RISK MANAGEMENT PRACTICES AND THEIR IMPACT ON FINANCIAL PERFORMANCE OF LIFE AND NON-LIFE INSURANCE FIRMS: EVIDENCE FROM SOUTH AFRICA.

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ABSTRACT: *This study examines the extent of the relationship between Risk Management (RM) practices and Financial Performance (FP) in life insurance (LI) and non-life insurance (NLI) companies in South Africa from 2018 to 2024. It proposes modeling risk management strategies in the insurance industry. The study aims to expand on strategic risk management practices in the insurance industry in emerging markets. This quantitative study uses a multivariate regression model. Secondary data computed from annual balance sheet statements were analyzed in a panel data framework, and OLS and fixed-effects regression models were applied. The results reveal that CR has a positive and significant relationship with the ROA of LI and NLI firms in SA, indicating a possible risk transfer mechanism to other financial institutions. Although OP, LI, CR, and MR have positive but insignificant relationships with ROE, future studies should consider increasing the sample size to enhance the generalizability of the findings. Practical implications – This study has implications for the effectiveness of risk strategies in the insurance industry. This study fulfills the identified need to study how risk management affects the financial performance of life and non-life insurance firms in South Africa.*

JEF CODE: G32 Risk Management, Financial Risk, Financial Performance, G22 Insurance, C32Panel Data Model

KEYWORDS: Life and non-life insurance companies, financial management, financial performance, longitudinal and cross-sectional panel data analysis.

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INTRODUCTION

Over the years, insurance coverage has been a crucial tool in managing risks within organizations and promoting socio-economic growth, particularly during financial crises, economic hardship, and political tumult worldwide. Both Life Insurance (LI) and non-Life Insurance (NLI) policies help mitigate losses, provide financial stability, ensure property safety, and offer peace of mind during turbulent events. For example, Apergis and Poufinas (2020) state that insurance coverage provides multifaceted benefits, including income protection, mortgage coverage, health benefits, property protection, and other related consequences of extreme flooding. However, Kiptoo et al. (2021) analyzed the global insurance industry performance in top developed countries and concluded that despite some improvement in growth in the US and Europe, the industry is witnessing declining premiums, high underwriting losses, and negative net income, which calls for an expeditious Risk Management Analysis (RMA). Recently, Odunaiya et al. (2024) documented the impact of climate change on both the USA and African insurance companies. Their analysis yielded specific challenges for both regions.

In the USA, insurance companies faced extreme hurricanes, wildfires, and floods, compared to Africa, with extreme weather events, such as droughts and storms, which impact both the agricultural and infrastructural industries. Recognizing the application of technology, data analytics, and collaboration with climate scientists in mitigating the climate change crisis in the US economy, the challenges in Africa have not been fully addressed. This study seeks to investigate the relationship between RM and FP in the LI and NLI in South Africa (SA), with a particular focus on recommending strategies for improvement. Ongoing studies have used different methodologies to address the RM and FP issues of insurance companies in developed and developing countries.

In 2002, although the SA insurance industry experienced a strong recovery, as indicated by the South African Insurance Industry Survey (SAIS), future contemporary challenges, including emerging risks, populated the insurance industry. The financial statements as of December for the NLI firms indicate that NLI witnessed a -13 million South African Rand (ZAR) Net Profit Before Tax and Dividend (EBTD) with an increase in Net Claim Paid (NCP) of 185,523 million ZAR from 15,590 million in 2021. The LI witnessed a decline in the Net Premium (NP) from 165,733 million ZAR to 140,239 million ZAR in 2022. These statistics will continue to increase in 2024, as indicated by the NLI's financial statements. It shows a dramatic increase in the NCP of 19,125 million ZAR from 17,559 million ZAR, revealing a growth rate of -8.2 percent.

This study makes several contributions to risk management (RM) literature:

First, it adopts the framework of Kiptoo et al. (2021) but applies different indicators to measure credit risk (CR), operational risk (OP), liquidity risk (LR), and market risk (MR) to assess their impact on the financial performance (FP) of life insurance (LI) and non-life insurance (NLI) firms in South Africa (SA). Unlike earlier studies that focused mainly on risk identification and supervision, this study directly examined the RM–FP relationship across both sectors.

Second, it investigates how these risks influence FP in the LI and NLI firms. To the best of my knowledge, no prior research in Africa has analyzed this relationship, and few global studies have been conducted across both types of industry.

