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ESTIMATION OF VALUE AT RISK FOR GENERAL INSURANCE COMPANY STOCKS USING THE GARCH MODEL

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ABSTRACT

Investment plays a crucial role in supporting economic development by allocating funds to generate future profits. Among various investment options, stock investment is widely popular. However, investors face the challenge of developing strategies to maximize returns while minimizing risks. Effective investment requires understanding the potential maximum risk of loss, known as Value at Risk (VaR). This research focuses on estimating VaR for four top general insurance companies in Indonesia: PT Lippo General Insurance Tbk (LPGI), PT Asuransi Tugu Pratama Indonesia Tbk (TUGU), PT Victoria Insurance Tbk (VINS), and PT Asuransi Dayin Mitra Tbk (ASDM). These companies were selected due to their leading positions in the industry. The Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model, an extension of the ARIMA method designed to handle volatility clustering, is utilized for VaR estimation. Results at confidence levels of 90%, 95%, and 99% reveal that VINS carries the highest risk, with a maximum VaR of IDR 2,848,710 at 99% confidence, while LPGI shows the lowest risk, with a maximum VaR of IDR 22,677. For TUGU, the maximum possible loss is IDR 517,589, and for ASDM, it is IDR 1,532,267. Backtesting confirms the reliability of the models, with some accepted at specific significance levels. Based on this analysis, the results can help investors make investment decisions that minimize potential losses, specifically in the four stocks analyzed.

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1. INTRODUCTION

Investment refers to the activity of allocating money or capital (valuable assets) with the expectation of earning a profit in the future. Stock investment is popular because it offers opportunities for large gains, although it comes with high risk due to market fluctuations, the global economy, and company performance [1]. Risk refers to the level of potential loss that occurs because the expected investment returns are not as expected [2]. There is a direct relationship between risk and return: higher potential returns come with higher risks. Investors aim to find stocks with high-profit potential while minimizing risk. One approach to measuring risk in stock investments is calculating Value at Risk (VaR), which estimates the maximum potential loss within a certain period and confidence level [3]. VaR is a key tool that helps investors determine the level of risk they are willing to accept [4]. With the increasing volatility in financial markets, it is critical for institutions to utilize more advanced and accurate methods for estimating VaR to better manage and mitigate potential risks.

In 1982, Robert Engle developed the Autoregressive Conditional Heteroscedasticity (ARCH) model, which is a time series model that contains an element of heteroscedasticity. Heteroscedasticity refers to a condition where the variance of the error term is not constant. The ARCH model becomes less effective when analyzing data in a large order. To solve the problem in 1986, Dr. Bollerslev developed the ARCH model into the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model [5]. The GARCH model improves volatility estimation by directly incorporating both historical volatility data and residual variance into the calculation.

Several related studies have been conducted on the estimation of VaR using the GARCH model. First, the VaR calculation for blue-chip stocks in the financial industry listed on the Indonesia Stock Exchange (IDX), such as BRI, BCA, and Bank Mandiri, from May 25, 2005, to May 21, 2021, using the GARCH, EGARCH, or TGARCH model, showed that with a 95% confidence level, and an initial investment of IDR 10,000,000. This indicates that Bank Mandiri's stock has the highest investment risk level, while BCA has the lowest [6]. Second, researched predicting stock returns and risk of the top ten stocks on the Indonesia Stock Exchange using the ARIMA-GJR-GARCH model from December 17, 2018, to December 14, 2021. The VaR analysis shows that BBCA, TLKM, PTBA, and UNVR performed better, with VaR values of 0.025227 for PTBA, 0.014661 for TLKM, 0.012222 for UNVR, and 0.047088 for BBCA [7]. Third, the predicted VaR for the GJR-GARCH aggregation model with a confidence level of 99%, 95%, and 90%. The data used is stock data of ASII and AALI from January 2, 2020, until May 31, 2022. From the result, it can be concluded that to define the VaR prediction result of an aggregated return, GARCH (1,1) and GJR-GARCH (1,1) models can be used [8].

