Eduvest – Journal of Universal Studies
Volume 6 Number 8, August, 2026
p- ISSN 2775-3735- e-ISSN 2775-3727

# The Effect of Performance on Reinsurance Decisions of Indonesian General Insurance Companies: An Empirical Review of the Pandemic and Post Pandemic Period

**Helena Nadine Hapsari*, Lukman Hanif Arbi**
Universitas Indonesia, Indonesia
Email: helenanadinehapsari@gmail.com*, lukman.hanif@ui.ac.id

**Keywords**
Reinsurance;
Firm Performance;
Return On Equity;
Panel Data;
Pandemic Period;
Indonesian General Insurance Companies.

**ABSTRACT**
This research aims to analyze the effect of ROE on REINS of general insurance companies in Indonesia, comparing the pandemic period (2020–2022) and the post-pandemic period (2023–2024). Using panel data from 50 companies over the 2020–2024 period (250 observations), this study employs three empirical models: Model 1 (2SLS two-way fixed effect with insurance leverage as instrument), Model 2 (OLS one-way fixed effect with contemporaneous ROE), and Model 3 (OLS one-way fixed effect with a one-period lag of ROE). Estimation results show that in Model 1 and Model 2, ROE has no significant effect on REINS. In Model 3, the lag of ROE has a positive coefficient (0.01967) and is significant at the 10% level ($p = 0.074$), which does not support the underinvestment hypothesis. Financial leverage consistently shows a positive effect, while premium growth consistently shows a negative effect. Comparative period analysis reveals that during the pandemic, the lag of ROE is not significant, whereas in the post-pandemic period, the lag of ROE becomes positive (0.199) and significant ($p = 0.009$). The Chow test yields a p-value of 0.05758, significant at the 10% level. Model 3 is selected as the main model as it better reflects the real-world decision-making process. This study concludes that the effect of ROE on REINS in Indonesia differs from previous findings, and that the relationship pattern changed after the pandemic. These findings have implications for insurance company management and regulators in formulating reinsurance strategies based on past performance, leverage, and premium growth.

## INTRODUCTION

Globally, the reinsurance industry showed very strong fundamentals throughout 2024. Reinsurance special capital reached a record USD769 billion, supported by growth in retained earnings and improved investment performance (Gallagher Re, 2025). The reported combined ratio improved to 86.8%, while the return on equity (ROE) was recorded at 17.0% despite higher natural disaster losses and a number of liability reserves in the US (Gallagher Re, 2025). In the European region, reinsurance accounted for 18.8% of the total gross premiums of the insurance and reinsurance sector in the European Economic Area (EEA) in 2023, with 62% of transactions occurring within the European Union (EIOPA, 2024). However, European supervisors are wary of the reliance on third-country reinsurance as well as the complexity of structures such as asset-intensive reinsurance and mass-lapse reinsurance that can trigger imperfect risk transfers (EIOPA, 2024). With thick capital reserves and ever-improving underwriting profitability, global reinsurance currently has enough cushion to absorb major shocks, including the impact of the Los Angeles fire which is expected to reduce ROE by only 2–3 percentage points in 2025 (Gallagher Re, 2025).

On the other hand, Asia is facing four major transitions, namely climate, energy, digital, and demographics, which actually open up huge opportunities for reinsurance. Economic losses in Asia Pacific in 2023 reached USD65 billion, but 91% of them were uninsured, indicating a very wide protection gap (Gan Kim Yong, 2024). To address these challenges, Singapore is strengthening its role as Asia's reinsurance hub, with 16 of the world's 25 largest reinsurers making it a regional hub. Initiatives such as the development of parametric insurance, insurance-linked securities (ILS), and the use of artificial intelligence (AI) in underwriting are the main focuses (Gan Kim Yong, 2024). Meanwhile, demand for life and health reinsurance continues to be driven by an aging population and a rising middle class, with Asia currently accounting for 39% of the global life insurance market and growing above 5% per year (Gan Kim Yong, 2024). Thus, reinsurance not only serves as a risk absorber, but also as a catalyst for sustainable growth in the world's most dynamic region (Hall & Walsh, 2025; Luthuli, 2025; Marangwanda, 2025).

In practice, the decision to buy reinsurance has two-sided implications for insurance companies. On the one hand, reinsurance provides significant benefits in the form of increased capacity, performance stabilization, and reduced risk of bankruptcy. On the other hand, the purchase of reinsurance also incurs costs that can reduce profitability, because the premiums received must be shared with the reinsurance company, so that low premium retention has the potential to reduce profits (Lee & Lee, 2012). Furthermore, Lee & Lee (2012) showed that the relationship between reinsurance and company performance is interdependent: companies with higher profitability tend to buy less reinsurance, while high reliance on reinsurance can lower the company's performance. In other words, there is a trade-off between risk management through the transfer of premiums to reinsurance and the potential for a decline in profits due to reduced retained premium income. This is a challenge for insurance companies, especially in emerging markets such as Indonesia, where the general insurance industry continues to grow but is faced with fluctuating profitability pressures (Hasanah et al., 2024; Puspitasari et al., 2026; Rahma et al., 2025; Suryanto et al., 2020; Widyani, 2023).

In Indonesia, the general insurance industry is showing dynamic development. Based on data from the Financial Services Authority (OJK), the number of general insurance companies continues to transform in line with policies to increase capital and strengthen governance. In this context, the use of reinsurance is one of the important strategies for general insurers to manage underwriting risks, comply with self-retention provisions set by regulators, and maintain solvency ratios. However, an interesting phenomenon to study is that although dependence on reinsurance in Indonesia is relatively high, the profitability of general insurance companies represented by return on equity (ROE) often shows fluctuations that are not always in the same direction. This indicates a complex relationship between reinsurance and performance, where an increase in the use of reinsurance is not necessarily followed by an increase in profitability, in fact (Griffith & Liebenberg, 2021; Horvey & Odei-Mensah, 2025; Park et al., 2021; Shiu, 2020; Y. Zhang, 2016).

