

## ANALYZING THE RELATIONSHIP BETWEEN CAPITAL AND RISK IN INDONESIAN LIFE INSURANCE COMPANIES

Restu Ananda Putra<sup>1\*</sup>, Adhitya Ronnie Effendie<sup>1</sup>, Siti Nur Aisah<sup>3</sup>, Jashinta Regina Christy<sup>1</sup>, Evangeline Christine Feriardag Marpaung<sup>1</sup>, Muhammad Zikril Hakim Syarkowi<sup>1</sup>, Paramita Kumala Devi<sup>1</sup>

<sup>1</sup>Department of Mathematics, Faculty of Mathematics and Natural Sciences, Universitas Gadjah Mada, Yogyakarta, Indonesia

\* restuanandaputra@ugm.ac.id

#### Abstract

This study aims to investigate the correlation between capital and risk within Indonesian life insurance firms, focusing on the regulatory framework of Risk-Based Capital (RBC) that dictates the balance of capital against company-held risks. The 2SLS (Two-Stage Least Squares) and GMM (Generalized Method of Moments) methods are applied in this research. The research finds a positive correlation between capital levels and risks in these firms. The findings indicates that the GMM approach more effectively models investment and underwriting risks, whereas the 2SLS method is better in modelling the capital ratio.

*Keywords*: Capital Ratio, Investing Risk, Life Insurance, Two-Stage Least Squares, Generalized Method of Moments.

# **1** Introduction

Capital plays a crucial role in ensuring the sustainability and stability of companies, including the life insurance industry. Capital serves various purposes, such as facilitating the production process, paying employee salaries, maintaining reserve funds, and enhancing the trust of stakeholders. The relationship between capital and risk is a fundamental aspect that deserves careful examination, as it directly impacts the financial well-being and decision-making of life insurance companies.

Sherieves and Dahl (1992) and Cummins and Sommer (1996) found positive relationships in commercial banks and property-liability insurance markets, respectively, emphasizing regulatory pressure and the trade-off between default risk and franchise value[1, 2]. Aggarwal and Jacques (2001) observed temporal variations, with negative relationships in 1991-1992 but positive in 1993, underscoring the impact of regulatory changes[3]. Beatty and Gron (2001) noted

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a positive relationship, particularly for low-capital banks, highlighting non-linearity[4]. Baranoff and Sager (2002, 2003) distinguished between asset and product risks in life insurance, finding positive relationships for asset risk but negative for product risk[5, 6].

Further studies continued to reveal nuanced relationships. Heid et al. (2003) found the relationship depends on capital levels, being positive for high-capital banks but negative for lowcapital ones[7]. Bichsel and Blum (2004) observed a positive relationship in Swiss banks, emphasizing market discipline effects[8]. Baranoff et al. (2007) examined different risk measures in large insurers[9], while Deelchand and Padgett (2009) found a negative relationship in cooperative banks[10]. Jokipii and Milne (2011) noted the relationship's dependence on capitalization levels[11]. Finally, Hu and Yu (2014) found a negative relationship between investing risk and capital in Taiwanese life insurers, highlighting the role of regulatory regimes[12]. These studies collectively demonstrate that the capital-risk relationship varies based on factors such as industry sector, time period, regulatory environment, firm size, and risk measure used.

Various hypotheses that predict the model and risk taking, such as risk subsidies, transaction costs, and regulatory costs, are examined. The risk subsidy hypothesis assumes that risk and capital have a negative relationship. The regulatory cost hypothesis shows a positive relationship between risk and capital. And the risk transaction cost hypothesis shows the relationship between risk and capital has a positive relationship.

The relationship between capital and risk holds significant importance for our study. This paper focuses on analyzing the relationship between capital and risks specifically in Indonesia. Additionally, the paper will also review the relationship between capital and risk in Taiwan, because a previous study has explored the relationship between capital and risk in life insurance companies in Taiwan. Therefore, we will compare the relationship observed in life insurance companies in both Indonesia and Taiwan.

There are several objectives that will be achieved by completing this paper. Firstly, this paper aims to enhance the understanding of relationship between capital and risk in life insurance companies. Secondly, this paper compares the relationship between capital and risk in life insurance companies in Indonesia and Taiwan. Lastly, this paper considers two types of risks concurrently, namely investing risk and underwriting risk.

# 2 Analysis of Indonesia Insurance Condition

Indonesia has a legal framework for insurance that includes laws regarding life insurance. The insurance law is regulated in Law (Undang-Undang) No. 40 of 2014 or the Insurance Law, which consists of 18 chapters and 92 articles. Article 2 and article 3 of chapter II state that life insurance companies can only engage in life insurance business, including annuity business, health insurance business, and personal accident insurance business. On the other hand, Sharia life insurance companies can only engage in Sharia life insurance business, including annuity business based on Sharia principles, and personal accident insurance business based on Sharia principles, and personal accident insurance business based on Sharia principles, and personal accident insurance business based on Sharia principles, and personal accident insurance business based on Sharia principles. The insurance industry in Indonesia also has a unique characteristic as it allows foreign ownership up to a maximum of 80%, as regulated by Government Regulation Number 14 of 2018 regarding Foreign Ownership in Insurance Companies. However, foreign ownership can exceed the limit as long as domestic ownership can be maintained. This means that Indonesia has policy flexibility without violating liberalization commitments, where the limit of foreign ownership depends on how strictly Indonesia wants to regulate it.