In this research, VaR estimation will be performed using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model and carried out for four general insurance companies' stock prices. The urgency of this study lies in the increasing complexity and volatility of financial markets, which expose investors to significant risks. Insurance companies, as key players in financial markets, are particularly vulnerable to market fluctuations, making effective risk management critical for their stability and performance. By estimating VaR, this research provides valuable insights into the potential maximum loss that can occur within a specific time horizon at varying confidence levels. The findings equip investors and financial institutions with a robust tool for managing and mitigating risks, ensuring better decision-making in an uncertain economic environment.

By applying the ARIMA-GARCH method to the stocks of selected general insurance companies, this study aims to identify the best-fitting model for each stock that can provide accurate volatility forecasts. The Autoregressive Integrated Moving Average (ARIMA) method is utilized to model and predict time series data by capturing trends and patterns, while the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model extends this approach to account for time-varying volatility, which is crucial for financial data. Together, these methods enable precise estimation of VaR by modeling both the underlying data structure and volatility clustering.

This research uses stock data from PT Lippo General Insurance Tbk (LPGI), PT Asuransi Tugu Pratama Indonesia Tbk (TUGU), PT Victoria Insurance Tbk (VINS), and PT Asuransi Dayin Mitra Tbk (ASDM), leading insurance companies in Indonesia. Unlike previous studies focused on the financial sector, telecommunication, and consumer goods [6] [7] [8], this study uniquely analyzes the risk profiles of insurance companies in the context of VaR. Through backtesting, the study assesses the reliability of VaR estimates, ensuring their effectiveness in real-world risk management within the insurance industry.

2. RESEARCH METHODS

2.1 Return

Stock returns refer to the benefits of share ownership, including dividends and capital gains or losses. In securities analysis, the natural logarithm ratio method is commonly used, where the result of the expected return is not significantly large compared to the conventional method [9]. Here, R_t represents the stock return at time t, P_t is the closing stock price in period t, and P_{t-1} is the closing stock price in period $t-1$. Stock returns can be calculated using the following formula:

$$R_t = ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

2.2 Stationary

In the analysis of time series, stationary is an important concept in observing data. Time series can be said to be stationary if the relative data does not show a significant change in value for data around a constant mean value. The Augmented Dickey-Fuller (ADF) test developed by Dickey-Fuller is one of the methods to check the stationarity of data in the mean.

To determine if the data is stationary or not, the $\boldsymbol{p}$-value of the Augmented Dickey-Fuller (ADF) test is compared to the significance level (alpha) specified in the analysis. In this study, alpha levels of 10% (0.10), 5% (0.05), and 1% (0.01) are used, corresponding to confidence levels of 90%, 95%, and 99%, respectively. If the $\boldsymbol{p}$-value of the ADF test is smaller than the chosen alpha, the data is considered stationary. Conversely, if the $\boldsymbol{p}$-value is greater than the specified alpha, the data is not stationary and requires differencing to achieve stationarity.

2.3 Autoregressive Moving Average (ARMA) Model

The combination of the autoregressive model, denoted by AR(p), and the moving average (MA) model of order q, is known as the Autoregressive Moving Average model [10]. The equation is:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q} \tag{2}$$

where Y_t is the time series variable, ϕ_p denotes constant or AR parameter, e_t denotes residual at time t, and θ_q denotes constant or the parameter of MA.

2.4 Autoregressive Integrated Moving Average (ARIMA) Model

ARIMA is an attempt to determine the most appropriate data pattern from a set of data. Hence, it requires completely historical data along with current data to forecast future values in time series. The ARIMA model is generally denoted as ARIMA (p, d, q) which implies that the model uses p-dependent lag values or degree of Autoregressive (AR), d levels of the differentiation process, and q residual lags or degree of Moving Average (MA).