\

Previous studies on the relationship between reinsurance and insurance company performance have shown mixed results. Some studies have found that reinsurance has a positive effect on performance (Ma & Elango, 2008), while other studies have found a negative effect (Choi, 2010; Lee & Lee, 2012) or unclear relationships (Choi & Weiss, 2005). In particular, Lee & Lee (2012) show that reinsurance and corporate performance are interdependent: companies with higher return on assets (ROA) tend to buy less reinsurance, and companies with higher reinsurance dependencies tend to have lower levels of performance. In addition, factors such as company size, financial leverage, underwriting risk, return on investment, market share, as well as company characteristics such as listed status on the stock exchange have also been proven to influence reinsurance decisions and company performance (Lee & Lee, 2012).

This study focuses on the influence of financial performance, proxied by return on equity (ROE), on the reinsurance decisions of general insurance companies in Indonesia. In contrast to Lee & Lee (2012) who examined the interdependent relationship between reinsurance and performance, this study emphasizes more on the causality direction from performance to reinsurance. To overcome the potential for simultaneous bias while evaluating the consistency of results, this study uses three empirical models, namely Model 1 (2SLS) with a variable insurance leverage instrument that is theoretically able to correct endogeneity, Model 2 (OLS fixed effect) with contemporary ROE as a comparison without correction, and Model 3 (OLS fixed effect with a one-period ROE lag) which is designed to reduce simultaneity bias because the current year's reinsurance decision is based on in the previous year's performance that has been known.

In addition, to provide a sharper empirical review of the research, the observation period is divided into two parts, namely the pandemic period (2020–2022) and the post-pandemic period (2023–2024). The division aims to capture the impact of the global health crisis on reinsurance behavior and company performance, as well as to test whether the structure of the relationship between ROE and reinsurance decisions differs significantly between the two periods. Testing of differences in relationship structure between periods is carried out through sensitivity analysis with the Chow test (pool ability test), which will compare the regression coefficient between the pandemic and post-pandemic periods (Ananda & Ghani, 2026; Rachmawati & Handayani, 2026; Rizaldi et al., 2026; Tressel & Ding, 2021; W. Zhang & Zhang, 2026).

This study also included a number of control variables based on the literature, including firm size, financial leverage, reinsurance price, underwriting risk, premium growth, return on investment (ROI), market share, joint venture status, listed status on the stock exchange, and the existence of domestic and foreign parent companies in order to estimate the influence of ROE on the Reinsurance is unbiased. Taking all these aspects into account, this study is expected to make a significant empirical contribution to the risk management and corporate finance literature in Indonesia. The results of this study are also expected to be considered for regulators and insurance company management in formulating optimal reinsurance strategies, especially in the face of fluctuating economic conditions such as the pandemic and post-pandemic period.

This research is motivated by the high dependence of general insurance companies in Indonesia on reinsurance as encouraged in OJK regulations, especially POJK No.

23/POJK.05/2021, in the midst of diverse company profitability conditions during the pandemic and post-pandemic period. This study aims to analyze the influence of financial performance proxied through return on equity (ROE) on reinsurance decisions (REINS), as well as compare the estimated results between the 2SLS simultaneous model, the OLS model with contemporary ROE, and the OLS model with a one-period ROE lag. In addition, this study also identifies the influence of other factors such as company size, financial leverage, underwriting risk, premium growth, return on investment, market share, and company characteristics on the level of reinsurance dependence, as well as evaluating the differences in the relationship between variables in the pandemic and post-pandemic periods. The results of the research are expected to make a theoretical contribution to the development of risk management and reinsurance literature in emerging markets, as well as practical input for OJK, insurance companies, and reinsurance companies in developing reinsurance and risk management strategies that are more effective and adaptive to changing economic conditions.

## METHOD

### Uji Model Panel

After describing the data, then an estimate will be made of the three types of panel data models, namely the Common Effect Model (CEM) which assumes that there is no difference in interception between individuals, the Fixed Effect Model (FEM) which assumes that there is a difference in interception between individuals or between times, and the Random Effect Model (REM) which assumes that the intercept varies randomly. Once the model is estimated, the first formal step is the Chow Test (or Likelihood Ratio test) which aims to compare CEM with FEM. This test was performed with the zero hypothesis that CEM is more precise (there is no difference in interception between individuals). If the p-value of the Chow test is less than 0.05, then the null hypothesis is rejected, so FEM is preferred over CEM. On the other hand, if the p-value is greater than 0.05, then CEM is used (Baltagi, 2021).

Furthermore, the Hausman Test was carried out to compare FEM with REM. The Hausman test tests whether the difference in coefficients between FEM and REM is systematic. The zero hypothesis states that REM is consistent and efficient (there is no correlation between individual effects and independent variables). If the p-value is less than 0.05, then the null hypothesis is rejected, so the FEM is chosen. However, if the p-value is greater than 0.05, then REM is more appropriate (Wooldridge, 2016). If the Hausman test points to REM, then it is necessary to proceed with the Breusch-Pagan Lagrange Multiplier (LM) test to compare REM with CEM. The zero hypothesis of the LM test is that CEM is better (there is no variety of individual effects). If the p-value is less than 0.05, then REM is chosen, and vice versa CEM is used (Hsiao, 2014).

### Research Model

This study aims to examine the relationship between reinsurance decisions and the performance of general insurance companies in Indonesia by focusing on the effect of return on equity (ROE) on the reinsurance ratio (REINS). The study used a two-stage least squares (2SLS) approach with insurance leverage (IL) as an instrument variable to address the issue of endogeny and the reciprocal relationship between ROE and REINS. In addition, the study also used the Ordinary Least Squares (OLS) method as a comparative model to test the consistency

\

and robustness of the estimation results. The data used is in the form of panel data on Indonesian general insurance companies for the 2020–2024 period with various control variables that reflect company characteristics, underwriting risk, reinsurance prices, premium growth, and company institutional conditions.

