-values.