With $W_t = Y_t - Y_{t-1}$ the equation for ARIMA $(p, 1, q)$ is as follows:

$$W_t = \phi_1 W_{t-1} + \phi_2 W_{t-2} + \cdots + \phi_p W_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q} \tag{3}$$

2.5 ARCH

In regression analysis, it is important the variance of the residuals is constant or referred to as homoscedasticity. In some cases of analysis, the variance of the residuals is not constant, called heteroskedasticity. The Autoregressive Conditional Heteroscedasticity - Lagrange Multiplier (ARCH-LM) test is used to detect heteroscedasticity in residual. The basic idea is that the residual variance is not only a function of the independent variables but also depends on the squared residuals in the previous period, where r_t is the residuals at time t, and σ_t^2 is the residual variance at time t.

$$\sigma_t^2 = \alpha_0 + \alpha_1 r_{t-1}^2 + \cdots .. + \alpha_p r_{t-p}^2 \quad (4)$$

2.6 GARCH

Robert Engle developed the ARCH model in 1982. The ARCH model is a time series model that contains an element of heteroscedasticity. Heteroscedasticity refers to a situation where the variance of the error term is not constant. ARCH model is not effective when analyzing the model with a large order. To solve the problem in 1986, Dr. Bollerslev developed the ARCH model into the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model [11]. In general, the GARCH (p, q) model equation is as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i r_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \quad (5)$$

where, σ_t^2 is conditional variance, ω is a constant component, α_i is weighting on the previous period's return, r_{t-i} is residual at time $t-i$, β_j is weighting on the previous volatility estimate, and σ_{t-j}^2 is conditional variance at time $t-j$. The GARCH model implies the previous squared residual and the previous conditional variance in the equation [12].

2.7 Value at Risk

One of the instruments of risk measurement is Value at Risk, abbreviated to VaR, developed by J.P. Morgan [13]. The VaR method is used to estimate the maximum potential loss over a given period with a specific level of confidence. VaR has become a popular method for measuring financial risk [14]. Mathematically, VaR is defined as [15]:

$$VaR = \inf\{x \in \mathbb{R} : P(L \leq x) \geq \alpha\} \quad (6)$$

VaR is closely related to the GARCH model, which is often applied in cases of heteroskedasticity of return data and can estimate future volatility. This is one of the advantages of the GARCH method compared to ordinary variance estimation, which is unable to estimate forward predictions. The calculation of VaR at a period of t using the GARCH model is formulated as follows:

$$VaR(t) = S_0\big(\mu + (Z_\alpha \sigma_t)\big) \quad (7)$$

where, S_0 represents initial investment fund, μ represents average asset return, Z_α represents the standard normal distribution value corresponding to the α, and σ_t represents volatility at time t. In case the return is not normally distributed, the Z score needs to be adjusted using the Cornish-Fisher Expansion with the formula:

$$Z_{correction} = Z_\alpha + \frac{1}{6}(Z_\alpha^2 - 1)S + \frac{1}{24}(Z_\alpha^3 - 3Z_\alpha)(K-3) - \frac{1}{36}(2Z_\alpha^3 - 5Z_\alpha)S^2 \quad (8)$$

where S is skewness, and K is kurtosis [15].

2.8 Backtesting

Backtesting is a technique used to evaluate the accuracy of VaR. The VaR models are only useful if the model accurately predicts risk, which helps to determine whether the model will work well in the future. For VaR models, which predict the potential loss, backtesting involves comparing the predicted losses with actual historical losses.

One common method for backtesting the VaR model is Kupiec Test. The Kupiec Test checks whether the number of times actual losses exceed the VaR prediction (known as exceptions) matches what is expected from the model [16]. The formula for the Kupiec Test is:

$$LR_{uc} = -2ln[(1-p)^{T-N}p^N] + 2ln\left\{\left[1-\left(\frac{N}{T}\right)\right]^{T-N}\left(\frac{N}{T}\right)^N\right\} \quad (9)$$

where:

LR_{uc} : Loglikelihood ratio approach
T : Total observation data
N : Total failure
p : Probability $(1-\alpha)$