In 2014, life insurance in Indonesia generated a revenue of Rp167.76 trillion. This revenue increased by 33.3% compared to the previous year. The revenue of life insurance in Indonesia was derived from total premium income, investment returns, reinsurance claims, and other income. In

that year, there were also two slowdowns, namely a 2.4% slowdown in total premium income and a 48.7% decrease in the total number of insured individuals in group policies. The increase was also reflected in the total assets of life insurance companies in Indonesia. The assets in that year increased by 25.3% compared to the previous year, reaching Rp368.06 trillion. The total assets of life insurance companies in Indonesia accounted for 45.6% of the total assets of insurance companies.

Several insurance companies in Indonesia have undoubtedly faced challenges during their operations. Some of the challenges that have occurred include cases of payment defaults and mismanagement of investment funds. Therefore, it is necessary to assess the level of solvency of the companies through the Risk Based Capital (RBC) value, which is regulated in Minister of Finance Regulation Number 53/PMK.010/2012 concerning RBC. This regulation stipulates that insurance companies are required to set a minimum solvency target of at least 120% of the riskbased minimum capital each year. The risk-based minimum capital is the amount of funds needed to anticipate potential losses resulting from deviations in asset and liability management. The higher the RBC value, the healthier the company can be considered. With the minimum RBC value in place, the demands of life insurance companies to achieve profits will be limited because reaching the RBC target will involve a trade-off between underwriting risk and investment risk. In their efforts to achieve the target, companies can reduce underwriting risk by involving reinsurers in sharing a portion of the coverage. Another alternative for companies is to minimize investment risk by selecting balanced insurance instruments that are not excessively risky. Therefore, we will estimate the relationship between capital, investment risk, and underwriting risk in the life Insurance sector in Indonesia.

## 2.1 Hypotesis

H1: There is a negative relationship between capital and investment risk after controlling for underwriting risk. Investment risk is directly proportional to the investment returns generated. If the investment returns are high, the risk is also high. Life insurance companies choose to take on more investment risk in order to gain higher profits from their investments. These profits are a primary source of profitability for life insurance companies. Therefore, we assume that life insurance companies may increase investment risk when capital decreases. Hence, it can be said that there is a negative relationship between capital and investment risk. H2: There is a positive relationship between capital and underwriting risk after controlling for investment risk. Life insurance companies implement risky product strategies to maintain market share. However, this must be done cautiously because excessive exposure can deepen insurance interest losses. Health insurance is the riskiest type of insurance compared to others. If a life insurance company underwrites riskier products such as health insurance, the company will need to hold more capital to respond to higher risks. Higher risks lead to higher transaction costs and deplete capital, resulting in greater underwriting inefficiencies. Companies with more capital to underwrite riskier products are those with higher capitalization. Additionally, the regulatory costs for health insurance are high as regulators impose higher penalties compared to life insurance. Based on these factors, it can be stated that capital levels are positively related to underwriting risk.

## **3** Data and Methods

This study used financial statement data from life insurance companies in Indonesia during the period of 2014-2018. The data were collected from the annual statistical reports of Indonesian insurance companies available on the Indonesian Financial Services Authority (OJK) website. Based on this source, it is known that there were 49 life insurance companies in Indonesia in 2014.

However, the data in the subsequent years are unbalanced due to factors such as the entry of new companies, mergers between existing companies, and bankruptcies of some companies. Therefore, we decided to select the available 49 life insurance companies for each year of the study, which in this case represents the entire population.

There are three main variables, Capital Ratio (*CAR*), Investing Risk (*INR*), and Underwriting Risk (*UNR*). The capital ratio is a measure of capital adequacy, representing a company's ability to provide funds that can be used as reserves. Some literature defines the capital ratio as total equity divided by total risk-weighted assets after the implementation of RBC, while other literature defines it as total equity divided by total assets. In this paper, the capital ratio is defined as total equity divided by the total assets of the company. Investing risk refers to the potential losses that investors may experience from investment activities. In this paper, corresponding to a previous study, investing risk is defined as the amount of investment divided by total assets. Underwriting risk arises from the incompleteness, uncertainty, and complexity of insurance contracts in the process of buying and selling risky products, such as health insurance. Baranoff and Sager [5] and Pottier and Sommer (1997) [13] observed that health insurance carries greater risk compared to life insurance and annuities. While life insures rely heavily on mortality tables to predict longevity and manage their risks in life insurance and annuities, a sudden increase in the cost of health insurance is unpredictable due to the unavailability of relevant information. In this paper, underwriting risk is defined as the claims reserve divided by the total reserve.