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Third, the complex South African environment—characterized by climate change, flooding, inflation, and regulatory challenges—intensifies firms' exposure to diverse risks (Wyk et al., 2004). These findings may guide regulatory authorities in optimizing risk-adjusted returns and in determining sustainable capital requirements.

Finally, as an emerging economy, South Africa faces political and financial uncertainties (Wyk et al., 2004) that can affect investors' confidence in insurance firms. Since LI and NLI companies provide critical liability coverage, understanding how RM affects FP can enhance investor trust and competitiveness in South Africa's insurance sector.

Therefore, this study seeks to answer the following question:

To what extent does a relationship exist between risk management and financial performance in South Africa's life and non-life insurance firms?

The paper is organized into seven sessions, which include the Introduction, Theoretical Foundation and Empirical Literature, (4) Risk Management Framework; (5) Methodology and Data Analysis; and (6) Conclusion and Limitations

Theoretical Foundation

Following Kiptoo et al. (2021), this study draws on the Credit Risk Theory, Modern Portfolio Theory, Keynesian Liquidity Theory, and Resource-Based Theory as key frameworks for understanding risk management (RM) practices.

Credit Risk Theory and Merton's Model (1974)

Merton's (1974) model measures credit risk by relating a firm's asset value to its debt obligations. A firm defaults when its assets do not cover its liabilities. In this study, credit risk is represented by mortgages and loans divided by total assets, reflecting financial obligations relative to the asset value. Saunders and Allen (2002) support the asset-to-debt ratio as a reliable measure of credit risk.

Modern Portfolio Theory (MPT)

Developed by Markowitz and Sharpe, MPT links portfolio returns to market risk and emphasizes diversification to minimize exposure. Unlike Merton's model, which relies on book values, the MPT focuses on market values. Kiptoo et al. (2021) illustrate how insurance firms can effectively manage portfolios at specific levels of market risk.

Keynesian Liquidity Theory

Keynes (1929) explains that firms hold liquid assets for transactional, precautionary, and speculative reasons. Liquidity helps address uncertainties, supports daily operations, and provides investment opportunities. Consistent with Oyerogba and Gbolagade (2023), this study applies similar liquidity risk measures to assess the influence of the business environment on insurance firms.

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Resource-Based Theory

The Resource-Based Theory views internal resources as the foundation of a firm's competitive advantage. Effective RM depends on how firms apply their financial and operational resources to anticipate and manage risk.

LITERATURE REVIEW

Empirical literature on risk management (RM) and financial performance (FP) in insurance industries across developed and developing countries emphasizes the value of effective RM practices. Al-Haija and Houcine (2024) use Data Envelope Analysis (DEA) to evaluate RM efficiency in twenty Islamic insurance firms in the UAE and KSA (2018–2020) and find significant differences between both markets. While they highlight the business environment's influence on performance, this study focuses on LI and NLI insurance markets in South Africa.

Oyerogba and Gbolagade (2023) examine 25 listed Nigerian insurance firms (2011–2017) and find a positive relationship between operational and liquidity risks and FP, suggesting sound RM strategies. However, ongoing threats such as climate change, inflation, and cyber risk necessitate continuous evaluation of RM, particularly in SA, where studies are scarce.

In developed economies, Hoyt and Liebenberg (2008) report that effective RM frameworks (RMF) enhance firm value in U.S. insurers. Liedberg and Seifert (2015) note that Solvency II was unnecessary in the U.S. due to strong NAIC solvency standards, while Eckles et al. (2014) find a strong correlation between RMF and return on assets (ROA).

European findings are mixed. Noja et al. (2021) show RM positively affects FP, though Solvency II reduced ROA and ROE. Jurdi and Alghaimat (2021) find RMF increases insurance premiums, while Gonzalez et al. (2020) observe no positive RM–FP relationship among Spanish insurers.

In Asia, Wani and Dar (2015) identify capital management, solvency, and liquidity risks as key FP factors in Indian LI firms. Zainudin et al. (2018) find capital volume, firm size, and underwriting risk affect profitability across major Asian markets, while Chen and Wong (2004) reveal that liquidity, market, and size risks influence NLI insurers' financial health, showing regional differences in RM outcomes.