1. Dependent Variable: The dependent variable in this study is the reinsurance ratio (REINS) which is measured from the total reinsurance premiums divided by the total gross premiums. This ratio is used to describe the level of reliance a company has on reinsurance in shifting risk. The higher the value of REINS, the greater the proportion of risk transferred to the reinsurance company.
2. Independent Variables: The main independent variable in this study is return on equity (ROE) which is calculated from profit after tax compared to total equity. ROE is used to measure a company's ability to generate profits for shareholders. In addition, the study used insurance leverage (IL) as an instrument variable in the 2SLS model to address the simultaneous relationship between ROE and REINS.
3. Control Variables: The study included several control variables, namely firm size (FS), financial leverage (FL), reinsurance price (RP), underwriting risk (UR), growth of premium (GP), return on investment (ROI), and market share (MS). In addition, dummy variables in the form of listed dummy (LD), foreign parent (ILN), and domestic parent (IDN) are also used to control differences in the company's institutional characteristics.
4. Empirical Model of Research and Data Processing Techniques: The study compiled three empirical models, namely Model 1 using the 2SLS approach with variable instruments and two-way fixed effects, Model 2 using OLS fixed effect without instruments as a comparison model, and Model 3 using a one-period ROE lag to reduce the potential for simultaneity. The analysis was carried out using statistical software R with data from a panel of Indonesian general insurance companies for the 2020–2024 period and compared the pandemic and post-pandemic periods through sensitivity analysis and the Chow test.

**Test Residual Model**

Once the panel data regression model is estimated, it is necessary to perform a series of residual tests to ensure that the model meets the classical Gauss-Markov assumptions so that the estimation results are BLUE (Best Linear Unbiased Estimator). The test includes four main aspects, namely residual normality, multicollinearity, heteroscedasticity, and autocorrelation.

1. Residual Normality Test: The normality test aims to check whether the residual of the regression model is normally distributed. Abnormal residual can result in errors in hypothesis testing, especially in small samples. The test was carried out by the Jarque-Bera or Kolmogorov-Smirnov Test, as well as visual examination through histograms and Q-Q plots. If the p-value of the statistical test > 0.05, then the residual is considered to be normally distributed. If the normality assumption is not met, the data transformation can be performed using the Generalized Least Squares (GLS) method.
2. Multicollinearity Test: This test aims to detect a high correlation between independent variables. Multicollinearity can cause the estimation of regression coefficients to be unstable and standard errors to magnify. The measuring tool used is the Variance Inflation Factor (VIF). A VIF value of < 10 indicates the absence of serious multicollinearity, while a value of > 10 indicates a multicollinearity problem. If multicollinearity is detected, the

solution is to eliminate one of the highly correlated variables, perform a variable transformation, or use Principal Component Analysis.

3. Heteroscedasticity Test: A heteroscedasticity test is performed to check whether residual variance is constant between variables. Heteroscedasticity often occurs in panel data due to differences in characteristics between individuals. Testing can be done with the Breusch-Pagan Test or the White Test. If the test results are significant (p-value $< 0.05$), then there is heteroscedasticity. To overcome this, the study used robust standard errors or clustered standard errors, which are able to produce consistent standard errors even though the variance is not uniform.
4. Autocorrelation Test: Autocorrelation occurs when the residual of a given period correlates with the residual of the previous period, which is commonly found in time series data and panel data. To test autocorrelation, the Durbin-Watson Test or the Breusch-Godfrey Test is used. If autocorrelation is detected, the research can be addressed by using clustered standard errors at the individual (company) level, which allows residual correlation in the same individual over time. This approach results in standard errors that are more accurate and valid for statistical inference.

**Model Selection Process**

Once all residual tests have been performed and the classical assumptions have been met (or violated but have been corrected with robust/clustered standard errors), the next step is to perform a comparison and model selection to determine which model is most appropriate to use to answer the research hypothesis. This study compiled three models with different specifications and estimation methods, namely Model 1 (2SLS with IL instrument), Model 2 (OLS with ROE has the same time period as REINS), and Model 3 (OLS with ROE lag t-1). Comparisons between models are carried out based on several criteria, namely the statistical significance of the main independent variable (i.e. the ROE variable), the consistency of the coefficient direction with the theory (which is expected to be negative), the adjusted $R^2$ value as a measure of goodness-of-fit, and information criteria such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), where the smaller the AIC/BIC value indicates a better model.

In addition to statistical criteria, this study also considers the theoretical logic and practical relevance of each model. As already explained, Model 2 (ROE has the same time period as REINS) has the potential for simultaneity problems so its causal interpretation is weak. Whereas, Model 1 (2SLS) theoretically overcomes endogeny, but its validity is highly dependent on the quality of the instrument. The research with Model 1 will conduct a weakness test of the instrument with the F test in the first stage of regression and the overidentifying restriction test. If the instrument proves to be weak (F-statistic $< 10$) or invalid, then the 2SLS estimator may produce a greater bias than the OLS. However, if Model 1 does not have a significant influence, then this study does not continue testing the instrument variables because the validity or not of the instrument variables is no longer the main issue. Furthermore, Model 3 (ROE with a one-period lag) is considered the most reasonable from business logic because the reinsurance decision in year t is based on the previous year's known performance. Based on these considerations, the model to be chosen is a model that has a significant ROE coefficient with a theoretical direction, the lowest AIC/BIC value, and a strong theoretical justification. The results of the comparison of the three models will be presented in the form of a summary table in Chapter 4, and the best models will be used as the basis for hypothesis testing.

**Sensitivity Analysis Method: Comparison of Models in the Pandemic and Post-Pandemic Period**

To answer the research question that specifically reviewed the pandemic (2020–2022) and post-pandemic (2023–2024) periods, this study conducted a sensitivity analysis to evaluate whether the effect of performance (ROE) on reinsurance decisions (REINS) differed significantly between the two periods. Sensitivity analysis is an important step to test the robustness of the model against extreme changes in macroeconomic and policy conditions, such as those that occurred during the COVID-19 pandemic (Wooldridge, 2016). By separating the data into two sub-periods, this study can capture the potential changes in the relationship structure between variables that may occur due to external shocks.

The sensitivity analysis procedure was carried out by estimating the selected model separately in each sub-period. The estimated results in the pandemic period and the post-pandemic period will be compared, including the direction, significance, and magnitude of the coefficient of the main independent variables and control variables. In addition, to test whether the difference in coefficients between the two periods is statistically significant, a Chow test (pool ability test) was carried out with the null hypothesis that there is no difference in regression coefficient between the pandemic and post-pandemic periods. This test uses the Wald test approach which compares a restricted model with combined data across the period against an unrestricted model that allows for different coefficients between periods. If the p-value of the Chow test is less than the specified level of significance ($\alpha = 0.05$ or $\alpha = 0.1$), then the null hypothesis is rejected, indicating a significant structural difference.

