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Prediction of Motor Vehicle Insurance Claims Using ARIMA-GARCH Models

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Abstract

Motorized vehicles are one of the means of transportation used by Indonesian people. As of 2021, the Central Statistics Agency (CSA) recorded the growth of motorized vehicles in Indonesia reaching 141,992,573 vehicles. Lack of control over the number of motorized vehicles results in losses for various parties, such as accidents, damage and other unwanted losses. The size of insurance claims has the potential to fluctuate, because it is influenced by several factors, such as policy changes, market conditions and economic conditions. This research aims to predict the size of motor vehicle insurance claims using the ARIMA-GARCH model which is used to predict the size of vehicle insurance claims by dealing with non-stationarity and heteroscedasticity in time series data. Based on research, the best model obtained is the ARIMA (2,1,3) - GARCH (1,0) model which produces seven significant parameters. Meanwhile, based on the MAPE value, it shows that the ARIMA (2,1,3)-GARCH (1,0) model is quite accurate. The results of this research can be taken into consideration in predicting the size of insurance claims in the future.

Keywords: Prediction, insurance claim, motor vehicle, ARIMA-GARCH

1. Introduction

As time progresses and the mobility of activities increases, humans need transportation. Motorized vehicles are one of the means of transportation used by Indonesian people. Based on the Pew Researcher Center, Indonesia is in third place for the highest use of motorbikes in the world. Meanwhile, as of 2021, CSA (Central Statistics Agency) recorded the growth of motorized vehicles in Indonesia reaching 141,992,573 vehicles. Lack of control over the number of motorized vehicles results in losses for various parties, such as accidents, damage and other unwanted losses. This event can affect the economy so guarantees are needed to reduce the risk.

Insurance companies are one solution for society to face risks that may occur. Based on the Commercial Code, an agreement known as insurance or coverage binds the insurer to the insured. In this case, the insured can submit a claim to the insurance company to obtain compensation for the risks that must be included in the policy (Ajib, 2019).

The size of insurance claims has the potential to fluctuate, because it is influenced by several factors, such as policy changes, market conditions and economic conditions. To overcome the risk of loss, insurance companies can make predictions for future planning. Predicting the size of insurance claims has an important role in helping companies manage risk more effectively and plan finances better. This research uses the ARIMA-GARCH model. The ARIMA-GARCH model is used to predict the size of vehicle insurance claims by handling data non-stationarity (Wei, 2006) and heteroscedasticity in series data (Engle, 1982). Meanwhile, Maximum Likelihood Estimation (MLE) will be used to obtain parameter estimates for a model by maximizing the likelihood function.

Based on the explanation above, this research aims to predict the size of motor vehicle insurance claims using the ARIMA-GARCH model. The data used in this research is the size of PT Sompo Insurance Indonesia's insurance claims using the ARIMA-GARCH model.

2. Literature Review

2.1. ARIMA Model

This model is produced from three processes, namely autoregressive which has order p, moving average which has order q, and integrated which has order d to show that the data has been carried out a differential process in stationaryizing the data into an average. The Autoregressive Integrated Moving Average (ARIMA) model with the order (p, d, q) which is denoted by ARIMA(p, d, q) is as follows (Wei, 2006):

$$Z_t = \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \cdots + \phi_p Z_{t-p} + \varepsilon_t - \theta_q \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q}, \quad (1)$$

Z_t : variable value at time t
c : intercept
ϕ_p : AR model parameter
Z_{t-p} : variable value at the previous time
ε_t : residual at time t
θ_q : MA model parameter
ε_{t-q} : residual value at the previous time
p : AR order
q : MA order
d : differencing order

2.2. GARCH Model

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model introduced by Bollerslev in 1986 is a development of the ARCH model. GARCH(p, q) assumes that the variance of fluctuation data is influenced by a number p of previous fluctuation data and a number q of previous volatility data. ACF and PACF residuals can help identify orders in ARCH and GARCH (Bollerslev, 1986). The GARCH model with orders p and q which is denoted by GARCH(p, q) is as follows:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_p \varepsilon_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_q \sigma_{t-q}^2, \quad (2)$$

σ_t^2 : residual variance at time t
ω : intercept
α_p : model parameters
β_q : model parameters
ε_{t-p}^2 : square of the residual at the previous time $(t - p)$
σ_{t-q}^2 : square of the residual variance at the previous time $(t - q)$