In Africa, limited studies exist. In SA, Governor and Hassan-Bootha (2022) find that insurance firms' ethical standards fall below regulatory expectations. Fondem and Luo (2022) link weak ethics to poor financial outcomes. In Nigeria, Saka and Abere (2022) report no significant RM–FP link due to poor accountability, while in Kenya, Kiptoo et al. (2021) find a positive relationship between RM and FP but a negative one between credit risk and FP.

This study extends prior research by examining the relationship between RM and FP in South Africa's LI and NLI insurance sectors.

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Hypotheses

- Null hypothesis H_0: There is no significant relationship between the level of RM practices and the FP of LI and NLI companies in SA.
- Alternative hypothesis H_1: There is a significant positive relationship between the level of RM practices and FP of LI and NLI companies in SA.

Summary of Variables Definition and Expectation

This study examines the effect of key risk management indicators on the financial performance of life and non-life insurance firms in South Africa from 2018 to 2024. Financial performance is measured using **Return on Assets (ROA)** and **Return on Equity (ROE)**, which capture managerial efficiency in utilizing assets and shareholders' funds, respectively.

The independent variables represent major dimensions of enterprise risk management. **Liquidity Risk (LR)**, proxied as cash deposits to gross technical provisions, is expected to positively affect performance, as adequate liquidity enhances a firm's ability to meet obligations and reduce financial distress. **Credit Risk (CR)**, measured as mortgages and loans to total assets, is anticipated to negatively influence performance, consistent with risk–return trade-off and agency theories, which suggest that poor credit management erodes profitability. **Operational Risk (OPR)**, represented by net premiums to total assets, is expected to have a positive relationship with performance since efficient operational systems strengthen cost control and value creation.

Similarly, **Market Risk (MR)**, expressed as the ratio of total investments to investment income, is expected to negatively affect performance because exposure to market volatility can reduce investment returns. Finally, **Firm Age (AG)**, measured by the number of years since incorporation, is expected to positively influence financial performance, as mature firms benefit from accumulated experience, economies of scale, and more robust risk management systems.

Overall, these variables are selected to capture how distinct dimensions of risk management jointly determine profitability and financial stability within South Africa's insurance sector.

METHODOLOGY AND DATA ANALYSIS

This study adopts an explanatory quantitative research design using panel data regression analysis to examine the causal relationship between risk management (RM) practices and the financial performance (FP) of life (LI) and non-life (NLI) insurance firms in South Africa from 2018 to 2024. The explanatory design is appropriate because the study seeks to establish how variations in specific risk management indicators—such as liquidity, operational, credit, and market risks—affect firm-level financial outcomes. Panel data estimation is employed because it allows the analysis of both cross-sectional and time-series variations, thereby improving the reliability and efficiency of the estimates while controlling for unobserved firm-specific effects.

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The study employs both Pooled Ordinary Least Squares (OLS) and Fixed Effects (FE) estimations. The Pooled OLS model serves as a baseline to estimate the overall relationship between risk management indicators and firm performance. However, because insurance firms differ in unobservable characteristics such as managerial capacity and internal control systems, the Fixed Effects model is adopted to control time-invariant heterogeneity across firms. This approach enhances the internal validity of the results by isolating within-firm variations over time. The selection between the models was guided by the Hausman specification test, which determines the consistency of estimators under the assumption of correlation between the regressors and unobserved effects.

The Econometric Framework of the Multivariate Regression Model

$$Y_{it} = \alpha_1 \; + \beta_{it}X_{it} \; + \varepsilon_1$$

$$Z_{it} = \alpha_2 \; + \beta_{it}X_{it} \; + \varepsilon_2$$

$$\begin{pmatrix} Y_{it} \\ Z_{it} \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} + \begin{pmatrix} \beta_{it} \\ \beta_{it} \end{pmatrix} X_{it} \; + \varepsilon_{it}$$

Y_{it} dependent variables such as ROA of LI and NLI, which are denoted as firm (*i)* over time t

Z_{it} dependent variables such as ROE of LI and NLI, which are denoted as firm (*i)* over time t

V_{it} dependent variables such as LOSSR of LI and NLI, which are denoted as firm (*i)* over time

X_{it} The vectors of the metric of risk factors, such as liquidity risk, market risk, operational risk, and credit risk of the LI and NLI firms

β_{it} is the vector coefficient of the metric that indicates the estimate of parameters in the model.