2.9 Research Flowchart

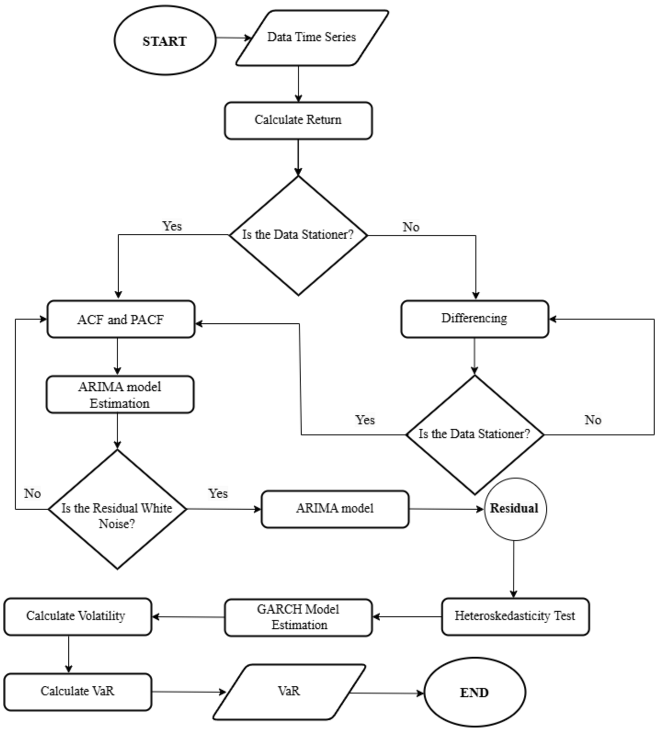


Figure 1. Research Flowchart

3. RESULTS AND DISCUSSION

3.1 Descriptive Statistics

In this research, the data used is the daily stock close price data of general insurance companies, including LPGI, TUGU, VINS, and ASDM, obtained from the Yahoo Finance website for the period August 16th, 2021, to April 30th, 2024, with a total of 656 data. After collecting the data, the return for each stock was calculated using **Equation (1)**. The details of the calculation return are presented in **Table 1**.

Table 1. Descriptive Statistics of Data Return

No.	Code	Maximum	Minimum	Mean
1	LPGI	0.22254277	-0.120702746	0.00113334
2	TUGU	0.178923083	-0.111669685	0.000458658
3	VINS	0.300104592	-0.236388778	0.000629596
4	ASDM	0.143455391	-0.101782694	-0.000152643

3.2 Return Data Stationarity Test

In ARIMA-GARCH modeling, it is essential to check whether the data is stationary. If the data is not stationary, differencing is required. In this study, a stationary test was conducted on the returns of the data using the Augmented Dickey-Fuller (ADF) Test. The stationarity test includes the following steps:

H_0: the data is not stationary
H_1: the data is stationary

The results of the stationarity test are given in Table 2.

Table 2. Result of ADF Test

	LPGI	TUGU	VINS	ASDM
***p*-value**	0.01	0.01	0.01	0.01

According to Table 2, the probability value of each stock return has a p-value of 0.01 which is less than the probability value used. This means that the stock return data for LPGI, TUGU, VINS, and ASDM are stationary.

3.3 ARIMA Model Specifications

The ARIMA model can be identified by analyzing the Partial Autocorrelation Function (PACF) and Autocorrelation Function (ACF) on the correlogram plot. After identifying the model based on the ACF and PACF correlogram plots, the ARIMA model parameters for each stock return were estimated. Based on Table 2, for the four stock return data, the differencing process was not performed because the four stock return data were stationary at the level. Thus, the differencing process applied is 0, and the model process follows Equation (2). The following will explain the results of the identification and estimation of the ARIMA model on each stock return data.

3.3.1 ARIMA Model Estimation of LPGI

In the process of estimating the ARIMA model for LPGI return stock, the PACF and ACF plots on the correlogram diagram were analyzed. While the ACF and PACF plots show cut-offs at lags 2, 4, and 8, these were not included in the resulting model due to the principle of parsimony, which prioritizes simpler models that adequately explain the data. The final ARIMA (2,0,2) model for LPGI stock was selected, identifies the Autoregressive (AR) with order p equal to 2, the differencing process is 0, and the value of 2 indicates the Moving Average (MA) with order q.

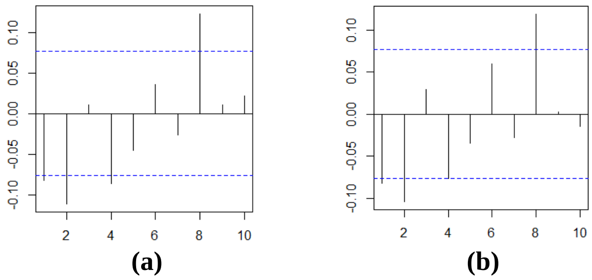


Figure 2. Plot for LPGI (a) PACF (b) ACF

By getting several models formed from the ARIMA (2,0,2) model, the following parameter estimation coefficients consist of AR1, AR2, MA1, MA2, MSE, AIC, and Log-Likelihood, which will be considered in conducting further analysis.

