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ARIMA-ARCH-Based Economic Growth Prediction for Lampung Province

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Abstract

Economic growth is an important indicator of regional economic performance and is influenced by dynamic changes over time. This study aims to analyze the forecasting of economic growth in Lampung Province using the ARIMA-ARCH method. The study uses quarterly secondary data on Lampung Province's economic growth derived from Gross Regional Domestic Product (GRDP) at constant prices for the period 2010Q1–2025Q4. The analysis was conducted using the EViews 10 software through several stages, including stationarity testing, ARIMA model identification, parameter estimation, diagnostic testing, ARCH-LM testing, and the formation of the ARIMA-ARCH model. The results indicate that the ARIMA(1,0,0) model is the most appropriate model for describing the mean process of economic growth. The ARCH-LM test indicates the presence of conditional heteroskedasticity in the ARIMA residuals, so the analysis is continued using the ARCH model. The ARIMA(1,0,0)-ARCH(1) model is selected as the final model because the parameters are statistically significant and the model provides a parsimonious representation of the residual volatility. The resulting model is then used to forecast Lampung Province's economic growth for the period 2026Q1–2027Q4. The findings are expected to provide information that can support regional economic planning and policy formulation.

Keywords: Economic Growth, Forecasting, ARIMA, ARCH, Lampung Province

INTRODUCTION

Economic growth is one of the important indicators used to describe the performance and development of a region's economy. It reflects changes in a region's ability to produce goods and services over a certain period and is commonly used as a basis for evaluating economic development. Sustainable economic growth can support increases in income, employment opportunities, and community welfare, while economic slowdowns or

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contractions may affect various social and economic aspects. Therefore, information regarding the development and future tendency of economic growth is important as supporting information for regional development planning and economic policy formulation.

Lampung Province is one of the strategic regions on the island of Sumatra, with economic activities supported by various sectors. The development of the regional economy can be observed through the Gross Regional Domestic Product (GRDP) and economic growth indicators, which may change over time. Regional economic dynamics are also related to various economic and social conditions within a region. Aji et al. (2023) showed that economic and socio-demographic factors are associated with regional development dynamics on the island of Sumatra. Meanwhile, Yuliawan and Emalia (2025) used industrial sector GRDP as one of the indicators in analyzing the relationship between economic activity and environmental quality in Indonesia. These studies indicate that regional economic indicators play an important role in understanding the dynamics and development of a regional economy.

Economic growth in Lampung Province does not always move constantly but may fluctuate across periods. Such changes can be influenced by various economic dynamics originating from both internal and external conditions. One of the major shocks affecting economic activity was the COVID-19 pandemic, which caused significant changes in production, consumption, trade, and investment activities. These conditions demonstrate that economic growth is a dynamic time-series phenomenon, requiring an analytical approach capable of utilizing historical patterns to provide information regarding future economic conditions.

One approach that can be applied to forecast economic data is time-series analysis. The Autoregressive Integrated Moving Average (ARIMA) model is widely used to model and forecast variables based on their historical patterns. ARIMA captures the temporal dependence of observations through three components: Autoregressive (AR), Integrated (I), and Moving Average (MA). Previous studies have demonstrated the application of ARIMA in forecasting regional economic indicators. Tutupoho et al. (2024) applied the ARIMA method to forecast economic growth in Maluku Province, while Utama and Wirawan (2014) used the Box-Jenkins approach to forecast GRDP in Bali Province. These studies indicate that ARIMA can be used to capture historical patterns and generate forecasts of regional economic indicators.

However, the ARIMA model primarily focuses on modeling the conditional mean and does not explicitly model changes in the variance of residuals over time. Economic data may exhibit periods of relatively stable and highly fluctuating residuals, indicating the presence

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of conditional heteroskedasticity. When such a condition occurs, the information contained in the changing variance of residuals may not be adequately represented by the ARIMA model alone. The Autoregressive Conditional Heteroskedasticity (ARCH) model introduced by Engle (1982) provides an approach for modeling conditional variance that changes over time and depends on information from previous periods.