ε_1 is the stochastic error term of the models

Specifically, the following multivariate linear regression model is constructed to investigate the relationship between RM and FP of the LI and NLI firms in SA from 2018 to 2024. A similar model has been constructed by Soladoye et al. (2024) when investigating how RM influences an Insurance Company's profitability in Nigeria.

$$ROA_{it} = \alpha_0 + \alpha_1 LR_{it} + \alpha_2 OPR_{it} + \alpha_3 CRS_{it} + \alpha_4 MR_{it} + \alpha_5 AG_{it} + \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots\ldots 1$$

$$ROE_{it} = \alpha_0 + \alpha_1 LR_{it} + \alpha_2 OPR_{it} + \alpha_3 CRS_{it} + \alpha_4 MR_{it} + \alpha_5 AG_{it} + \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots\ldots 2$$

Where Financial performance metrics are: ROA_{it} and ROE_{it}

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Definition of Variables in Models

- **ROA is the return on assets,** which is computed as EBTD divided by the total assets. This variable is less aggressive in measuring financial performance because the percentage contribution of assets to profitability indicators does not account for tax and dividend deductions.

- **ROE is the return on Equity**, which is computed as EBTD divided by the shareholders' equity (Basic own funds).

- **LR is a liquidity risk,** which is proxied as the ratio of cash deposited to gross technical provision of both the LI and NLI firms in SA. If the ratios are high, it indicates a low liquidity risk. If the ratios are low, it indicates a high liquidity risk. The gross technical provision is the portion of money the LI and NLI firms allocate to address future financial obligations to policyholders. Understanding the effect of LR on FP in the LI and NLI firms would help regulatory authorities to determine the minimum liquidity standards to ensure they hold sufficient funds to meet their obligations.

- **CR is credit risk,** which is measured as mortgages and loans to total assets of the LI and NLI firms. According to the European Central Bank report, this indicator can measure the credit risk of both banking and insurance firms. Using the mortgage and loans to total assets indicates that a high ratio reveals a high percentage of the firm's assets are allocated to credit risk. It would inform the managers in the insurance firms that there is inefficient management of the firm's assets. Similarly, Altman and Saunders (1997) use individual loans, a portfolio of loans, and factors affecting mortality risk in evaluating the level of credit risk in a firm. In assessing the risk and return of the loan portfolio, the firm can determine the level of credit risk embedded in the portfolio.

- **OP is operational risk**, which is proxied as the ratio of NP to total assets because the magnitude of premiums the firm collects to the total assets is an effective indicator of the size of its operations. Therefore, this variable could indicate the LI and NLI industries' exposure to operational risks. According to the International Association of Insurance Supervisors (IAIS), this indicator is important in measuring operational risk.

- **MR is the market risk variable**, which is proxied as total investment to investment income. Although it might not directly capture all the systemic risk in the insurance markets, this variable is reliable to measure the exposure of the LI and NLI firm investment portfolio to the global market risks. Therefore, in a Bull Market condition, the portfolio return will increase, whereas in a Bear market condition, the portfolio value will fall.

- ε_{it} is the stochastic error term

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DATA

I obtained public financial statements from the SA Reserve Bank database from 2018 to 2024. The study deploys these secondary data to investigate the relationship between RM and FP of LI and NLI companies in SA. The period captures significant risk factors in the insurance industry in both developing and developed economies. The data was constructed into a long panel data framework in which the following regression model techniques, including descriptive statistics, correlations, and regression analyses, were performed. Precisely, the ERM is proxied as the size of the liquidity risk (LR), credit risk (CR), financial risk, age of the firm AG, and Operational risk (OR). The financial performance metrics are ROA, and ROE.

To develop the multiple regression model, I adopted a similar model developed.

To examine the correlation between ERM and the performance of the LI and NLI insurers in South Africa, I designate the dependent variables as ROA and ROE, while the independent variables are LR, OPR, CRS, and MR.

Mathematical Framework of Risk Management in an Insurance Firm.