In addition, a goodness-of-fit comparison between periods will also be carried out by comparing the values of the determination coefficient ($R^2$), the Akaike Information Criterion (AIC), and the Bayesian Information Criterion (BIC). Higher $R^2$ values indicate better model clarity, while lower AIC and BIC values indicate a more efficient model in balancing compatibility with parameter complexity. All of the results of this sensitivity analysis will be presented in the form of a table and discussed in depth in Chapter 4 as part of the answer to the research question that emphasizes the empirical review of the pandemic and post-pandemic period.

## RESULT AND DISCUSSION

After determining the fixed effects model (FEM) as the selected model, then an estimate of the three model specifications as formulated in sub-chapter 3.3 is carried out. All three models use robust standard errors (HC1) to correct for heteroscedasticity, and the estimated results are presented in Table 4.7, Table 4.8, and Table 4.9.

**1. Model 1: Simultaneous Equations with Instrument Variables**

Model 1 estimates the effect of ROE on REINS with a two-way fixed effect approach using variable instruments to address endogenicity. Based on Table 4.3, the ROE variable has a positive coefficient of 0.05986 but is not significant at the conventional test level (p-value = 0.358). This indicates that after correcting for endogeny, the company's performance (ROE) has not been statistically proven to influence reinsurance purchasing decisions. Among the control variables, financial leverage (FL) showed a positive and significant influence (coefficient = 0.39675; $p < 0.01$), meaning that companies with higher debt levels were more likely to buy more reinsurance, according to the hypothesis that reinsurance is used to reduce the risk of bankruptcy. Growth of premium (GP) has a negative and very significant coefficient (coefficient = -0.00752; $p < 0.001$), indicating that companies with high premium growth actually reduce the use of reinsurance. The variables of underwriting risk (UR) and return on investment (ROI) were significant at the level of 10% respectively with a positive direction, while the other variables were not significant.

**Table 1. Model 1 Estimation Result: Simultaneous Equations with Instrument Variables**

| Variable | Estimate | Std_Error | t_value | Pr(>\|t\|) |
|---|---|---|---|---|
| **ROE** | 0.059863 | 0.064979 | 0.9213 | 0.35809015 |
| **FS** | -0.078718 | 0.0635 | -1.2396 | 0.21665345 |
| **FL** | 0.396752 | 0.120987 | 3.2793 | 0.00123999 ** |
| **RP** | 0.00029 | 0.000248 | 1.1731 | 0.24224239 |
| **UR** | 0.065675 | 0.037103 | 1.7701 | 0.07833563. |
| **GP** | -0.007517 | 0.001665 | -4.5155 | 0.00001113 *** |
| **KING** | 1.262599 | 0.717588 | 1.7595 | 0.08011863. |
| **MS** | -1.849176 | 2.064519 | -0.8957 | 0.37156205 |

Source: Data processing using R

**2. Model 2: Individual Fixed Effect OLS Without Instrument**

Model 2 estimates the same relationship as Model 1 (ROE has the same time period as REINS) but uses a one-way fixed effect OLS without instruments. The results in Table 4.4 show that the ROE coefficient is negative but very small (-0.00951) and insignificant ($p = 0.702$). Thus, whether using instruments or without instruments, ROE has not been proven to have a significant effect on REINS in the context of Indonesian data for the 2020–2024 period. The firm size (FS) variable in this model was significantly negative (coefficient = -0.10841; $p < 0.05$), indicating that larger firms tend to buy less reinsurance. FL was again significantly positive (coefficient = 0.50479; $p < 0.001$), GP was significantly negative (coefficient = -0.00841; $p < 0.001$), and UR and ROI were significant at the level of 10% with a positive direction. These findings are consistent with Model 1, except for the FS variable which is only significant in Model 2.

**Table 2. Model 2 Estimation Result: Individual Fixed Effect OLS Without Instrument**

| Variable | Estimate | Std_Error | t_value | Pr(>\|t\|) |
|---|---|---|---|---|
| **ROE** | -0.009512 | 0.024788 | -0.3837 | 0.70161410990 |
| **FS** | -0.108413 | 0.042107 | -2.5747 | 0.01078583119 * |
| **FL** | 0.504792 | 0.112502 | 4.487 | 0.00001242751 *** |
| **RP** | 0.000152 | 0.000225 | 0.6757 | 0.50003561236 |
| **UR** | 0.062409 | 0.037619 | 1.659 | 0.09874740321. |
| **GP** | -0.008412 | 0.001398 | -6.0167 | 0.00000000885 *** |
| **KING** | 1.054609 | 0.621119 | 1.6979 | 0.09114353526. |
| **MS** | -1.419031 | 1.890065 | -0.7508 | 0.45370161372 |

Source: Data processing using R

**3. Model 3: Individual Fixed Effect OLS with One-Period Lag ROE**

Model 3 replaces ROE that has the same time period as REINS with the previous year's ROE (lag 1) to reduce simultaneity bias. The estimated results in Table 4.5 show that the ROE lag has a positive coefficient of 0.01967 and is significant at the level of 10% ($p = 0.074$).

\

These findings provide weak evidence that the company's performance in the previous year had a positive effect on reinsurance purchases in the following year, although its significance was only marginal. In other words, companies that were more profitable in the past tended to slightly increase the use of reinsurance, in contrast to the initial hypothesis. Other significant variables were FS (negative, $p < 0.01$), FL (positive, $p < 0.05$), UR (positive, $p < 0.05$), and GP (negative, $p < 0.001$). Meanwhile, ROI and MS are not significant in this model.