This paper also uses several other variables, namely ROA, SIZE, FOR, FHG, and PUB, where FOR, FHG, and PUB are dummy variables. ROA (Return on Asset) is a ratio that measures a company's ability to generate profit from its assets, defined as net income divided by total assets. ROA holds an important role in determining the level of capital and risk. SIZE is a variable that represents the size of the company, defined as the natural logarithm of total assets. FOR is a variable that indicates whether the company is a multinational company, represented by 1 for multinational company and 0 for non-multinational company. Foreign ownership investors tend to trade based on market momentum and have achieved significant investment returns, which may result in foreign insurance companies having different approaches to capital and risk management compared to local insurance companies [14]. FHG (Financial Holding Group) is a variable that indicates whether the company is a holding company, represented by 1 for holding companies and 0 for non-holding companies. If an insurance company is part of a larger financial group, it will have better access to capital and investment opportunities due to different performance control mechanisms [1]. PUB (Publicly Held Company) is a variable that indicates whether the company is a publicly owned company, represented by 1 for publicly owned companies and 0 for non-publicly owned companies.

## **3.1** Two-stage Least Squares

The relationship between capital ratio, investing risk, and underwriting risk can be modelled using a simultaneous equation model. A simultaneous equation model is a model consisting of more than one dependent variable and more than one equation. In a simultaneous equation model, a dependent variable in one equation can appear as an independent variable in another equation, creating inter-dependencies among the equations. This results in the correlation of the dependent variables with the error term of the equation in which they appear as independent variables. If simple ordinary least squares (OLS) method is used in this analysis, it will produce biased and inconsistent parameter estimates. Therefore, to address this issue, the two-stage least squares (2SLS) method can be employed to estimate the parameters of the model.

The 2SLS method is one of the regression methods that falls into the category of structural equation analysis. The two-stage least squares (2SLS) method is an extension of the OLS method. The 2SLS method is used when there is a correlation between the error term of the model and

its independent variables. In this method, there are two types of variables: endogenous variables that serve as both dependent and independent variables and exogenous variables that serve as independent variables in the simultaneous equation model.

In general, the structural equation form of a simultaneous equation model is as follows

$$Y_{1} = \alpha_{12}Y_{2} + \alpha_{13}Y_{3} + \dots + \alpha_{1m}Y_{m} + \beta_{11}X_{1} + \beta_{12}X_{2} + \dots + \beta_{1k}X_{i} + \epsilon_{1}$$

$$Y_{2} = \alpha_{21}Y_{1} + \alpha_{23}Y_{3} + \dots + \alpha_{2m}Y_{m} + \beta_{21}X_{1} + \beta_{22}X_{2} + \dots + \beta_{2k}X_{i} + \epsilon_{2}$$

$$Y_{3} = \alpha_{31}Y_{1} + \alpha_{32}Y_{2} + \dots + \alpha_{3m}Y_{m} + \beta_{31}X_{1} + \beta_{32}X_{2} + \dots + \beta_{3k}X_{i} + \epsilon_{3}$$

$$\vdots$$

$$Y_{i} = \alpha_{i1}Y_{1} + \alpha_{i2}Y_{2} + \dots + \alpha_{i,i-1}Y_{m} + \beta_{i1}X_{1} + \beta_{i2}X_{2} + \dots + \beta_{i}X_{i} + \epsilon_{i}$$
(1)

where  $Y_1, Y_2, \dots, Y_i$  represents the endogenous variable i for  $i = 1, 2, \dots, m; X_1, X_2, \dots, X_m$ represents the exogenous variable i for  $i = 1, 2, \dots, n; \epsilon_1, \epsilon_2, \dots, \epsilon_i$  represents the error term i for  $i = 1, 2, \dots, m; \alpha, \beta$  represents the regression parameter coefficients.

This study utilizes data from life insurance companies in Indonesia over a 4-year period (2014-2018). This may potentially result in auto-correlation. To address this issue, the auto-regressive 2SLS method can be used, which is capable of correcting for auto-correlation in simul-taneous equations by employing instrumental variables [5].Similar to previous studies Jin-Li Hu and Hsueh-E Yu [12] and Baranoff and Sager [5], the disturbances can be modeled through a first-order auto-regressive process. This process yields a diagonal structure for the covariance matrix of the disturbances [5]. So based on the available data, the equation form of the simultaneous equation model to analyze the relationship between capital risk, investing risk, and underwriting risk is as follows.

$$CAR_{it} = \alpha_0 + \alpha_1 UNR_{it} + \alpha_2 INR_{it} + \alpha_3 ROA_{it} + \alpha_4 CAR(-1)_{it} + \alpha_5 SIZE_{it} + \alpha_6 FOR_{it} + \alpha_7 FHG_{it} + \alpha_8 PUB_{it} + \epsilon_1$$

$$(2)$$

$$INR_{it} = \beta_0 + \beta_1 CAR_{it} + \beta_2 UNR_{it} + \beta_3 ROA_{it} + \beta_4 INR(-1)_{it}\beta_5 SIZE_{it} + \beta_6 FOR_{it} + \beta_7 FHG_{it} + \beta_8 PUB_{it} + \epsilon_2$$
(3)

$$UNR_{it} = \gamma_0 + \gamma_1 CAR_{it} + \gamma_2 INR_{it} + \gamma_3 ROA_{it} + \gamma_4 UNR(-1)_{it} + \gamma_5 SIZE_{it} + \gamma_6 FOR_{it} + \gamma_7 FHG_{it} + \gamma_8 PUB_{it} + \epsilon_3$$

$$(4)$$

where *CAR* - ratio of total equity to total assets of insurer *i* in year *t*; *UNR* - ratio of claim reserves to total reserves of insurer *i* in year *t*; *INR* - ratio of investment amount to total capital of insurer *i* in year *t*; *ROA* - return on total assets of insurer *i* in year *t*; SIZE - total assets of insurer *i* in year *t*; FOR - whether the insurer *i* is a foreign company or not: one for a foreign company and zero otherwise - for insurer in year *t*; *FHG* - whether the insurer is a holding company or not: one for a holding company or not: one for a publicly held company and zero otherwise - for insurer in year *t*; and  $\alpha, \beta, \gamma$  - the estimated coefficients of the regression, where  $\epsilon$  represents the error term of the model.