This study investigates the relationship between RM and FP of LI and NLI firms in an emerging market. Adopting the OLS and Fixed Effect statistical approach, it becomes clear for organizations to quantify and evaluate risks based on their ongoing business objectives. As theoretical models stipulate that the RMF starts with the identification, assessment, management, evaluation, monitoring, and reporting of both internal and external risk factors exposed to the firm. In the LI and NLI companies,

Empirical Results: Interpretation and Conclusion

Table 1: Descriptive Statistics

Statistics	ROE	ROA	OP	MR	LR	CR
Mean	0.045867	0.011713	0.085000	27.84672	0.236430	0.017648
Median	0.055862	0.005782	0.075685	28.27835	0.193745	0.018695
Maximum	0.084422	0.041885	0.146380	62.39140	0.449710	0.026950
Minimum	-0.000225	-7.00E-05	0.037950	-36.12325	0.055730	0.006260
Std. Dev.	0.027888	0.013408	0.045461	23.06972	0.178984	0.008424
Skewness	-0.517627	1.199786	0.123165	-1.309173	0.082839	-0.134578
Kurtosis	1.890266	3.012274	1.171584	5.465388	1.095248	1.258644
Jarque-Bera	1.343569	3.358890	1.985541	7.544761	2.132391	1.811112
Probability	0.510796	0.186477	0.370549	0.022997	0.344316	0.404317
Sum	0.642140	0.163982	1.190000	389.8541	3.310024	0.247070
Sum Sq. Dev.	0.010111	0.002337	0.026867	6918.753	0.416461	0.000923
Observations	14	14	14	14	14	14

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Table 1 shows the descriptive statistics of the multivariate regression equations. The dependent variables are ROE and ROA, whose effects are estimated with the independent variables OP, MR, LR, and CR. The data was collected from the South African Reserve Bank database (SARB), and variables are measured in millions of South African Rand (ZAR). Despite the small sample size of 14 observations, the power of statistical regression methods yields reliable and valid results, as indicated by the test of normality. Analyzing the FP variables of ROE and ROA with a mean score of 0.045 and 0.0117, respectively, indicates low financial performance. Specifically, OP and CR have a mean score of 0.085 and 0.017, respectively. It indicates low operational risk and credit risk, which signifies that management is implementing stringent RM strategies in both LI and NLI companies in SA. However, the MR and LR mean scores of 27.84 and 0.23 are relatively high, showing that the LI and NLI are more exposed to MR and LR.

Table 2: Pearson Correlation Results

	ROE	ROA	OP	MR	LR	CR
ROE	1	0.62940511...	-0.0796965...	-0.3238076...	-0.1079121...	0.28528689...
ROA	0.62940511...	1	0.65795253...	0.06963163...	0.64433801...	-0.4228676...
OP	-0.0796965...	0.65795253...	1	0.38193488...	0.98577084...	-0.9302522...
MR	-0.3238076...	0.06963163...	0.38193488...	1	0.40668207...	-0.5100594...
LR	-0.1079121...	0.64433801...	0.98577084...	0.40668207...	1	-0.9433068...
CR	0.28528689...	-0.4228676...	-0.9302522...	-0.5100594...	-0.9433068...	1

Table 2 indicates the Pearson correlation table, which illustrates the relationship between the dependent and the independent variables in the models. This study seeks to provide answers to the question: To what extent does there exist a relationship between RM and FP of an insurance company in SA?

Although the Pearson correlation test is the preliminary test for the relationship among variables in a Panel data, it serves as an important indication of the likelihood of a relationship among existing variables. From Table 2, a negative relationship exists between OP and ROE, MR and ROE, and LR and ROE. Conversely, CR has a positive relationship with ROE. The ROA, OP, MR, and LR are all positive. However, CR has a negative relationship with ROA. Nevertheless, to check for the heterogeneity that could be present among the different cross-sections (LI and NLI), I conduct the Pool ordinary Least Squares (OLS) and Fixed effect models to investigate the relationship between FP and RM in the SA insurance industry. The GLR Random effects estimation requires that the number of cross-sections be greater than the number of estimated coefficients in the model. For this reason, the GLR Rand effect models were not estimated.