**Table 3. Model 3 Estimated Results: Individual Fixed Effect OLS with 1-Period Lag ROE**

| Variable | Estimate | Std_Error | t_value | Pr(>\|t\|) |
|---|---|---|---|---|
| **Lag (ROE)** | 0.019673 | 0.010926 | 1.8005 | 0.0739012126. |
| **FS** | -0.169761 | 0.057113 | -2.9724 | 0.0034720640 ** |
| **FL** | 0.347818 | 0.15989 | 2.1754 | 0.0312580445 * |
| **RP** | 0.000471 | 0.000265 | 1.7747 | 0.0780845465. |
| **UR** | 0.070476 | 0.034601 | 2.0368 | 0.0435233080 * |
| **GP** | -0.00702 | 0.00128 | -5.483 | 0.0000001858 *** |
| **KING** | 1.01848 | 0.738039 | 1.38 | 0.1697616150 |
| **MS** | -0.782311 | 1.889260 | -0.4141 | 0.6794380794 |

Source: Data processing using R

**4. Goodness of Fit Comparison Test Between Models**

In addition to comparing the significance and direction of the coefficients, the evaluation of the three models was also carried out based on goodness-of-fit criteria, namely the determination coefficient ($R^2$), the Akaike Information Criterion (AIC), and the Bayesian Information Criterion (BIC). A summary of the comparative results is presented in Table 4.6. Model 1 (2SLS two-way fixed effect) has an $R^2$ value of 0.3341, which means that an independent variable is able to explain about 33.41% variation in REINS. Model 2 (OLS one-way fixed effect without instruments) has an $R^2$ of 0.3941, slightly higher than Model 1. Meanwhile, Model 3 (OLS fixed effect with ROE lag) shows the highest $R^2$ value of 0.5036, indicating that this model has the best explanatory power for REINS variations. The adjusted $R^2$ value is not available (NA) in all three models because in fixed effect estimation with robust standard errors, the measure is not produced by default in the R output.

In terms of information criteria, models with lower AIC and BIC values showed a better match rate with a more economical number of parameters. Model 2 had the lowest AIC value (-461.06), followed by Model 1 (-442.46) and Model 3 (-376.71). Similarly to BIC, Model 2 had the lowest score (-256.82), followed by Model 1 (-224.13), and Model 3 (-185.4). Thus, based on AIC and BIC, the Model 2 is the best model in balancing goodness-of-fit and parameter complexity. However, keep in mind that Model 2 has the potential to contain simultaneity bias because it uses an ROE that is the same time period as REINS and without instrument variables. Meanwhile, Model 3 has the highest $R^2$ but also the highest AIC/BIC value (at worst), suggesting that the addition of lag variables does not necessarily improve model efficiency. Overall, no single model excels in all criteria. The selection of the final model remains based on theoretical considerations (ability to overcome endogenicity) and residual test results.

**Table 4. Goodness of Fit Test Results**

| Model | R_squared | Adj_R_squared | AIC | BIC |
|---|---|---|---|---|
| **Model 1** | 0.3341 | ON | -442.46 | -224.13 |
| **Model 2** | 0.3941 | ON | -461.06 | -256.82 |
| **Model 3** | 0.5036 | ON | -376.71 | -185.40 |

Source: Data processing using R

**Model Residual Test Results**

After estimating all three models, the next step is to test whether the residual model meets the classical Gauss-Markov assumptions. A summary of residual test results for Model 1, Model 2, and Model 3 is presented in Table 3.

**Table 5. Model Residual Test Results**

| Test | Model1 | Model2 | Model3 |
|---|---|---|---|
| Normalitas (Shapiro-Wilk) | p = 0 | p = 0 | p = 0 |
| Multicollinearity (max LIVE) | 2.83 (Light (<=10)) | 2.83 (Light (<=10)) | 2.83 (Light (<=10)) |
| Heteroscedasticity (BP) | p = 0 | p = 0 | p = 0 |
| Autokorelasi (Wooldridge/DW) | p = 0 | p = 0.1907 | p = 0.0381 |

Source: Data processing using R

**1. Residual Normality Test**

The normality test using the Shapiro-Wilk method yielded a value of p = 0.000 for all three models. Thus, the null hypothesis (normally distributed residuals) is rejected at a significance level of 1%. This means that the residues of the three models are not normally distributed. However, in the context of panel data with a relatively large number of observations (n = 250), violations of normality do not lead to bias in the estimated coefficients, especially if the sample size is large enough that the Central Limit Theorem applies. In addition, the use of robust standard errors (HC1) across models has mitigated the impact of abnormalities on statistical inference.

**2. Multicollinearity Test**

Multicollinearity detection was carried out by calculating the Variance Inflation Factor (VIF). The maximum VIF value for all three models is 2.83, which is well below the threshold of 10. This indicates that there is no serious multicollinearity problem between independent variables. Thus, the regression coefficient estimation can be considered stable and the standard error does not magnify, so the coefficient significance test is reliable.

**3. Heteroscedasticity Test**

Heteroscedasticity testing using the Breusch-Pagan (BP) test showed a value of p = 0.000 for Model 1, Model 2, and Model 3. This result rejects the null hypothesis that states that residual variance is constant (homoskedasticity). In other words, all three models contain heteroscedasticity, which is common in panel data due to differences in characteristics between companies. To overcome this problem, all estimates in this study have used robust standard errors (HC1) as presented in sub-chapter 4.3. This approach results in consistent standard errors despite heteroscedasticity, so the coefficient significance test is valid.

**4. Autocorrelation Test**

Residual autocorrelation was tested using the Wooldridge method (for panel data) or Durbin-Watson. The results showed that Model 1 had a value of p = 0.000 (significant), Model 2 had a value of p = 0.1907 (insignificant at $\alpha = 0.05$), and Model 3 had a value of p = 0.0381 (significant at $\alpha = 0.05$). Thus, the Model 2 is free of autocorrelation, while the Model 1 and Model 3 still contain residual autocorrelation. Autocorrelation on Model 1 and Model 3 can occur due to the use of instrument variables or lag that has not completely eliminated serial correlation. To address this, further research can apply clustered standard errors at the company level, allowing for residual correlations between time within the same individual. However, the use of robust standard errors in the model still provides a level of protection against assumption violations.

**Model Selection Results**

Based on the results of the estimation of the three models as well as the evaluation of the residual and goodness-of-fit tests, a model selection process was carried out to determine the most appropriate model to answer the research hypothesis. Referring to the criteria that have been set in subchapter 3.5 (statistical significance of the ROE variable, consistency of the coefficient direction with the theory, AIC/BIC values, and theoretical logic), the three models are compared systematically.