Table 3. Parameter Estimation Result of LPGI

ARIMA Model	AR1	AR2	MA1	MA2	MSE	Log Likelihood	AIC
ARIMA (0,0,1)			-0.10		7.737×10^{-4}	1416.92	-2829.83
ARIMA (0,0,2)			-0.09	-0.12	7.642×10^{-4}	1420.95	-2835.91
ARIMA (1,0,0)	-0.08				7.751×10^{-4}	1416.32	-2828.64
ARIMA (2,0,0)	-0.09	-0.11			7.654×10^{-4}	1420.41	-2834.83
ARIMA (1,0,1)	0.50		-0.62		7.67×10^{-4}	1419.75	-2833.51
ARIMA (1,0,2)	-0.18		0.09	-0.13	7.639×10^{-4}	1421.07	-2834.15
ARIMA (2,0,1)	-0.40	-0.13	0.31		7.647×10^{-4}	1420.71	-2833.42
ARIMA (2,0,2)	-0.11	0.13	0.02	-0.26	7.633×10^{-4}	1421.32	-2832.65

According to **Table 3**, the ARIMA model that has the lowest AIC is the ARIMA (0,0,2) model with an AIC value of -2835.91. After getting the best ARIMA model for LPGI stock, the subsequent step is to test for residual white noise. The result of the p-value for the white noise test is 0.9687. This value means that the residual of the ARIMA (0,0,2) model is not autocorrelated because the p-value > 0.05. Here the ARIMA (0,0,2) model using **Equation (2)**:

$$Y_t = 0.0902e_{t-1} - (-0.1194e_{t-2}) + e_t \tag{10}$$

3.3.2 ARIMA Model Estimation of TUGU

In the next section of this research, the TUGU stock return data was analyzed. The PACF and ACF plots for TUGU show cut-offs at lags 1 and 6. However, these lags were not included in the resulting model due to the principle of parsimony, which favors simpler models that still provide a good fit to the data. The ARIMA model obtained is the ARIMA (1,0,1) model.

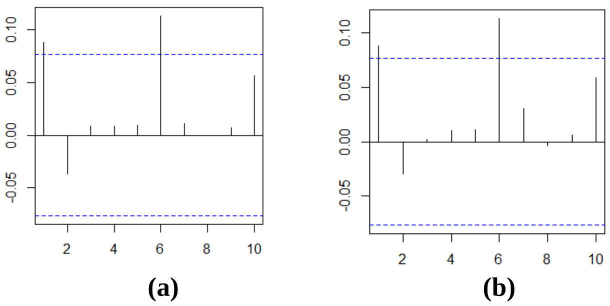


Figure 3. Plot for TUGU (a) PACF (b) ACF

Parameter estimation will be an important input for the next analysis. Here are the details of the estimated parameters of each model.

Table 4. Parameter Estimation Result of TUGU

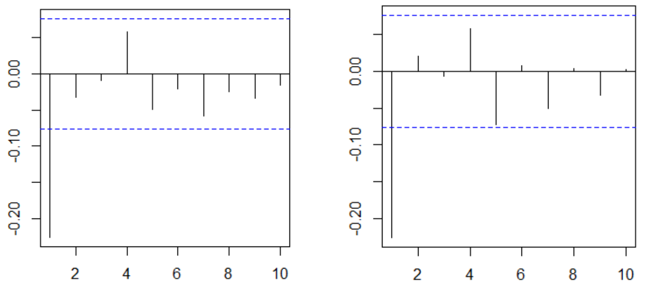
ARIMA Model	AR1	MA1	MSE	Log Likelihood	AIC
ARIMA (0,0,1)		0.09	8×10^{-4}	1404.16	-2804.33
ARIMA (1,0,0)	0.09		8×10^{-4}	1403.98	-2803.96
ARIMA (1,0,1)	-0.23	0.32	8×10^{-4}	1404.40	-2802.80