In the above model, the variables investing risk (*INR*), underwriting risk (*UNR*), and capital ratio (*CAR*) are dependent variables, while the variables *ROA*, *SIZE*, *FOR*, *FHG*, *PUB* are independent variables. Equation (2) represents the insurer's *CAR* determined by endogenous variables such as *UNR* and *INR* along with other exogenous variables (*ROA*, *SIZE*, *FHG*, *FOR*, *PUB*). Equation (3) represents the insurer's *INR* determined by endogenous variables such as *CAR* and *UNR* along with other exogenous variables. Equation (4) represents the insurer's *UNR* determined by endogenous variables such as *CAR* and *INR* along with other exogenous variables.

## **3.2 Generalized Method of Moments**

The Generalized Method of Moments (GMM) is a statistical approach used to obtain parameter estimates of a model by using sample moments. This method is an extension of the method of moments. The method of moments cannot be used to estimate parameters when the number of instrumental variables exceeds the number of parameters to be estimated, while GMM can handle such conditions. GMM works by equating the population moments with the sample moments [15]. This method can address situations where assumptions in regression analysis are violated, such as endogeneity, autocorrelation, and heteroskedasticity.

In a simultaneous equation model, the Generalized Method of Moments (GMM) estimation involves constructing a moment function that represents the discrepancy between the sample moments and the population moments. The moment function is minimized to obtain the parameter estimates. The following is the general equation for GMM estimation in simultaneous equations.

In this paper, a simultaneous equation system with three equations and three endogenous variables is considered. The model can be represented as:

$$Y = X\beta + u$$

where: *Y* is an 3 x 1 vector of endogenous variables; *X* is an 3 x 9 matrix of explanatory variables;  $\beta$  is a 9 x 1 vector of parameters to be estimated; and *u* is an 3 x 1 vector of error terms.

The moment conditions for the GMM estimation are derived from the theoretical restrictions implied by the model. Let  $g(\beta)$  represent the 3 × 1 vector of moment conditions, defined as:

$$g(\beta) = E[z(Y, X, \beta)]$$

where  $z(Y, X, \beta)$  is an 3 × 1 vector of functions that define the moment conditions.

To estimate the parameters  $\beta$ , the GMM objective function is defined as the weighted sum of squared moments [15].

$$J(\beta) = g(\beta)' W g(\beta)$$

where W is an  $3 \times 3$  positive definite weighting matrix. The weighting matrix determines the relative importance of each moment condition in the estimation. Different weighting schemes can be used, with the optimal GMM weighting matrix aiming to minimize the asymptotic variance of the parameter estimates.

The GMM estimation involves minimizing the objective function  $J(\beta)$  with respect to  $\beta$ . By minimizing the moment function, GMM finds the parameter estimates that make the difference between the sample moments and the population moments as close to zero as possible, thus providing consistent and efficient estimates for the simultaneous equations model.

The measurement of error for the formed model is conducted using two methods root means squared error and mean absolute error.

## 3.2.1 Root Mean Squared Error

Root Mean Squared Error (RMSE) is a way to evaluate a regression model by measuring the accuracy level of the model's estimated results. RMSE measures the square root of the average of the squared differences between the predicted values and the actual values. The RMSE value can range from 0 to  $\infty$ . The accuracy of a model is indicated by a low RMSE value. When the RMSE value is close to 0, it indicates that the estimation results are close to the actual data. On the other hand, a larger RMSE value indicates that the model is inaccurate and the predicted results are far from the actual values. One characteristic of RMSE is that it assigns greater weight to large errors due to squaring, thus able to reveal outliers or significant errors [16].

The following is the general formula for calculating RMSE:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\hat{y}_i - y_i)^2}$$

where *n* is the total number of observations,  $\hat{y}_i$  represents the predicted values and  $y_i$  represents the actual values.

#### 3.2.2 Mean Absolute Error

Mean Absolute Error (MAE) is used to measure the accuracy of a statistical model in making predictions or forecasts. MAE is the average of the absolute differences between the actual values and the predicted values [17]. This method of error calculation disregards the direction of the error and provides an indication of how much the predicted values differ from the actual values.

The following is the general formula for calculating MAE:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i|$$

where *n* is the total number of observations,  $\hat{y}_i$  represents the predicted values and  $y_i$  represents the actual values.

## **4 Results and Discussion**

Table 1 shows the mean of each variables. It can be seen that the mean of capital ratio continues to decreasing every year. Investing risk is actively fluctuating, reaching the lowest value of 80.28% in 2015. Underwriting risk is also fluctuating with the highest value in 2014 of 5.51%. While the return on assets in general was not good and only obtained a positive value in 2015.