2.3. Stationarity Test

A stationary model indicates that the process is in statistical equilibrium, where its probabilistic properties do not change over time. This indicates that the process tends to fluctuate around an average level and has a constant variance. In addition, data is also considered stationary with respect to variance when it has a rounded value (λ) of 1 (E.P.Box, G. et al., 2015). ADF (Augmented Dickey-Fuller) is a data stationarity test against the average developed by D.A. Dickey and W.A. Fuller, known as the Dickey-Fuller unit root test.
The hypothesis used is as follows,
$H_0: \delta = 0$, the data has a unit root or is not stationary.
$H_1: \delta < 0$, data has no unit root or stationary data.
Test statistics,

$$t = \frac{\hat{\delta}}{se(\hat{\delta})}, \quad (3)$$

t : the ratio value between the estimated parameter value and the standard error
$\hat{\delta}$: least squares estimator of δ
$se(\hat{\delta})$: standard error of $\hat{\delta}$

The test criteria are based on a significance level of 5% as follows,
If $|t| > |t_{critical}|$ or p-value < $\alpha = 5\%$, then H_0 is rejected.
If $|t| \leq |t_{critical}|$ or p-value > $\alpha = 5\%$, then H_0 is accepted.

Meanwhile, the Box-Cox transformation is one way to achieve a stable variance parameterized by λ. The Box-Cox transformation is formulated as follows,

$$T(Z_t) = \begin{cases} \frac{Z_t^{\lambda}-1}{\lambda} ; \lambda \neq 0 \\ \ln Z_t \quad ; \lambda = 0 \end{cases}, \tag{4}$$

λ *:* transformation parameter

2.4. Parameter Significance Test

The significance test is used to determine whether a parameter has an effect on the variables in the model. After estimating the temporary model, the next step is to carry out a significance test on the appropriate model parameters (Hartati, 2018).
The hypothesis used is as follows,
H_0: $\rho_j = 0$, (insignificant parameter).
H_1: $\rho_j \neq 0$, (significant parameter).

Test statistics,

$$t = \frac{\hat{\rho}_j}{se(\hat{\rho}_j)}, \tag{5}$$

ρ_j : model parameters
$\hat{\rho}_j$: estimated model parameters
$se(\hat{\rho}_j)$: standard error of ρ_j

The test criteria are based on a significance level of 5% as follows,
If $|t| > |t_{\frac{\alpha}{2},df=n-n_p}|$ or p-value < $\alpha = 5\%$, then H_0 is rejected.
If $|t| \leq |t_{\frac{\alpha}{2},df=n-n_p}|$ or p-value > $\alpha = 5\%$, then H_0 is accepted.

2.5. Ljung-Box Test

The Ljung-Box test is a test to evaluate whether the model residuals meet the white noise assumption. The white noise assumption test on the residuals is carried out to see whether the residuals are independent. The independent residual test used is the Ljung-Box-Q (LBQ) test with the following hypothesis (Wei, 2006).
The hypothesis used is as follows,
H_0: $\rho_1 = \cdots = \rho_k = 0$, (between residuals are not correlated).
H_1: there is at least one $\rho_k \neq 0$, (between correlated residuals).

Test statistics,

$$Q = n(n+2)\sum_{k=1}^{K}(n-k)^{-1}\hat{\rho}_k^2, \tag{6}$$

K : maximum lag
$\hat{\rho}_k^2$: quadratic autocorrelation for lag $k, k = 1,2,\dots,K$
n : number of observations

The test criteria are based on a significance level of 5% as follows,
If $Q \geq \chi^2_{(\alpha,K-p-q)}$ or p-value < $\alpha = 5\%$, then H_0 is rejected.
If $Q < \chi^2_{(\alpha,K-p-q)}$ or p-value > $\alpha = 5\%$, then H_0 is accepted.

2.6. ARCH-LM Test

ARCH (Autoregressive Conditional Heteroskedasticity) LM (Lagrange Multiplier) test is a test used to check the ARCH effect and detect the presence of heteroscedasticity in the model residuals.
The hypothesis used is as follows,

H_0: $\alpha_1 = \cdots = \alpha_k = 0$, (no ARCH effect).
H_1: there is at least one $\alpha_k \neq 0$, (there is an ARCH effect).

Test statistics,

$$\text{LM} = nR^2, \tag{7}$$

$R = \frac{\sum_{t=1}^{n}(\hat{X}_t - \bar{X})^2}{\sum_{t=1}^{n}(X_t - \bar{X})^2}$,
R^2 : coefficient of determination in the model
n : the number of residuals in the data

The test criteria are based on a significance level of 5% as follows,
If LM $\geq \chi^2_{(\alpha,K)}$ or p-value < $\alpha = 5\%$, then H_0 is rejected.
If LM $< \chi^2_{(\alpha,K)}$ or p-value > $\alpha = 5\%$, then H_0 is accepted.