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Table 3: Pooled OLS Results

Dependent Variable: ROA

Total panel (balanced) observations: 14

Variable	Coefficient	Std. Error	t-Statistic	Prob.
OP	0.255004	0.297122	0.858245	0.4130
MR	3.08E-05	0.000119	0.260200	0.8006
LR	0.105935	0.082616	1.282254	0.2318
CR	2.773373	0.886558	3.128249	0.0122*
C	-0.084811	0.027663	-3.065844	0.0134

R-squared	0.746907	Mean dependent var	0.011713
Adjusted R-squared	0.634421	S.D. dependent var	0.013408
S.E. of regression	0.008107	Akaike info criterion	-6.519730
Sum squared resid	0.000592	Schwarz criterion	-6.291495
Log likelihood	50.63811	Hannan-Quinn criterion.	-6.540857
F-statistic	6.640010	Durbin-Watson stat	2.105871
Prob(F-statistic)	0.009002**		

Output test Data regression panel Pooled OLS with Eviews. P-value, *P<0.05, **P<0.01, and ***P<0.001

Table 3: Pooled OLS Model. The assumption in the pooled OLS is that there is no heterogeneity or individual effect within the cross-section in the panel data. There is a fixed intercept and constant slope between the LI and NLI firms. The Pooled OLS results show that CR, measured as mortgage and loans to total assets, typically represent the LI and the NLI companies' total assets investment in debt instruments. The CR has a significant positive relationship with the ROA at a p-value of 5%. The results are similar to the findings of Madugu et al. (2020), who affirm a positive and significant effect of CR on profitability in the banking sector in Ghana. It reveals that from 2018 to 2024, there is effective CR management by the LI and NLI companies in SA. Both the R-squared and adjusted R-squared values of 74% and 59% indicate a substantial explanatory power of the independent variables on the dependent variable.

The other independent variables, such as OP, LR, and MR, have a positive but insignificant relationship with ROA. However, the Pooled OLS results are efficient, and the best linear unbiased estimators are indicated by no endogeneity in the model. The Durbin-Watson test statistic of 2 falls in an acceptable range of 1.5 and 2, indicating no autocorrelation in the model. Therefore, I conduct the Breusch-Pagan test to check if there is a cross-sectional effect or a time-varying effect due to the nature of the panel data. Panel data has a longitudinal and a cross-sectional characteristic; therefore, the Breusch-Pagan test is used to check if there is no autocorrelation in the models.

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Table 4: Brusch-Pegan Test Results.

H_0: No effects
H_1: Two-sided (Breusch-Pagan) and one-sided
(all others) alternatives

	Test Hypothesis		
	Cross-section	Time	Both
Breusch-Pagan	1.165388 (0.2804)	0.485425 (0.4860)	1.650813 (0.1988)
Honda	-1.079531 (0.8598)	-0.696725 (0.7570)	-1.256003 (0.8954)
King-Wu	-1.079531 (0.8598)	-0.696725 (0.7570)	-1.262789 (0.8967)
Standardized Honda	-0.800241 (0.7882)	-0.915151 (0.8199)	-4.830455 (1.0000)
Standardized King-Wu	-0.800241 (0.7882)	-0.915151 (0.8199)	-6.499994 (1.0000)
Gourieroux, et al.	--	--	0.000000 (1.0000)

Output test Data regression panel Brusch-Pegan with Eviews. P-value in parentheses $^{*}P<0.05$, $^{**}P<0.01$, and $^{***}P<0.001$

The results of the Breusch-Pagan test statistics indicate that for both cross-section and time, there is no significant effect. It means both fixed effects and random effects are not necessary because there is no cross-sectional effect and time-varying effect in the model. Hence, the Pooled OLS is the appropriate model. To confirm the robustness of the Pooled OLS results, the fixed effect model is estimated. The fixed effect results are identical to the Pooled OLS. This is because there is no variation across the groups (LI and NLI). Therefore, the fixed effect model, which focuses on the panel variation, yields similar results to the pooled OLS, which mainly analyzes the entire variation in the data.

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Table 5: Fixed Effect Results (Robustness Test)

Dependent Variable: ROA
Total panel (balanced) observations: 14

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.085212	0.029373	-2.901086	0.0199
CR	2.639715	1.206186	2.188481	0.0601
MR	2.62E-05	0.000128	0.204809	0.8428
LR	0.112533	0.095121	1.183054	0.2708
OP	0.270625	0.326762	0.828201	0.4316
	Effects Specification			
Cross-section fixed (dummy variables)				
R-squared	0.747888	Mean dependent var		0.011713
Adjusted R-squared	0.590317	S.D. dependent var		0.013408
S.E. of regression	0.008582	Akaike info criterion		-6.380755
Sum squared resid	0.000589	Schwarz criterion		-6.106873
Log likelihood	50.66528	Hannan-Quinn criterion.		-6.406108
F-statistic	4.746376	Durbin-Watson stat		2.051036
Prob(F-statistic)	0.026028			

Output test Data regression panel fixed effect with Eviews. P-value, *P<0.05, **P<0.01, and ***P<0.001

Table 5 shows the results of the fixed-effect model, which is closely similar to the Pooled OLS, confirming the robustness of the Pooled OLS results. However, CR has a positive but weak, significant relationship with ROA.