Variable	Year					
ratio	2014-2018	2014	2015	2016	2017	2018
Capital Ratio	0.5279	0.4508	0.3757	0.3412	0.3078	0.2770
Investing Risk	0.8241	0.8188	0.8028	0.8215	0.8337	0.8394
Underwriting Risk	0.0375	0.0551	0.0374	0.0381	0.0246	0.0331
Return on Assets	-0.0146	-0.0156	0.0028	-0.0203	-0.0083	-0.0339
Foreign Comp.	0.3864	0.3673	0.3829	0.3696	0.3478	0.3478
Publicly Held	0.1266	0.1224	0.1276	0.1304	0.1304	0.1087
Holding Comp.	0.1688	0.1633	0.1702	0.1522	0.1522	0.1739

Table 1: The Mean of Indonesian Data Variables

In Figure 1, a comparison of investment risk, underwriting risk, and capital ratio between Indonesia and Taiwan can be observed. The investment risk graph is the highest among the others. Investment risk represents the potential risk that a company may incur as a result of its investment activities. Investment risk is directly proportional to the investment returns obtained by the company. If the returns are high, the risk assumed by the insurance company will also be high. As previously explained, life insurance companies employ riskier strategies to obtain higher profits. Therefore, the resulting investment risk graph is high. The difference between Indonesia and Taiwan in this graph is not significantly different because the risks borne by companies in both



Figure 1: Comparison of investing risk, underwriting risk, and capital ratio between Indonesia and Taiwan

countries are not significantly different. Although the Indonesian graph appears higher, it may be due to insurance companies in Indonesia investing in high-return products.

In the underwriting risk graph, it can be seen that it is the lowest among the other graphs. Underwriting is essentially the process of identifying and selecting risks imposed on potential insureds who want to insure themselves with an insurance company. Underwriting risk occurs when a company makes mistakes in classifying policyholders. Such mistakes are likely to occur less frequently compared to investment risk. The reason for the higher underwriting risk in Indonesia compared to Taiwan is the higher health risks in Indonesia compared to Taiwan, due to differing levels of health. Additionally, Taiwan is likely better at risk selection, resulting in a lower underwriting risk graph compared to Indonesia.

A comparison of the capital ratios between Indonesia and Taiwan can be seen. This graph appears different compared to the investment risk and underwriting risk graphs. In this capital ratio graph, the difference between Indonesia and Taiwan is significant. The capital ratio represents the adequacy of capital that can be used to absorb risks. If there is a considerable time gap, the minimum capital requirements to be fulfilled by each company will differ and increase. One of the reasons for the increase in minimum capital requirements is to adapt to changes and economic developments to remain in line with the changing economic environment. For example, there have been changes in the minimum capital requirements for life insurance companies in Indonesia. In 2008, life insurance companies in Indonesia set the minimum capital requirements for conventional life insurance licenses at Rp150 billion for license A, Rp75 billion for license B, and Rp50 billion for license C. In 2014, the policy was changed to Rp100 billion for license A, Rp50 billion for license B, Rp25 billion for license C, and additional rules were introduced for sharia life insurance with a minimum capital of Rp100 billion. In this case, the data used by Indonesia and Taiwan have a significant difference. Taiwan uses data from 2005, while the data used for Indonesia starts from 2014. This difference can lead to a significant discrepancy in the capital ratio. Additionally, the data used for Taiwan is from 2005-2009, during which Taiwan experienced a global crisis in 2008. This can also be a supporting factor for the significant difference in the capital ratio graph between Indonesia and Taiwan. Overall, the Indonesian graph is consistently higher than Taiwan's. However, this indicates that despite the large risks in Indonesia, insurance companies in Indonesia are still able to manage their risks effectively.

## 4.1 2SLS and GMM Models

Both models we shows in this paper are not the first models we obtained. Using backward selection method, we eliminate the variables that are not significant to the model with the aim to get simpler model with a higher level of accuracy. Using a significance level of 5%, we also assume that endogenous variables and their first lag as an important variable due to when we eliminate

these variables, the accuracy of model decreases even though these variables are not significant based on their p-values.

Variable	Estimate	S.E.	<b>T-Statistics</b>	p-value
Intercept	0.652431	0.260901	2.501	0.0133
INR	0.951109	0.176558	5.381	$2.21 \times 10^{-7}$
UNR	3.289165	0.698942	4.706	$5.01 \times 10^{-6}$
SIZE	-0.082388	0.010562	7.800	4.7310 <sup>-13</sup>
<i>CAR</i> (-1)	0.011130	0.005849	1.903	0.0587

Table 2: 2SLS Capital Ratio Equations

Variable	Estimate	S.E.	<b>T-Statistics</b>	p-value
Intercept	0.26526	0.34225	0.77504	0.43832
INR	1.1823	0.22636	5.2233	$1.7572 \times 10^{-7}$
UNR	4.5373	0.12284	3.6938	$2.2093 \times 10^{-4}$
SIZE	-0.071035	0.014991	-4.7384	$2.1542 \times 10^{(-6)}$
PUB	-0.10670	0.049174	-2.1698	0.030024
<i>CAR</i> (-1)	0.010142	0.0031648	3.2045	$1.3529 \times 10^{-3}$