Model 1, which uses a two-way fixed effect 2SLS approach with an insurance leverage (IL) instrument, is theoretically the most superior model because it is able to overcome the endogeny of the simultaneous relationship between REINS and ROE. However, the results of the estimation show that the ROE coefficient (0.05986) is not statistically significant ($p = 0.358$) and has a positive direction, contrary to the underinvestment hypothesis that expects a negative influence. In addition, Model 1 had the lowest $R^2$ value (0.3341) and contained heteroscedasticity and residual autocorrelation ($p = 0.000$ for both tests). Meanwhile, the Model 2 (OLS one-way fixed effect without instruments) has an advantage in the information criteria with the lowest AIC (-461.06) and BIC (-256.82) values among the three models, as well as a higher $R^2$ (0.3941) than Model 1. However, the ROE coefficient was very small (-0.00951) and insignificant ($p = 0.702$), so it did not provide empirical support for the hypothesis. Although Model 2 was shown to be free of autocorrelation ($p = 0.1907$), its main drawback lies in the potential simultaneous bias because ROE and REINS were measured in the same period, so the causal relationship cannot be interpreted conclusively.

Model 3 (OLS fixed effect with a one-period ROE lag) is specifically designed to reduce simulity bias by using the previous year's performance. The results showed that the ROE lag had a positive coefficient (0.01967) and was significant at the level of 10% ($p = 0.074$). Although this coefficient direction is contrary to the initial hypothesis of expecting a negative influence, such marginal significance provides weak evidence that past performance influences reinsurance decisions in the current year. Model 3 had the highest $R^2$ value (0.5036), but AIC (-376.71) and BIC (-185.40) were the worst of the three models, and the model also contained heteroscedasticity ($p = 0.000$) and residual autocorrelation ($p = 0.0381$), although both have been corrected with robust standard errors.

From this comparison, no single model perfectly meets all the ideal criteria, namely a negative significant ROE coefficient, the lowest AIC/BIC, free from violation of classical assumptions, and has a strong theoretical justification. The Model 2 excels in terms of AIC/BIC and is autocorrelation-free, but is theoretically weak due to simultaneity issues. Model 1 is theoretically the most accurate but the estimated results are not significant and have autocorrelation problems. Considering that the main objective of the study was to test the effect of ROE on REINS and the importance of addressing simultaneity, Model 3 (OLS with a one-period ROE lag) was chosen as the main model. This decision is based on the reason that the use of lag is more reflective of a realistic decision-making process, i.e. the company's management tends to look at the known performance of the past year to determine the need for reinsurance in the current year. In addition, the existence of marginal significance in Model 3 provides empirical clues that are worth noting, although the direction of the coefficient does not correspond to the underinvestment hypothesis. These findings indicate that in the context of the general insurance industry in Indonesia, companies that were more profitable in the past tended to slightly increase reinsurance purchases in the following year. This is a different pattern from the findings of Lee & Lee (2012) in Taiwan. Therefore, the estimated results from Model 3 will be used as the basis for discussing the research questions.

**Sensitivity Analysis Results: Comparison of Models in the Pandemic and Post-Pandemic Periods**

Based on the results of the selection of models that chose Model 3 (OLS fixed effect with lag ROE) as the main model, then sensitivity analysis was carried out by reestimating the model in each sub-period. The estimated results are presented in Table 4.12 and Table 4.13, while the summary of the Chow and goodness-of-fit tests is presented in Table 4.14 and Table 4.15.

**1. Estimated Results in the Pandemic Period (2020–2022)**

In the pandemic period, the Model 3 estimate (OLS fixed effect with ROE lag) showed that the ROE lag coefficient was negative (-0.015168) and not statistically significant (p = 0.390). This indicates that during the pandemic, the previous year's financial performance did not have a significant effect on the reinsurance decisions of general insurance companies in Indonesia. Among the control variables, underwriting risk (UR) had a positive coefficient (0.06210) and was significant at the level of 10% (p = 0.064), while return on investment (ROI) also showed a positive influence (1.85598) and significant at the level of 5% (p = 0.042). Other variables such as firm size (FS), financial leverage (FL), reinsurance price (RP), growth of premium (GP), and market share (MS) were not proven to be significant in this period. These findings suggest that during the pandemic, only underwriting risk and investment performance had an influence on reinsurance decisions, while equity performance did not play a significant role.

**Table 6. Estimated Results of the Pandemic Period (2020–2022)**

| Variable | Estimate | Std_Error | t_value | p_value |
|---|---|---|---|---|
| **lag_ROE** | -0.015168 | 0.017476 | -0.8679 | 0.390359 |
| **FS** | -0.0162 | 0.067864 | -0.2387 | 0.812487 |
| **FL** | -0.167557 | 0.205413 | -0.8157 | 0.419269 |
| **RP** | 0.008697 | 0.005761 | 1.5097 | 0.138605 |
| **UR** | 0.062102 | 0.032678 | 1.9004 | 0.06426 |
| **GP** | -0.023591 | 0.025519 | -0.9245 | 0.360532 |
| **KING** | 1.855984 | 0.885745 | 2.0954 | 0.042204 |
| **MS** | -3.013431 | 4.875586 | -0.6181 | 0.53987 |

Source: Data processing using R

\

## 2. Estimated Results in the Post-Pandemic Period (2023–2024)

In the post-pandemic period, the Model 3 estimate (OLS fixed effect with ROE lag) showed significantly different results compared to the pandemic period. The ROE lag coefficient was positive (0.199236) and significant at the level of 1% (p = 0.009). These findings indicate that after the pandemic ends, general insurers in Indonesia that had higher performance (ROE) in the previous year tend to increase reinsurance purchases in the following year. Among the control variables, financial leverage (FL) showed a positive coefficient (0.58175) and was significant at the level of 1% (p = 0.008), meaning that companies with higher debt levels were more likely to buy more reinsurance. Meanwhile, the market share (MS) has a negative coefficient (-6.83896) and is significant at the level of 5% (p = 0.023), indicating that companies with a larger market share actually reduce their dependence on reinsurance. The variables of firm size (FS), reinsurance price (RP), underwriting risk (UR), growth of premium (GP), and return on investment (ROI) were not proven to be significant in this period. Overall, the post-pandemic period showed a change in the pattern of stronger relationships between performance, leverage, market share, and reinsurance decisions, reflecting the industry's adaptation to post-pandemic economic normalization.