The combination of ARIMA and ARCH provides an approach for modeling both the conditional mean and conditional variance of a time series. Several previous studies have developed combined or hybrid forecasting models. Hasan and Djakaria (2021) compared Hybrid ARIMA-NN and ARIMA-GARCH approaches, while Fadhilah et al. (2024) applied ARIMA-GARCH to stock return forecasting. Other studies have applied hybrid approaches to macroeconomic forecasting. Chaudhary (2024) employed Hybrid ARIMA-ANN for GDP forecasting in Nepal, while Perone and Zambrano-Monserrate (2025) developed a hybrid ensemble approach for GDP forecasting. These studies demonstrate the development of forecasting approaches that combine ARIMA with volatility models or other forecasting methods to improve the representation of complex time-series characteristics.

Although previous studies have widely applied ARIMA and hybrid approaches to economic forecasting, studies specifically applying the ARIMA-ARCH model to forecast regional economic growth in Indonesia remain limited. Previous research has more commonly applied ARIMA as a standalone forecasting model or combined it with GARCH and artificial intelligence methods. Therefore, the application of ARIMA-ARCH to regional economic growth provides an opportunity to model the conditional mean and conditional variance simultaneously, particularly when the residuals of the ARIMA model exhibit an ARCH effect.

Based on this research gap, this study aims to analyze and forecast the economic growth of Lampung Province using the ARIMA-ARCH model. The study uses quarterly economic growth data for the period 2010Q1–2025Q4. The ARIMA model is first applied to identify and model the conditional mean of economic growth, followed by the ARCH-LM test to examine the presence of an ARCH effect in the residuals. When an ARCH effect is identified, the ARIMA model is combined with the ARCH model to capture the conditional variance. The resulting model is then used to forecast the economic growth of Lampung Province for the period 2026Q1–2027Q4. This approach is expected to provide more comprehensive information regarding the dynamics of regional economic growth and contribute to economic planning and policy formulation in Lampung Province.

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THEORETICAL REVIEW

Economic Growth

Economic growth is one of the important indicators used to describe the development and performance of an economy in a region over a certain period. Economic growth reflects an increase in the production of goods and services generated by an economy and is commonly used to assess changes in economic activity over time. At the regional level, economic growth can be measured using the growth rate of Gross Regional Domestic Product (GRDP).

GRDP is an important indicator for describing the economic performance of a region. GRDP at constant prices is commonly used to measure economic growth because it eliminates the influence of price changes, allowing changes in the value of production to more accurately reflect changes in the volume of economic activity. Therefore, quarterly economic growth data can be analyzed as a time series to identify historical patterns and provide information regarding future economic conditions.

Forecasting and Time Series Analysis

Forecasting is the process of estimating future values of a variable based on historical information and patterns observed in previous periods. In the economic context, forecasting can provide information regarding potential future developments in economic indicators and can serve as supporting information for planning and decision-making.

Time series analysis is an analytical approach used for data observed sequentially over time. The observations in a time series may exhibit patterns such as trends, seasonal movements, cycles, and temporal dependence. In economic data, observations in the current period may be related to observations in previous periods. Therefore, time series methods can be applied to identify these relationships and use them to generate forecasts.

The application of time series forecasting requires attention to the statistical characteristics of the data. One important characteristic is stationarity. A stationary time series has statistical properties that remain relatively stable over time. Stationarity is important in ARIMA modeling because non-stationary data may produce unreliable relationships and affect the validity of the forecasting model. Therefore, stationarity testing is conducted before the identification of the ARIMA model.

Autoregressive Integrated Moving Average (ARIMA)

Autoregressive Integrated Moving Average (ARIMA) is a time series model commonly used to analyze and forecast data based on historical observations. The ARIMA model is represented as ARIMA((p,d,q)), where (p) represents the order of the autoregressive (AR)

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component, (d) represents the degree of differencing, and (q) represents the order of the moving average (MA) component.

The autoregressive component represents the relationship between the current value of a variable and its previous observations. The moving average component represents the relationship between the current observation and previous random shocks or error terms. Meanwhile, the integrated component represents the differencing process applied to achieve stationarity when the original time series is non-stationary.