2.7. Akaike Information Criteria (AIC)

Determining the best model is seen based on the AIC (Akaike Information Criteria) value of the model. The model that has the smallest AIC value is the best model (Wei, 2006). The AIC equation is as follows:

$$\text{AIC} = 2m - 2\ln L, \tag{8}$$

m : number of parameters in the model
L : the value of the likelihood function evaluated on the estimated parameters

2.8. Model Evaluation

The model is evaluated based on the Mean Absolute Percentage Error (MAPE) value with the model evaluation criteria listed in Table 1. The MAPE value can be calculated using the following formula (Montgomery et al., 2008):

$$\text{MAPE} = \frac{\sum_{t=1}^{n}\left|\frac{Z_t - \hat{Z}_t}{Z_t}\right|}{n}, \tag{9}$$

Z_t = observation value at time t
$\hat{Z}_t$ = predicted value at time t
n = number of observations

Table 1: Model evaluation criteria

MAPE	Interpretation
MAPE < 10%	Highly accurate forecasting
10% ≤ MAPE ≤ 20%	Good forecasting
20% < MAPE ≤ 50%	Reasonable forecasting
MAPE > 50%	Inaccurate forecasting

3. Materials and Methods

3.1. Materials

The data used is weekly data on the size of motor vehicle insurance claims at PT Sompo Insurance Indonesia from March 2016 – September 2023, totaling 395 data. The tools used in this research are Microsoft Excel, Rstudio and eviews.

3.2. Methods

a) Test the stationarity of the data using equation (3).
b) Testing the significance of ARIMA model parameters using equation (5).

c) Testing the ARIMA model diagnostics using the Ljung-Box test in equation (6).
d) Test ARCH-LM using equation (7).
e) Testing the significance of ARIMA-GARCH model parameters using equation (5).
f) testing the ARIMA model diagnostics using the Ljung-Box test in equation (6).
g) Predictions using the best ARIMA-GARCH model with the criteria in Table 1.

4. Results and Discussion

a) Stationarity Test

The collected data will go through a stationarity test using the Augmented Dickey-Fuller (ADF) test for stationary against the average and the Box-Cox test for stationary against variance using the help of eviews software, with the results can be seen in Table 2.

Table 2: Stationarity test results 1

Data	P-value	Box-Cox (λ)
Size of the claim	0.0004	0.4

Based on Table 2, the p-value of the ADF test is 0.0004. The p-value is smaller than the significance level $\alpha = 0.05$, causing H_0 to be rejected. So, it is concluded that the research data is stationary with respect to the average. However, because the round Box-Cox value obtained is $\lambda \neq 1$. Next, the solution is carried out using the differencing to obtain the value $\lambda = 1$ and the data can be said to be stationary regarding variance. The results of the second stationary test are shown in Table 3.

Table 3: Stationarity test results 2

	Box-Cox 1 (λ)	P-value
Differencing	1.14	0.0000

Table 3 shows that the round Box-Cox value $\lambda = 1$ was successfully obtained through the differencing once. Meanwhile, the p-value of the process is $< \alpha = 0.05$ which causes H_0 to be rejected. So, it can be concluded that the transformation and differencing data are stationary, both regarding the average and variance.

b) Significance Test of ARMA Model Parameters

Table 4: ARIMA model parameter estimation results

Model	Parameter	Estimation	P-value
ARIMA(1,1,0)	ϕ_1	-0.411926	0.0000
ARIMA(1,1,1)	ϕ_1	0.036762	0.4939
	θ_1	-0.921178	0.0000
ARIMA(2,1,0)	ϕ_1	-0.570241	0.0000
	ϕ_2	-0.380670	0.0000
ARIMA(2,1,3)	ϕ_1	0.257306	0.0000
	ϕ_2	-0.961460	0.0000
	θ_1	-1.173973	0.0000
	θ_2	1.126494	0.0000
	θ_3	-0.793209	0.0000
ARIMA(3,1,0)	ϕ_1	-0.707082	0.0000
	ϕ_2	-0.586673	0.0000
	ϕ_3	-0.364259	0.0000
	θ_1	-0.707082	0.0000
ARIMA(0,1,1)	θ_1	-0.916357	0.0000

Based on Table 4, it can be seen that the ARIMA model parameters are significant. This can be seen from the p-value < 0.05, so that H_0 is declared accepted. So, the significance test is fulfilled for the ARIMA(1,0 ARIMA(1,1,0), ARIMA(2,1,0), ARIMA(2,1,3), ARIMA(3,1,0), ARIMA(0,1,1).

c) Diagnostic Test of ARMA Model

Model diagnostic tests were carried out to determine the feasibility of the selected ARMA model. The test will check whether the residual model meets the white noise assumption.