**Table 7. Estimated Results of the Post-Pandemic Period (2023–2024)**

| Variable | Estimate | Std_Error | t_value | p_value |
|---|---|---|---|---|
| **lag_ROE** | 0.199236 | 0.072617 | 2.7437 | 0.008897 |
| **FS** | 0.016117 | 0.074517 | 0.2163 | 0.829807 |
| **FL** | 0.581746 | 0.210495 | 2.7637 | 0.008448 |
| **RP** | -8.7e-05 | 0.000163 | -0.5327 | 0.597074 |
| **UR** | 0.059885 | 0.062976 | 0.9509 | 0.347083 |
| **GP** | 0.000799 | 0.001789 | 0.4464 | 0.657623 |
| **KING** | 0.480543 | 0.51759 | 0.9284 | 0.358493 |
| **MS** | -6.838962 | 2.889611 | -2.3667 | 0.022631 |

Source: Data processing using R

## 3. Chow Test and Goodness-of-Fit Comparison

To test whether there are significant structural differences between the pandemic period (2020–2022) and the post-pandemic period (2023–2024), the Chow test (Wald test) is carried out with the null hypothesis that there is no difference in the regression coefficient between the two periods. Based on the test results, a statistical F-value of 1.7816 with free degrees of 12 and 130 was obtained, and a p-value = 0.05758. At a significance level of 5% ($\alpha = 0.05$), a p-value greater than 0.05 results in a subtraction failure, so there is not statistically enough evidence to state that the relationship structure between variables differs significantly between the two periods. However, at the 10% significance level ($\alpha = 0.1$), $H_0$ the p-value is less than 0.1 so the null hypothesis is rejected, which means that there is evidence that the regression coefficient differs significantly at the 90% confidence level.

**Table 8. Chow Test Results for the Pandemic and Post-Pandemic Period**

| Model | Res.Df | Df | F | Pr(>F) |
|---|---|---|---|---|
| Pooled model – entire period | 142 | | | |
| Separate Model (unrestricted) – per period | 130 | 12 | 1.7816 | 0.05758 |

Source: Data processing using R

Furthermore, the goodness-of-fit comparison shows that in the pandemic period, the $R^2$ value of the model reached 0.5916, which means that the independent variable was able to explain 59.16% of the variation in reinsurance decisions (REINS), higher than the post-pandemic period with an $R^2$ of 0.4552 (45.52%). In terms of information criteria, the post-pandemic period had lower AIC (-270.71) and BIC (-119.61) values compared to the pandemic period (AIC = -195.61 and BIC = -44.51), indicating that the model in the post-pandemic period was more efficient in balancing goodness-of-fit with parameter complexity.

**Table 9. Test Results Goodness of Fit Pandemic and Post-Pandemic Period**

| Period of project | R_squared | Adj_R_squared | AIC | BIC |
|---|---|---|---|---|
| Pandemic (2020–2022) | 0.5916 | ON | -195.61 | -44.51 |
| Post-Pandemic (2023–2024) | 0.4552 | ON | -270.71 | -119.61 |

Source: Data processing using R

Overall, the results of Chow's test showed a p-value = 0.05758. At a significance level of 5% ($\alpha = 0.05$), the p-value is greater than 0.05 so the null hypothesis is not rejected. This means that statistically there is not enough evidence to state that there is a difference in the regression coefficient between the pandemic and post-pandemic periods at a 95% confidence level. However, at a significance level of 10% ($\alpha = 0.1$), the p-value is less than 0.1 so the null hypothesis is rejected. Thus, at a 90% confidence level, there is sufficient statistical evidence that the relationship structure between variables differs significantly between the two periods. This difference is reinforced by the finding that the ROE lag coefficient changed from insignificant in the pandemic period to significant positive in the post-pandemic period. In addition, the goodness-of-fit comparison shows that although the $R^2$ values of the pandemic period are higher, the model in the post-pandemic period is more efficient based on the lower AIC and BIC values. Therefore, it can be concluded that there is a significant structural difference at the 90% confidence level and separate analysis between periods remains necessary to understand the dynamics of the relationship between performance and reinsurance decisions as emphasized in the study.

**4. Outcome Implications**

Based on the results of the Model 3 estimate in the post-pandemic period (2023–2024), several important implications can be drawn. First, a positive (0.199236) and significant ($p < 0.01$) ROE lag coefficient shows that any increase in one unit (or 100%) return on equity in the previous year will increase the reinsurance ratio (REINS) by 0.199236 units. In a business context, if ROE increases by 10%, then REINS is expected to increase by around 1.99%. These findings indicate that general insurers in Indonesia tend to use reinsurance more after periods of good performance, where it is possible that this is a strategy for earnings stabilization or expansion of underwriting capacity.

Second, a positive (0.581746) and significant ($p < 0.01$) financial leverage (FL) coefficient means that an increase of one unit in the ratio of total liabilities to total assets will increase REINS by 0.581746 units. In other words, companies that are more in debt (high leverage) buy more reinsurance, consistent with the hypothesis that reinsurance is used to reduce the risk of bankruptcy.

\

Third, a negative (MS) (-6.838962) and significant ($p < 0.05$) market share coefficient indicates that companies with a larger market share tend to have a lower reliance on reinsurance, likely due to economies of scale and ability to withstand risk on their own.

Overall, Model 3 (OLS fixed effect with ROE lag) proved to be feasible and robust to explain reinsurance decisions in the post-pandemic period, as evidenced by the presence of significant variables with a logical direction and lower AIC and BIC values compared to the pandemic period. This model can be recommended for insurance company managers and regulators as an analytical tool in formulating reinsurance strategies, especially in economic conditions that have stabilized after the crisis.