The identification of an ARIMA model generally follows the Box-Jenkins approach, which consists of model identification, parameter estimation, diagnostic checking, and forecasting. The identification stage involves examining the stationarity of the data and analyzing the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). The ACF provides information regarding the correlation between observations at different lags, while the PACF measures the correlation between observations after controlling for the effects of shorter lags.

In this study, the economic growth series was found to be stationary at the level. Therefore, no differencing process was required, resulting in a value of (d=0). Based on the identification of the ACF and PACF patterns and the estimation results, the ARIMA(1,0,0) model was selected to represent the conditional mean of economic growth.

Autoregressive Conditional Heteroskedasticity (ARCH)

The Autoregressive Conditional Heteroskedasticity (ARCH) model was introduced by Engle (1982) to model time-varying conditional variance. The ARCH model is used when the variance of a time series is not constant over time and the magnitude of current variance is related to information contained in previous error terms.

In time series data, particularly economic and financial data, large shocks may be followed by periods of relatively large fluctuations, while periods with small shocks may be followed by relatively stable observations. This phenomenon is commonly associated with conditional heteroskedasticity or volatility clustering. The ARCH model provides a framework for modeling such changes in conditional variance.

The presence of an ARCH effect can be examined using the Lagrange Multiplier (ARCH-LM) test. The null hypothesis of the ARCH-LM test states that there is no ARCH effect in the residuals, while the alternative hypothesis states that an ARCH effect is present. If the null hypothesis is rejected, the residuals exhibit conditional heteroskedasticity, indicating that the variance equation can be modeled using an ARCH specification.

An ARCH((q)) model expresses the conditional variance as a function of the squared residuals from previous periods. In an ARCH(1) model, the current conditional variance is

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influenced by the squared residual from the immediately preceding period. Therefore, the ARCH(1) model can be used to capture the effect of previous-period shocks on current conditional variance.

ARIMA-ARCH Model

The ARIMA-ARCH model combines the ARIMA model for the conditional mean equation with the ARCH model for the conditional variance equation. The ARIMA component is used to describe the systematic temporal pattern in the mean of the time series, while the ARCH component is used to capture changes in the variance of the residuals over time.

The use of the ARIMA-ARCH approach is relevant when a time series exhibits both temporal dependence in its mean and conditional heteroskedasticity in its residuals. In such a case, the ARIMA model alone may adequately represent the conditional mean but may not sufficiently capture the time-varying variance. The incorporation of an ARCH model allows the variance dynamics to be modeled simultaneously.

In this study, the ARIMA(1,0,0) model is used to represent the conditional mean of economic growth in Lampung Province. After the ARIMA model is estimated, the ARCH-LM test is applied to the residuals. The presence of a significant ARCH effect indicates that the residual variance changes over time. Therefore, the ARIMA(1,0,0) model is combined with ARCH(1), resulting in the ARIMA(1,0,0)-ARCH(1) model as the final model for forecasting economic growth.

Forecasting Accuracy Evaluation

Forecasting accuracy evaluation is conducted to assess the ability of a forecasting model to produce predictions that are close to the actual observations. Forecast errors are calculated based on the differences between actual and forecast values. Several statistical measures can be used to evaluate forecasting accuracy, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE).

Mean Absolute Error (MAE) measures the average absolute difference between actual and forecast values. A lower MAE indicates that the average magnitude of forecasting errors is smaller. Root Mean Square Error (RMSE) is calculated by squaring the forecast errors before averaging and taking the square root, which gives greater influence to larger errors. Meanwhile, MAPE measures the average absolute forecasting error relative to the actual value and expresses the result in percentage terms.

In addition to MAE, RMSE, and MAPE, forecasting performance can also be evaluated using the Theil Inequality Coefficient. This measure provides an overall indication of the difference between actual and forecast values, while its decomposition into bias, variance,

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and covariance proportions can provide additional information regarding the sources of forecasting error. In this study, forecasting accuracy is evaluated using error measures obtained from the forecasting evaluation procedure to assess the performance of the ARIMA(1,0,0)-ARCH(1) model in forecasting the economic growth of Lampung Province.