Table 6: The Pooled OLS Results

Dependent Variable: ROE
Total panel (balanced) observations: 14

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.110699	0.092392	-1.198144	0.2615
OP	0.561064	0.992349	0.565390	0.5856
MR	-9.05E-05	0.000396	-0.228615	0.8243
LR	0.080067	0.275926	0.290177	0.7783
CR	5.239442	2.960983	1.769494	0.1106
R-squared	0.347407	Mean dependent var		0.045867
Adjusted R-squared	0.057366	S.D. dependent var		0.027888
S.E. of regression	0.027076	Akaike info criterion		-4.107869
Sum squared resid	0.006598	Schwarz criterion		-3.879635
Log likelihood	33.75509	Hannan-Quinn criterion.		-4.128997
F-statistic	1.197784	Durbin-Watson stat		1.593776
Prob(F-statistic)	0.375574			

Output test Data regression panel Pooled OLS with Eviews. P-value, *P<0.05, **P<0.01, and ***P<0.001

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Table 6 shows the result of the Pooled OLS for ROE. This study examines the impact of MR, OP, LR, and CR on FP (ROE) on the LI and NLI companies in SA. Results displayed in Table 6 show that MR, OP, LR, and CR do not have a significant relationship with ROE. Based on these results, it is recommended that the LI and NLI companies in SA should continue with the RM strategies and pay close attention to MR because it has a negative relationship with ROE, even though it is not significant. Following the rule of thumb, the accepted Durbin-Watson test statistic should be between 1.5 to 2.0. From the results, there is no evidence of autocorrelation in the model.

The R-squared is 34.74%, indicating that the MR, OP, LR, and CR contributed 34.74% of ROE in the LI and NLI companies.

Table 7: Brusch-Pegan Test Results.

H_0: No effects
H_1: Two-sided (Breusch-Pagan) and one-sided
(all others) alternatives

	Test Hypothesis Cross-section	Time	Both
Breusch-Pagan	1.154038	0.884438	2.038476
	(0.2827)	(0.3470)	(0.1534)
Honda	-1.074262	-0.940446	-1.424613
	(0.8586)	(0.8265)	(0.9229)
King-Wu	-1.074262	-0.940446	-1.350028
	(0.8586)	(0.8265)	(0.9115)
Standardized Honda	-0.542901	-1.169727	-5.079855
	(0.7064)	(0.8789)	(1.0000)
Standardized King-Wu	-0.542901	-1.169727	-6.741672
	(0.7064)	(0.8789)	(1.0000)
Gourieroux, et al.	--	--	0.000000
			(1.0000)

Output test Data regression panel Brusch-Pegan with Eviews. P-value in parentheses *P<0.05, **P<0.01, and ***P<0.00

Table 8: Residual Diagnostic Test.

that the reliability and validity of the methodology ap
Residual Cross-Section Dependence Test
Null hypothesis: No cross-section dependence (correlation) in residuals
observations: 14

Test	Statistic	d.f.	Prob.
Breusch-Pagan LM	0.489246	1	0.4843
Pesaran scaled LM	-0.361157		0.7180
Pesaran CD	-0.699461		0.4843