Table 3: GMM Capital Ratio Equations

Table 2 and Table 3 shows the estimate parameters of both 2SLS and GMM method for Capital Ratio equation. Using 2SLS method, it's obtained that the final model for estimating Capital Ratio has Investing Risk, Underwriting Risk, size of the company, and the first lag of Capital Ratio itself as the explanatory variables with R-Squared and Adj R-Squared value respectively 0.377 and 0.3632. Meanwhile, using GMM method it's obtained that the final model for estimating Capital Ratio are Investing Risk, Underwriting Risk, size of the company, *PUB* (dummy variabel that indicates whether the company is a publicy owned or not), and the first lag of Capital Ratio itself as the explanatory variables with R-Squared and Adj R-Squared value respectively 0.07895 and 0.0534. From these models, we performed two error tests using RMSE and MAE method and it's obtained that 2SLS has RMSE and MAE value respectively 0.2096 and 0.1516. Meanwhile, for GMM method it's obtained that MAE and RMSE value respectively 0.2548 and 0.1734.

Variable	Estimate	S.E.	<b>T-Statistics</b>	p-value
Intercept	0.37158	0.07157	5.192	$5.54 \times 10^{-7}$
CAR	0.10678	0.06354	1.690	0.094576
UNR	-1.54077	0.39715	-3.880	0.000146
<i>INR</i> (-1)	0.57579	0.08621	6.679	$2.83 \times 10^{-10}$

Table 5: GMM Investing Risk Equations

Variable	Estimate	S.E.	<b>T-Statistics</b>	p-value
Intercept	0.14300	0.068654	2.0829	0.037264
CAR	0.028430	0.019140	1.4853	0.13745
UNR	-0.50860	0.26993	-1.8841	0.059545
<i>INR</i> (-1)	0.84591	0.076647	11.036	$2.550 \times 10^{-28}$

Table 4 and Table 5 shows the estimate parameters of both 2SLS and GMM method for Investing Risk equation. Either using 2SLS or GMM, it's obtained that the final model for estimating Investing Risk has Capital Ratio, Underwriting Risk, and the first lag of Investing Risk itself as the explanatory variables with R-Squared and Adj R-Squared value for 2SLS model respectively 0.5107 and 0.5027 and R-Squared and Adj R-Squared value for GMM model respectively 0.6689 and 0.6635. Using RMSE and MAE method, we obtained that RMSE and MAE value for 2SLS respectively are 0.1256 and 0.06962. Meanwhile, for GMM method it's obtained RMSE and MAE value respectively 0.1033 and 0.0535.

Variable	Estimate	S.E.	<b>T-Statistics</b>	p-value
Intercept	0.12565	0.02667	4.711	$4.89 \times 10^{-6}$
CAR	0.07422	0.02036	3.645	$1.357 \times 10^{-3}$
INR	-0.15303	0.03157	-4.847	$2.68 \times 10^{-6}$
PUB	0.02260	0.01134	1.993	0.047761
<i>UNR</i> (-1)	0.18267	0.05613	3.254	$1.357 \times 10^{-3}$

Table 6: 2SLS Underwriting Risk Equations

Table 7: GMM Underwriting Risk Equations

Variable	Estimate	S.E.	<b>T-Statistics</b>	p-value
Intercept	0.061892	0.024113	2.0829	0.037264
CAR	0.045952	0.020387	2.254016	0.024195
INR	-0.070905	0.024858	-2.491574	0.012718
<i>UNR</i> (-1)	0.344433	0.145030	2.374914	0.017553

Table 6 and table 7 shows the estimate parameters of both 2SLS and GMM method for Underwriting Risk equation. Using 2SLS method, it's obtained that the final model for estimating Underwriting Risk has Capital Ratio, Investing Risk, *PUB* (dummy variabel that indicates whether the company is a publicy owned or not), and the first lag of Underwriting Risk itself as the explanatory variables with R-Squared and Adj R-Squared value respectively 0.4125 and 0.3995. Meanwhile, using GMM method it's obtained that the final model for estimating Underwriting Risk has Capital Ratio, Investing Risk, and the first lag of Underwriting itself as the explanatory variables with R-Squared and Adj R-Squared value respectively 0.4227 and 0.4132. We also performed two error tests using RMSE and MAE method and it's obtained that 2SLS model has RMSE and MAE value respectively 0.0496 and 0.02695. Meanwhile, for GMM method it's obtained RMSE and MAE value respectively 0.0486 and 0.02153.

From both 2SLS and GMM models, it was found there are no differences in the relationship between each endogenous variables. Capital Ratio has positive relation with both Investing Risk and Underwriting Risk, Investing Risk has positive relation with Capital Ratio and negative relation with Underwriting Risk, and Underwriting Risk has positive relation with Capital Ratio and negative relation with Investing Risk.

Based on the error tests we performed on both models, we can conclude that 2SLS models has smaller RMSE and MAE value than GMM model for Capital Ratio equation. Meanwhile, GMM model for Investing Risk and Underwriting Risk equation has smaller RMSE and MAE value than 2SLS model. In general, we can say based on the error value, GMM model in general has slightly better accuracy than 2SLS model. The same result also obtained based on R-Squared and Adj R-Squared value. For Capital Ratio equation, 2SLS has bigger R-squared and Adj R-Squared and Adj R-Squared than 2SLS model. It means 2SLS has better accuracy for

Capital Ratio equation, but GMM has better accuracy for Investing Risk and Underwriting Risk equation.