METHOD

Research Design and Data

This study uses a quantitative approach with time-series analysis to analyze and forecast economic growth in Lampung Province. The data used are secondary data on quarterly economic growth in Lampung Province for the period 2010Q1–2025Q4. The data are obtained from the Central Statistics Agency (Badan Pusat Statistik/BPS) of Lampung Province. The analysis is conducted using EViews 10 software.

The economic growth data are analyzed using the Autoregressive Integrated Moving Average (ARIMA) model and the Autoregressive Conditional Heteroskedasticity (ARCH) model. The ARIMA model is used to identify and model the conditional mean of economic growth, while the ARCH model is applied to model the conditional variance when the residuals of the ARIMA model indicate the presence of an ARCH effect.

ARIMA Model Identification

The ARIMA modeling procedure follows the Box-Jenkins approach, which consists of model identification, parameter estimation, diagnostic checking, and forecasting. The first stage is to examine the stationarity of the economic growth data. The Augmented Dickey-Fuller (ADF) test is used to determine whether the time-series data are stationary. A stationary series has a stable statistical property over time, which is an important requirement in ARIMA modeling.

After determining the stationarity of the data, the appropriate ARIMA model is identified using the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). The ACF is used to identify the moving average (MA) component, while the PACF is used to identify the autoregressive (AR) component. Candidate ARIMA models are then estimated and compared based on their statistical significance and model selection criteria.

Diagnostic Checking

Diagnostic checking is conducted to evaluate whether the estimated ARIMA model adequately represents the data. The estimated parameters are examined based on their statistical significance, while the residuals are evaluated to determine whether they satisfy

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the required diagnostic conditions. A suitable ARIMA model should produce residuals that do not contain systematic autocorrelation.

The diagnostic stage is important before proceeding to the ARCH model because the residuals from the selected ARIMA model are used to identify whether conditional heteroskedasticity is present. If the residuals indicate an ARCH effect, the modeling process is continued using the ARCH model.

ARCH-LM Test and ARIMA-ARCH Model

The presence of conditional heteroskedasticity in the ARIMA residuals is examined using the Lagrange Multiplier (ARCH-LM) test. The null hypothesis states that there is no ARCH effect in the residuals, while the alternative hypothesis states that an ARCH effect is present. If the test indicates the presence of an ARCH effect, the variance equation is modeled using the ARCH approach.

The ARIMA-ARCH model combines the ARIMA model for the conditional mean equation and the ARCH model for the conditional variance equation. In this study, the ARIMA model is first used to represent the mean process of economic growth. The ARCH model is subsequently applied to the residuals when conditional heteroskedasticity is identified. The final model is selected based on the significance of the estimated parameters and the adequacy of the model in representing the characteristics of the data.

Forecasting and Forecast Evaluation

The selected ARIMA-ARCH model is used to forecast the economic growth of Lampung Province for the period 2026Q1–2027Q4. The forecasting results are evaluated to assess the accuracy of the model in predicting economic growth.

Forecasting accuracy is evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). MAE measures the average absolute difference between actual and forecast values, while RMSE gives greater weight to larger forecast errors. MAPE measures forecast error in percentage terms. These measures are used to evaluate the forecasting performance of the selected ARIMA-ARCH model.

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RESULTS

Economic Growth Development in Lampung Province



Source:EViews10, processed data2026

The descriptive analysis shows that the economic growth of Lampung Province experienced fluctuations throughout the observation period from 2010Q1 to 2025Q4. During 2010–2019, economic growth generally remained within the range of approximately 5% to 7%, indicating relatively stable regional economic activity before the occurrence of major economic shocks.

A significant change occurred in 2020 following the COVID-19 pandemic. Economic growth contracted sharply and reached approximately -3.58% in the second quarter of 2020, representing the lowest point during the observation period. The contraction reflects a structural shock caused by restrictions on economic and social activities, declining household consumption, slower investment, disruptions in the distribution of goods and services, and reduced trade activity.