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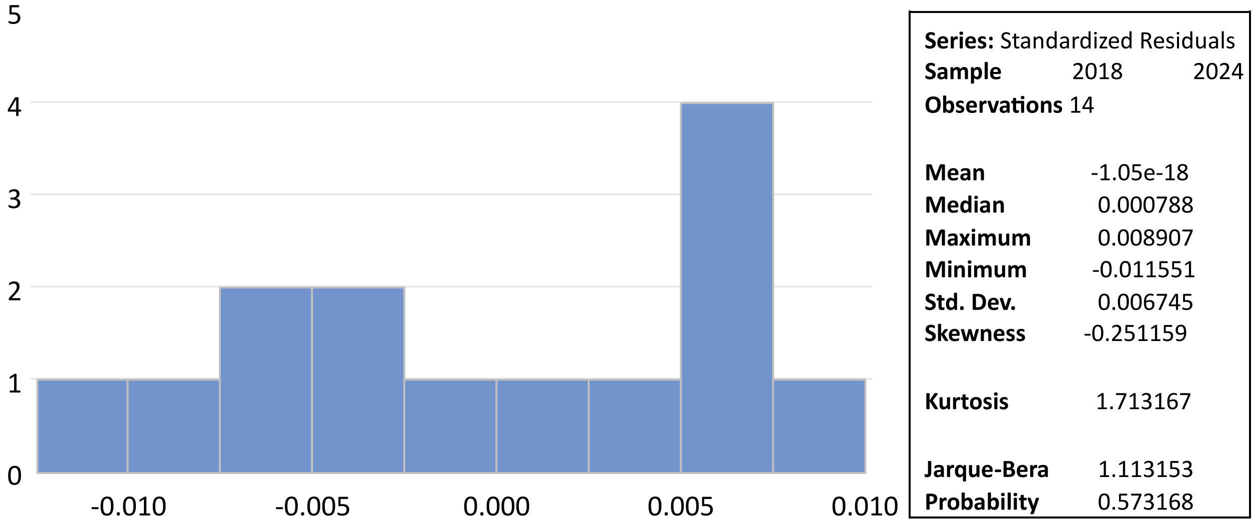
Figure 1: Test of Normality



Both Table 8 and Figure 1 provide useful information on the reliability of the regression analyses. Based on the P-value of 5% level of significance, the results indicate that the null hypothesis of normality of the residual error terms cannot be rejected in both the Breusch-Pagan and Histogram normality tests in the regression model with dependent variables ROA and ROE. Therefore, I confirm the normality of the error term at a 5% significance level. Although the sample size is from 2018 to 2024, the results obtained suggest that during this period, the SCL adopted in the LI and NLI companies in SA is adequate in their RM strategies.

CONCLUSION AND LIMITATION

This study explores the relationship between RM and FP of LI and NLI companies in SA from 2018 to 2024. The findings reveal that CR has a positive and significant relationship with ROA in LI and NLI in SA. These results appear to contradict the theoretical construction that CR should have a negative relationship with the FP because the policyholder might default on their premium payment. In contrast to the results of Kiptoo et al (2021), which indicate a negative effect of CR on FP of insurance firms in Kenya, this study reveals a positive and significant relationship between CR and FP of the LI and NLI firms in SA. It shows that the LI and NLI companies in SA are potentially transferring their risk to other financial institutions such as banks, credit unions, and other insurance companies. This means that the managers are effectively factoring the CR variables into their risk-adjusted strategy. The results support the ongoing RM and SCR effort by the SA Insurance Authorities. While OP, LR CR, and MR have an insignificant relationship with ROE, it is essential to validate these results despite the small sample size because the normality test indicates the reliability and validity of the results. However, no recommendation can be drawn from these results; therefore, future studies should improve the sample size. Based on these results, the LI and NLI insurance firms should implement a robust RM assessment in emerging risks like climate change, underwriter losses, and rigorously examine their financial statement quarterly. This study adds to the RM literature by providing an empirical analysis of the relationship of the various RM strategies implemented by LI and NLI firms in SA and provides suggestions that policymakers can review and adopt.

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These insurance firms would also integrate Artificial Intelligence AI for an effective analysis of their data to trace patterns of emerging risks. The results of this study make substantial contributions by providing appealing insight into the existing literature on risk management in the LI and the NLI companies in a developing economy, as it adopts a different research design that examines risk management in the LI and NLI companies in SA.

Limitation

As mentioned above, future studies should consider increasing the sample size to enhance the generalizability of the findings. Including data from a broader range of insurance firms, within and outside SA, could provide a more comprehensive understanding of the relationship between RM and FP. Moreover, future research could incorporate primary data, such as surveys or interviews with key stakeholders in the insurance firms. This would provide a more detailed understanding of the factors influencing RM decisions and the challenges firms face, particularly in terms of non-financial risks that are not captured in financial statements.

About the Author

Dr. Divine B. Fondem, is an instructor at the University of the Cumberlands. He earned his DBA in Finance from Liberty University, and his research interest focuses on international financial policies, corporate social sustainability, corporate governance, and the global capital markets and international finance.

Ethical Compliances

All procedures performed in this study did not involve human participation. The author uses secondary data from the South African Reserve Bank database.

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