Table 5: ARMA model diagnostic test results

Model	Ljung-Box		AIC
	Q	$\chi^2_{(\alpha,16-p-q)}$	
ARIMA(1,1,0)	160.3984	24.9958	45.6472
ARIMA(2,1,0)	107.6589	23.6848	45.4975
ARIMA(2,1,3)	6.1793	19.6751	45.2059
ARIMA(3,1,0)	36.4802	22.3620	45.3621
ARIMA(0,1,1)	50.0905	24.9958	45.2639

Based on Table 5, only the ARIMA (2,1,3) model has a value of $Q < \chi^2_{(\alpha,16-p-q)}$ so the null hypothesis is accepted. So, the residuals of ARIMA (2,1,3) models are white noise. The best ARMA model was obtained, namely ARIMA (2,1,3) with an AIC value of 45.2059.

d) ARCH-LM Test

Before proceeding to the GARCH modeling stage, it is necessary to carry out the ARCH-LM test. This test functions to see whether or not there is heteroscedasticity in the residuals of the ARIMA model. If the model residuals show heteroscedasticity, then the stage can proceed to GARCH modeling. However, when the residual model does not show heteroscedasticity, then the stage is completed until we get the Box-Jenkins model. The ARCH-LM test results are shown in Table 6.

Table 6: ARCH-LM test results ARIMA model

Model	P-value	Information
ARIMA (2,1,3)	0.0162	There is a heteroscedasticity effect

The ARCH-LM test results show a p-value $= 0.0033$ for the ARIMA (2,1,3) model. Because the p-value is less than the significance level $\alpha = 0.05$, it was decided that H_0 was rejected. So, it is concluded that there is a heteroscedasticity effect on the residuals of the ARIMA (2,1,3) model and the GARCH modeling stage can be carried out.

e) Significance Test of GARCH Model Parameters

Table 7: ARIMA-GARCH model parameter estimation results

Model	Parameter	Estimation	P-value
ARIMA (2,1,3)-GARCH (1,0)	ϕ_1	0.245852	0.0000
	ϕ_2	-0.958581	0.0000
	θ_1	-1.163147	0.0000
	θ_2	1.124716	0.0000
	θ_3	-0.803067	0.0000
	α_1	0.166388	0.0226
	ω	1.99×10^{18}	0.0000

Based on Table 7, it can be seen that the ARMA model parameters are significant. This can be seen from the p-value < 0.05, so that H_0 is declared accepted. So, the significance test is fulfilled for the ARIMA(2,1,3)-GARCH(1,0) model.

f) Diagnostic Test of GARCH Model

Model diagnostic tests were carried out to determine the feasibility of the selected ARMA-GARCH model. The test will check whether the residual model meets the white noise assumption.

Table 8: ARIMA-GARCH model diagnostic test results

Model	Ljung-Box		AIC
	Q	$\chi^2_{(\alpha,16-p-q)}$	
ARIMA(2,1,3)-GARCH(1,0)	4.4734	19.6751	45.1630

Based on Table 8, the ARIMA (2,1,3)-GARCH (1,0) model has a value of $Q < \chi^2_{(\alpha,16-p-q)}$ so the null hypothesis is accepted. So, the residuals of the ARIMA (2,1,3)-GARCH (1,0) model are white noise. The best ARMA model was obtained, namely ARIMA (2,1,3)-GARCH (1,0) with an AIC value of 45.1630. Next, using equations (1) and (2), the modeling is described as follows:

Table 9: ARIMA-GARCH modeling

Model	Modeling
ARIMA (2,1,3)	$\hat{Z}_t = 0{,}245852Z_{t-1} - 0{,}958581Z_{t-2} + 1{,}163147\varepsilon_{t-1} - 1{,}124716\varepsilon_{t-2} + 0{,}803067\varepsilon_{t-3}$
GARCH (1,0)	$\hat{\sigma}_t^2 = (1{,}99 \times 10^{18}) + 0{,}166388\varepsilon_{t-1}^2$

g) Data Prediction

Prediction calculations were carried out using the best selected ARIMA (2,1,3)-GARCH (1,0) model. The results of calculating predictions for the size of insurance claims for the next 3 periods, carried out using the help of eviews software, can be seen in Table 10 below.

Table 10: Results of predicting the size of insurance claims

Actual Data (IDR)	ARIMA(2,1,3)-GARCH(1,0) Model Prediction (IDR)	MAPE
5,280,343,011	5,260,490,331	0.3760
3,192,000,912	5,079,847,877	59.1431
3,077,602,294	4,463,756,391	45.0401
MAPE		34.8530%

The predictions made resulted in a MAPE value of 34.85%. Based on Table 10, this shows that the prediction data results are quite accurate.

5. Conclusion

Based on the test process that has been carried out, the best model is obtained, namely the ARIMA (2,1,3)-GARCH (1,0) model with the AIC value for each model being 45.1630. The MAPE value from the best model prediction results shows that both models are quite accurate with the MAPE value of the ARIMA(2,1,3)-GARCH(1.0) = 34.85% model, so that the model can predict the size of insurance claims at PT Sompo Insurance Indonesia in future.

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