Based on **Table 4,** the smallest AIC of the 3 models formed is -2804.33. Then, the ARIMA (0,0,1) model will be used to test the white noise in the residuals using the Ljung-Box Test. Referring to the result of the white noise test, the p-value has a value of 0.9454 which fulfills the assumption that there is no significant correlation between the residual in the ARIMA (0,0,1) model. Below is the ARIMA (0,0,1) model using **Equation (2)**

$$Y_t = 0.0941e_{t-1} + e_t \tag{11}$$

3.3.3 ARIMA Model Estimation of VINS

In the case of VINS stock data, the ARIMA (1,0,1) model was obtained after analyzing the ACF and PACF patterns on the correlogram plot.



(a) **(b)**

Figure 4. Plot for VINS (a) PACF (b) ACF

The parameter estimates of the models are shown below.

Table 5. Parameter Estimation Result of VINS

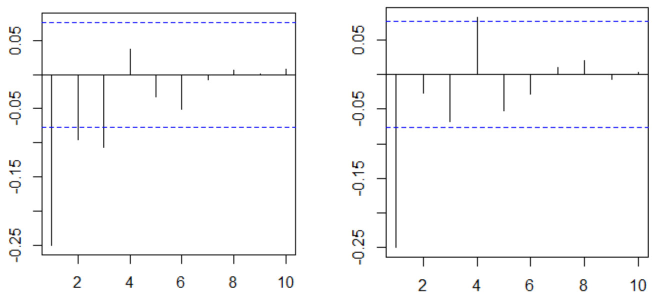
ARIMA Model	AR1	MA1	MSE	Log Likelihood	AIC
ARIMA (0,0,1)		-0.23	2.63×10^{-3}	1015.96	-2027.91
ARIMA (1,0,0)	-0.23		2.63×10^{-3}	1015.96	-2027.92
ARIMA (1,0,1)	-0.12	-0.12	2.63×10^{-3}	1016.20	-2026.41

According to **Table 5**, the best model for VINS stock data is an ARIMA (1,0,0) model based on the lowest AIC value of -2027.92. Although the value is almost the same as the parameter estimation value of the ARIMA (0,0,1) model, the AIC value of the ARIMA (0,0,1) model and the ARIMA (1,0,0) model still have a difference of 0.01. So it can be concluded that the VINS stock data model to be used in the test of white noise is the ARIMA (1,0,0) model. The p-value on the white noise test is $0.87 > 0.05$, which means that there is no autocorrelation in the residual value. The following is the ARIMA (1,0,0) model using **Equation (2)**

$$Y_t = -0.2295Y_{t-1} + e_t \tag{12}$$

3.3.4 ARIMA Model Estimation of ASDM

ASDM stock data is the last data to be analyzed in the estimation of the ARIMA model before proceeding to the next process. The ACF plot for ASDM shows a cut-off at lag 4; however, this lag was not included in the resulting model due to the principle of parsimony, which aims to select the simplest model that still captures the essential features of the data. The ARIMA (3,0,1) model was obtained in this data analysis.



(a) **(b)**

Figure 5. Plot for ASDM (a) PACF (b) ACF

The following are the details of the estimated parameters for each model.

Table 6. Parameter Estimation Result of ASDM

ARIMA Model	AR1	AR2	AR3	MA1	MSE	Log Likelihood	AIC
ARIMA (0,0,1)				-0.30	2.183×10^{-4}	1831.23	-3658.45
ARIMA (1,0,0)	-0.25				2.211×10^{-4}	1827.03	-3650.06
ARIMA (2,0,0)	-0.28	-0.09			2.190×10^{-4}	1830.15	-3654.29
ARIMA (3,0,0)	-0.29	-0.13	-0.11		2.166×10^{-4}	1833.87	-3659.75
ARIMA (1,0,1)	0.20			-0.48	2.176×10^{-4}	1832.37	-3658.74
ARIMA (2,0,1)	0.29	0.04		-0.57	2.175×10^{-4}	1832.46	-3656.93
ARIMA (3,0,1)	-0.62	-0.22	-0.14	0.34	2.162×10^{-4}	1834.45	-3658.90