# **4.2** Comparison of *CAR*, *INR*, and *UNR* Estimation with 2SLS and GMM Methods

### 4.2.1 Comparison on CAR Variable

The predicted *CAR* values using 2SLS follow a similar pattern as the actual *CAR* data. However, at certain points, there are values where the 2SLS predictions are higher or lower than the actual data. This indicates that the model can predict the ups and downs of the *CAR* values, but sometimes it provides predictions that are either too high or too low (imprecise). It can also be observed that the 2SLS estimation results have a wider spread compared to the actual data.



Figure 2: Comparison of The Actual Value of CAR and The Results of 2SLS Estimation

The predicted *CAR* values using GMM follow a similar pattern as the actual *CAR* data. However, at certain points, there are values where the GMM predictions are both higher and lower than the actual data. Furthermore, at some points, there are GMM predictions that are significantly higher than the actual data. This indicates that the model can predict the ups and downs of the *CAR* values, but when it comes to providing *CAR* value predictions, it can be excessively high or low (imprecise). It can also be observed that the GMM estimation results have a wider spread compared to the actual data.



Figure 3: Comparison of The Actual Value of CAR and The Results of GMM Estimation

The *CAR* prediction results using GMM have the same pattern as the 2SLS prediction results. The predictions using both methods yield results that are very close to each other. However, it can be observed that at certain points, the GMM predictions are higher than the 2SLS predictions, while at other points, the GMM predictions are lower. This indicates that the spread of the GMM prediction results is larger compared to the 2SLS predictions. Thus, it can be concluded that the 2SLS model is better than the GMM model in modeling the *CAR* variable. This is consistent with the larger error values of the *CAR* GMM model compared to the *CAR* 2SLS model. (*RMSE GMM: 0.2548501 ; RMSE 2SLS: 0.2096622 ; MAE GMM: 0.1733544 ; MAE 2SLS: 0.15166799*)



Figure 4: Comparison of The Results of 2SLS and GMM Estimation

#### 4.2.2 Comparison on *INR* Variable

The *INR* prediction results using 2SLS have the same pattern and are very similar to the actual *INR* data. The 2SLS predictions can be considered to be close to the actual *INR* data. However, it can be observed that there are points where the 2SLS predictions are significantly higher or lower than the actual data (although not as much as in the *CAR* model). Thus, it can be said that the 2SLS estimation results for *INR* have a wider spread compared to the actual data.



Figure 5: Comparison of The Actual Value of INR and The Results of 2SLS Estimation

The predicted *INR* values using GMM follow a similar and very close pattern to the actual *INR* data. The GMM predictions can be considered to be close to the actual *INR* data. However, it can be observed that there are points where the GMM predictions are higher or lower than the actual data (although not as much as in the *CAR* model). Thus, it can be said that the GMM estimation results for *INR* have a wider spread compared to the actual data. However, considering the pattern and the close predictions of GMM to the actual *INR* data, it can be concluded that this model is good enough for predicting the *INR* variable.



Figure 6: omparison of The Results of 2SLS and GMM Estimation in Variable INR

The predicted *INR* values using GMM follow a similar pattern to the predicted values from 2SLS. The predictions using both methods yield very close estimates. However, it can be observed that at certain points, the 2SLS predictions are higher than the GMM predictions, while at other

points, the 2SLS predictions are lower. This indicates that the spread of the 2SLS prediction results is larger compared to the GMM predictions. Thus, it can be concluded that the GMM model is better than the 2SLS model in modeling the *INR* variable. This is consistent with the smaller error values of the *INR* GMM model compared to the *INR* 2SLS model. (*RMSE GMM: 0.1032846; RMSE 2SLS: 0.1256254; MAE GMM: 0.05353578; MAE 2SLS: 0.696166*)



Figure 7: Comparison of The Actual Value of INR and The Results of GMM Estimation

#### 4.2.3 Comparison on UNR Variable

The predicted *UNR* values using 2SLS follow a similar pattern to the actual *UNR* data. However, at some points, the 2SLS predictions are lower than the actual data. This means that the model can predict the ups and downs of the *UNR* values, but sometimes provides predictions that are too low (not precise). It can also be observed that the 2SLS estimation results have a smaller spread compared to the actual data.



Figure 8: Comparison of The Actual Value of UNR and The Results of 2SLS Estimation

The predicted *UNR* values using GMM follow a similar pattern to the actual *UNR* data. However, at some points, the GMM predictions are lower than the actual data. This means that the model can predict the ups and downs of the *UNR* values, but it provides predictions that are too low (not precise). It can also be observed that the GMM estimation results have a smaller spread compared to the actual data.