## CONCLUSION

This study aims to analyze the effect of return on equity (ROE) on the reinsurance decisions (REINS) of general insurance companies in Indonesia for the 2020–2024 period during the pandemic and post-pandemic. The results of the study show that ROE does not have a negative effect on REINS as the underinvestment theory, even in Model 3 with a one-period ROE lag was found to have a significant positive effect, so companies with better financial performance tend to increase reinsurance purchases. In addition, financial leverage (FL) has a significant positive effect on REINS, while growth of premium (GP) has a significant negative effect on all models. The research also shows that there is a change in the dynamics of the relationship between ROE and reinsurance decisions in the post-pandemic period, so that the company's reinsurance strategy is influenced by financial conditions, capital structure, premium growth, and changes in the economic environment. Based on the findings that ROE's effect on reinsurance decisions differs between periods and that financial leverage and premium growth consistently influence REINS, several recommendations can be proposed. OJK should encourage reinsurance policies based on profitability trends rather than annual fluctuations, tighten supervision on high-leverage companies, and prepare contingency frameworks for crisis periods. Insurance companies should consider past performance in reinsurance decisions, optimize capital structure and risk retention, and ensure rapid premium growth does not compromise solvency. Domestic reinsurers should monitor partners' financial performance, offer competitive risk-sharing schemes to high-growth companies, and leverage local understanding to expand market reach. Future research should expand the observation period and include additional variables such as claims experience and catastrophe risk for more comprehensive insights.

## REFERENCES


Ananda, A., & Ghani, M. (2026). Modeling risk-based capital for life insurance companies in Indonesia: a comparative study of panel data regression and Gaussian Process Boosting. *Quality & Quantity*, 1–40.

Ananda, A., & Ghani, M. (2026). Modeling risk-based capital for life insurance companies in Indonesia: A comparative study of panel data regression and Gaussian Process Boosting. *Quality & Quantity*, *1–40*.

Baltagi, B. H. (2021). *Econometric analysis of panel data* (6th ed.). Springer.

Griffith, T. G., & Liebenberg, A. P. (2021). The effect of incidental reinsurance assumption on insurer performance. *North American Actuarial Journal, 25*(4), 503–523.

Hall, L., & Walsh, P. P. (2025). *Insurance and sustainable development: Partnering on risk,*

*resilience, and*. *(Lengkapi data penerbit jika merupakan buku atau laporan.)*
Hasanah, N., Al Farisi, F. S., Maharani, R., & Risakotta, Z. R. (2024). Challenges and opportunities in the development of the insurance industry in Indonesia: A comprehensive analysis. In *Proceedings of the 4th International Conference on Social Sciences and Law (ICSSL 2024)* (pp. 747–761).
Horvey, S. S., & Odei-Mensah, J. (2025). Re-examining the microeconomic and macroeconomic determinants of nonlife insurers profitability in South Africa: Insights from linear and threshold analysis. *Journal of Innovation and Entrepreneurship, 14*(1), 30.
Hsiao, C. (2014). *Analysis of panel data* (3rd ed.). Cambridge University Press.
Lee, H.-H., & Lee, C.-Y. (2012). An analysis of reinsurance and firm performance: Evidence from the Taiwan property-liability insurance industry. *The Geneva Papers on Risk and Insurance: Issues and Practice, 37*(3), 467–484. https://doi.org/10.1057/gpp.2012.9
Luthuli, S. (2025). *Natural disasters and economic growth: Exploring the intervening role of insurance and reinsurance* (Master's thesis). University of the Witwatersrand.
Marangwanda, A. (2025). Reinsurance as a strategic governance tool: Enhancing risk resilience in Africa's insurance sector. *International Journal of Advanced Business Studies, 4*(4), 18–38.
Park, J., Choi, B. P., & Ho, C.-L. (2021). The impact of internal and external reinsurance on insurers' performance and price. *Managerial Finance, 47*(7), 937–950.
Puspitasari, N., Aryasantana, A. F. G. P., Utami, W. S. A., Mufidah, A., & Munandari, D. (2026). Efficiency and productivity of Islamic life insurance companies in Indonesia: A DEA-Malmquist approach. *Journal of Islamic Accounting and Business Research*, 1–24.
Rachmawati, E., & Handayani, N. (2026). Beyond firm age: Corporate governance, CSR, and operational scale as financial performance drivers. *Journal of Accounting Science, 10*(2), 418–438.
Rahma, M., Masyita, D., Sudarsono, R., & Anwar, M. (2025). Determinants of insolvency in life insurance companies: A systematic literature review and bibliometric analysis using Biblioshiny and VOSviewer. *Cogent Business & Management, 12*(1), 2573876.
Rizaldi, A., Setiawan, M., Kharisma, B., & Hasanah, A. (2026). Manufacturing foreign direct investment and sustainable industrial output in ASEAN-6 countries. *Sustainability, 18*(9), 4431.
Shiu, Y.-M. (2020). How does reinsurance and derivatives usage affect financial performance? Evidence from the UK non-life insurance industry. *Economic Modelling, 88*, 376–385.
Suryanto, T., Dimasqy, D., Ronaldo, R., Ekananda, M., Dinata, T. H., & Tumbelaka, I. (2020). The influence of liberalization on innovation, performance, and competition level of insurance industry in Indonesia. *Sustainability, 12*(24), 10620.
Tressel, M. T., & Ding, X. (2021). *Global corporate stress tests—Impact of the COVID-19 pandemic and policy responses*. International Monetary Fund.
Weiss, M. A., & Chung, J.-H. (2004). U.S. reinsurance prices, financial quality, and global capacity. *The Journal of Risk and Insurance, 71*(3), 437–467. https://doi.org/10.1111/j.0022-4367.2004.00099.x
Widyani, D. (2023). The impact of insurtech on the insurance business model in Indonesia. *The International Journal of Financial Systems, 1*(2), 151–184.
Wooldridge, J. M. (2020). *Introductory econometrics: A modern approach* (7th ed.). Cengage Learning.
Zhang, W., & Zhang, E. (2026). Carbon intensity, renewable energy consumption and SDG8–Decent Work and Economic Growth in MINT countries. *Problemy Ekorozwoju, 21*(1), 205–228.

\

Zhang, Y. (2016). *Reinsurance counterparty analysis in life insurance industry: The impact on firm performance/mergers and acquisitions in global insurance industry*. *(Lengkapi jenis publikasi dan institusi apabila merupakan tesis atau disertasi.)*