Referring to **Table 6**, the ARIMA (3,0,0) model is a model that has the smallest AIC value with a value of -3659.75. The result from the test fulfills the assumptions that are useful for continuing to the next analysis. With a p-value of 0.9244 for the white noise test which indicates no significant correlation in the residual data of ASDM. The ARIMA (3,0,0) model can be formed using the **Equation (2)**

$$Y_t = -0.2863Y_{t-1} - 0.1272Y_{t-2} - 0.1067Y_{t-3} + e_t \tag{13}$$

For the residuals of the fourth dataset, the results of the Shapiro-Wilk test show a p-value close to zero, indicating that the return data does not follow the normal distribution. Despite this non-normality of the ARIMA residuals, the continuation of this study is justified, as the assumption of normality in ARIMA is not critical for the overall modeling process. This is because the subsequent GARCH model is specifically designed to address heteroskedasticity and capture the time-varying volatility in the residuals, which is a more significant characteristic in financial data. Furthermore, the primary focus of this research is on the predictive performance of the ARIMA-GARCH model in estimating VaR. The resulting VaR estimates will be evaluated using backtesting tests, ensuring that the model provides accurate and robust risk measures despite the non-normality of residuals.

3.4 The Lagrange Multiplier Test

The Lagrange Multiplier (LM) test aims to check and verify the effects of ARCH or heteroskedasticity on the residuals of the model. The hypotheses for the test are as follows:

H_0: There is no heteroskedasticity in the residuals
H_1: There is heteroskedasticity in the residuals

If the p-value of the Lagrange Multiplier (LM) test is less than 0.05, we reject H_0 and conclude that there is evidence of heteroskedasticity in the residuals. Conversely, if the p-value is greater than or equal to 0.05, we fail to reject H_0, indicating insufficient evidence of heteroskedasticity. The following are the results of the Lagrange Multiplier (LM) test on each data based on the residual of the best ARIMA model that has been selected.

Table 7. Result of Lagrange Multiplier Test

	LPGI	TUGU	VINS	ASDM
***p*-value**	0.005204	0.000001212	0.0000008897	0.0000002551

The Lagrange Multiplier (LM) test results show all p-values are less than 0.05; it can be concluded that the selected ARIMA model on each data will be used further in the estimation of VaR

3.5 GARCH Model

The GARCH modeling is very crucial before estimating the VaR because it measures the volatility that will be used in the calculation. The following are the equations for the best estimation of the GARCH model selection for each data set.

Table 8. GARCH Model Equation

Name	GARCH Model	Equation of Model
LPGI	GARCH (1,1)	$\sigma_t^2 = 0.00003163 + 0.1953r_{t-1}^2 + 0.8094\sigma_{t-1}^2$
TUGU	GARCH (1,1)	$\sigma_t^2 = 0.00002648 + 0.148r_{t-1}^2 + 0.8339\sigma_{t-1}^2$
VINS	GARCH (1,1)	$\sigma_t^2 = 0.0009106 + 0.6204052r_{t-1}^2 + 0.1923281\sigma_{t-1}^2$
ASDM	GARCH (1,2)	$\sigma_t^2 = 0.00004421 + 0.593r_{t-1}^2 + 0.07876\sigma_{t-1}^2 + 0.2331\sigma_{t-2}^2$

3.6 Value at Risk

The VaR estimation using the GARCH model can be performed after the mean and variance modeling is carried out by following the steps described in the previous section. Based on the Shapiro-Wilk test, the return data is confirmed to deviate from normality. To address this, the Z-score is corrected using the Cornish-Fisher Expansion, as detailed in **Equation (8)**, which adjusts for skewness and kurtosis. The result of calculations of the VaR with a confidence level of 90%, 95%, and 99% and the initial investment is IDR 10,000,000 is an arbitrary figure chosen to illustrate the investment scenario. The analysis can be scaled proportionally to different investment amounts without affecting the overall findings, by using **Equation (7)** are given in **Table 9**:

Table 9. The Result of VaR

Data	Confidence Level								
	90%			95%			99%		
	VaR (%)	VaR (IDR)		VaR (%)	VaR (IDR)		VaR (%)	VaR (IDR)	
LPGI	0.23%	IDR	22,677.39	1.16%	IDR	116,212.07	5.30%	IDR	530,262.15
TUGU	1.54%	IDR	153,585.60	2.36%	IDR	236,199.95	5.18%	IDR	517,589.57
VINS	4.74%	IDR	474,356.73	8.91%	IDR	891,220.32	28.49%	IDR	2,848,710.02
ASDM	0.65%	IDR	64,784.37	3.49%	IDR	349,031.00	15.32%	IDR	1,532,267.72

The VaR calculated in this study is based on actual historical data. The analysis uses real market data to estimate potential losses at a given confidence level, ensuring that the results reflect real investment scenarios.

3.7 Backtesting

After calculating the VaR values for each data and confidence level, the next step is to backtest this result using the Kupiec Test, which employs the log-likelihood ratio approach. The purpose of this test is to evaluate whether the calculated VaR values are accurate in accordance with the requirements. The test is based on the following hypothesis:

H_0: The model's VaR predictions are consistent with the observed data at the confidence level α
H_1: The model's VaR predictions are inconsistent with the observed data at the confidence level α
H_0 is accepted if $LR_{uc} < X^2_{(\alpha:1)}$, otherwise is rejected.

The backtesting test results are presented in the table below.

Table 10. The Result of the Backtesting Test

Company	α	Total Data	Log-Likelihood Ratio	Chi-Square Critical Value	Decision
LPGI	0.01	656	75.809	6.635	Rejected
	0.05	656	12.173	3.841	Rejected
	0.1	656	0.033	2.706	Accepted
TUGU	0.01	656	42.110	6.635	Rejected
	0.05	656	9.159	3.841	Rejected
	0.1	656	0.482	2.706	Accepted
VINS	0.01	656	7.405	6.635	Rejected
	0.05	656	31.030	3.841	Rejected
	0.1	656	71.157	2.706	Rejected
ASDM	0.01	656	4.401	6.635	Accepted
	0.05	656	42.078	3.841	Rejected
	0.1	656	91.506	2.706	Rejected

From the backtesting results of VaR using the GARCH model for the four companies (LPGI, TUGU, VINS, and ASDM), it can be seen that the VaR values for LPGI and TUGU are only accurate at the $\alpha = 0.1$ significance level, but not at the stricter significance levels of $\alpha = 0.01$ and $\alpha = 0.05$. The model for VINS is not accurate at any significance level, while the model for ASDM is accurate at the $\alpha = 0.01$ significance level. This indicates that the GARCH model generally performs better at higher significance levels for most companies, except for ASDM, where it is more accurate at the stricter $\alpha = 0.01$ level.

4. CONCLUSIONS

This study aimed to estimate the VaR for general insurance companies' stocks using the ARIMA-GARCH model and evaluate the reliability of these estimates through backtesting. The analysis revealed that each company's stock required a distinct ARIMA-GARCH model to accurately capture volatility and risk, reflecting the unique characteristics of the historical data for each insurance company. The estimated VaR values for the companies under different confidence levels were as follows: for PT Lippo General Insurance Tbk (LPGI), the VaR was 0.23% with an alpha of 0.1; for PT Asuransi Tugu Pratama Indonesia Tbk (TUGU), the VaR was 1.45% with an alpha of 0.1; and for PT Asuransi Dayin Mitra Tbk (ASDM), the VaR was 15.32% with an alpha of 0.01. The backtesting results showed that these VaR estimates were accurate, confirming the model's ability to predict financial risk effectively for each company. Despite some models being less reliable at lower confidence levels, the findings provide valuable insights into risk management in the general insurance industry. In conclusion, this research highlights that customized ARIMA-GARCH models are essential for estimating VaR, enabling insurers to enhance their risk management strategies by considering specific volatility patterns and adjusting for desired confidence levels tailored to each company.

Future research could explore alternative risk models like Copula-GARCH or stochastic volatility to better capture asset dependencies in the insurance sector. Investigating the impact of macroeconomic factors and market events on insurance risk profiles could provide deeper insights into dynamic market conditions. Expanding the dataset to include more insurance companies or cross-country comparisons could further validate these findings.

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