The predicted *UNR* values using GMM have the same pattern as the 2SLS prediction results. The predictions using both methods yield very close results. However, it can be observed that at certain points, the 2SLS predictions are higher than the GMM predictions, while at other points, the 2SLS predictions are lower. This indicates that the spread of the 2SLS prediction results is larger compared to the GMM predictions. Thus, it can be concluded that the GMM model is better than the 2SLS model in modeling the *UNR* variable. This is consistent with the smaller error values of the *UNR* GMM model compared to the *UNR* 2SLS model. (*RMSE GMM: 0.04863499; RMSE 2SLS: 0.04962299; MAE GMM: 0.02153543; MAE 2SLS: 0.0269485*)



Figure 9: Comparison of The Actual Value of UNR and The Results of GMM Estimation



Figure 10: Comparison of The Actual Value of UNR and The Results of GMM Estimation

## 4.3 The Relationship Between Investing Risk, Underwriting Risk, and Capital Ratio

First, if Investing Risk is used as a response variable. By using the best model of the 2SLS method for Investing Risk, namely model 6, it is found that Underwriting Risk (UNR) has a significant negative effect on Investing Risk (INR), while Capital Ratio (CAR) has an insignificant positive effect on Investing Risk (INR). By checking the error from model 6, it is found that using RMSE is 0.1256254 and using MAE is 0.0696166. Using the GMM method for Investing Risk based on model 6, it is found that Underwriting Risk (UNR) has a significant negative effect on Investing Risk and Capital Ratio (CAR) has an insignificant positive effect on Investing Risk. Model 6 GMM after checking for errors using RMSE the value is 0.1032846 and using MAE the value is 0.05353578.

Second, if Underwriting Risk is used as a response variable. By using the best model of the 2SLS method for Underwriting Risk, namely model 5, it is found that Investing Risk (INR) has a significant negative effect on Underwriting Risk (UNR), while the Capital Ratio (CAR) has a significant positive effect on Underwriting Risk (UNR). By checking the error from model 5, it is found that using RMSE is 0.04962299 and using MAE is 0.0269485. Using the GMM method for Underwriting Risk based on model 6, it is found that Investing Risk (INR) has a significant negative effect on Underwriting Risk and Capital Ratio (CAR) has a significant positive effect on Underwriting Risk and Capital Ratio (CAR) has a significant positive effect on Underwriting Risk and Capital Ratio (CAR) has a significant positive effect on Underwriting Risk and Capital Ratio (CAR) has a significant positive effect on Underwriting Risk and Capital Ratio (CAR) has a significant positive effect on Underwriting Risk and Capital Ratio (CAR) has a significant positive effect on Underwriting Risk and Capital Ratio (CAR) has a significant positive effect on Underwriting Risk. Model 6 GMM after checking for errors using RMSE the value is 0.04863499 and using MAE the value is 0.02153543.

Third, if the Capital Ratio is used as the response variable. By using the best model of the 2SLS method for Capital Ratio, namely model 5, it is found that Investing Risk (INR) and Underwriting Risk (UNR) have a significant positive effect on Capital Ratio (CAR). By checking the error from model 5, it is found that using RMSE is 0.2096622 and using MAE is 0.15166799. By using the GMM method for Capital Ratio based on model 4, it is found that Investing Risk (INR) and Underwriting Risk (UNR) also have a significant positive effect on Capital Ratio. Model 4 GMM after checking for errors using RMSE the value is 0.2548501 and using MAE the value is 0.1733544.

## 4.4 The Relationship Between Exogenous Variables and Endogenous Variables

The exogenous variables referred to here are the exogenous variables found in the best model using 2SLS and GMM. Not all exogenous variables that have been mentioned in the material and methods section are used because backward selection has been caried out to eliminate variables that are not significant at a certain level of significance. The relationship between exogenous variables and endogenous variables in the best model is as follows. **Publicly Held Company** (*PUB*), the *PUB* variable is found in model 5 2SLS with the underwriting risk response variable, this *PUB* variable has a significant positive effect on underwriting risk. While the *PUB* variable has a significant negative effect on the capital ratio in the 4 GMM model. **Size**, the size variable has a significantly negative effect on the capital ratio in the best model produced using 2 methods, namely the 5 2SLS model and the 4 GMM model. For the response variable, namely investment risk, there are no exogenous variables in the best model, using 2SLS and GMM produces the same results.

# 5 Conclusion

The research findings indicate that *CAR* has a positive impact on *INR*, as observed in both model 6 *INR* with the 2SLS method and model 6 *INR* with the GMM method. In model 5 *UNR* with the 2SLS method and model 6 *UNR* with the GMM method, it was found that *CAR* positively influences *UNR*. In model 5 *CAR* with the 2SLS method and model 4 *CAR* with the GMM method, it is known that *INR* has a positive influence on *CAR*. Therefore, it can be concluded that the results support H2 and contradict H1.

Based on the analysis above, which is based on financial data of companies in Indonesia after the implementation of RBC, it can be concluded that companies have started to consider the risks they bear in relation to their capital. This can be seen from the analysis results that show a positive relationship between investing risk and underwriting risk with the capital ratio. This means that when companies bear greater risks, they will make more efforts to increase their capital. With the implementation of RBC, companies pay more attention to the adequacy of their capital/assets to remain proportional to the risks they bear, in accordance with the applicable regulations at that time (including RBC).

Therefore, with the findings of this research, companies are expected to always pay attention to and control the investing risk and underwriting risk they bear in line with their risk tolerance. Companies should not only focus on pursuing high profits while disregarding the risks they bear. Because if that happens, it can threaten the sustainability of the company itself.

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