Economic growth subsequently recovered in 2021, although fluctuations remained relatively high. During 2022–2025, the growth rate gradually became more stable and returned to approximately 5%. Overall, the time-series pattern indicates that following a major economic shock, economic growth gradually moved toward its long-term average, suggesting a mean-reverting pattern.

Stationarity Test

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.950419	0.0453
Test critical values:	1% level	-3.538362	
	5% level	-2.908420	
	10% level	-2.591799	

Source:EViews10, processed data2026

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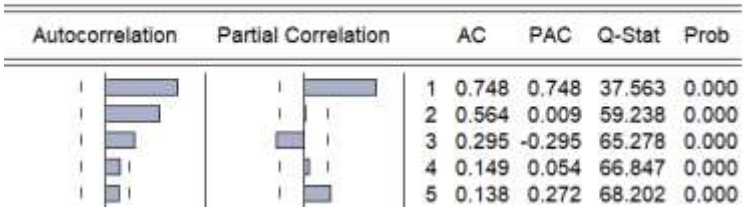
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The stationarity of the economic growth series was examined using the Augmented Dickey-Fuller (ADF) test. The results produced an ADF t-statistic of -2.950419 with a probability value of 0.0453. Since the probability value is lower than the 5% significance level, the null hypothesis of a unit root is rejected. In addition, the ADF t-statistic is lower than the MacKinnon critical value at the 5% significance level of -2.908420.

Therefore, the economic growth series is stationary at the level, or I(0). This result indicates that no differencing process is required before ARIMA model identification. The original economic growth data can therefore be directly used in the subsequent ARIMA modeling process.

ACF and PACF Identification

Date: 07/02/26 Time: 04:57
Sample: 2010Q1 2027Q4
Included observations: 64



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.748	0.748	37.563	0.000
		2	0.564	0.009	59.238	0.000
		3	0.295	-0.295	65.278	0.000
		4	0.149	0.054	66.847	0.000
		5	0.138	0.272	68.202	0.000

Source:EViews10, processed data2026

After confirming stationarity at the level, the model identification stage was conducted using the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). The ACF at the first lag was 0.748 and decreased gradually to 0.564 at the second lag before continuing to decline at subsequent lags. This gradual decline indicates the presence of an autoregressive component in the series.

Meanwhile, the PACF showed a significant value of 0.748 at the first lag, followed by a sharp decline at the second lag. The cut-off pattern after the first lag indicates an autoregressive process of order one, or AR(1). The Ljung-Box Q-statistic also indicated significant autocorrelation at several initial lags, suggesting that the original series had not yet satisfied the white-noise assumption.

Based on the ACF and PACF patterns, three candidate models were identified for further estimation: ARIMA(1,0,0), ARIMA(0,0,1), and ARIMA(1,0,1).

Selection of the Best ARIMA Model

Three candidate ARIMA models were estimated and compared based on parameter significance, model fit, and information criteria. The estimation results are summarized in

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Table 1.

Model	Key Parameter	Probability	R-squared	AIC	SC
ARIMA(1,0,0)	AR(1) = 0.741538	0.0000	0.563388	3.427891	3.529089
ARIMA(0,0,1)	MA(1) = 0.543534	0.0000	0.375518	3.778768	3.879965
ARIMA(1,0,1)	AR(1) significant; MA(1) insignificant	0.0000; 0.9635	0.564403	3.459105	3.594035

Source: processed data2026

The ARIMA(1,0,0) model produced a significant AR(1) coefficient of 0.741538 with a probability value of 0.0000. The model also produced an R-squared value of 0.563388, an AIC of 3.427891, and an SC of 3.529089. In comparison, the ARIMA(0,0,1) model produced a lower R-squared value of 0.375518 and higher AIC and SC values of 3.778768 and 3.879965, respectively.

The ARIMA(1,0,1) model showed that the AR(1) component was significant, while the MA(1) component was not significant, with a probability value of 0.9635. Therefore, the MA component did not provide a significant contribution to the model.

Based on these results, ARIMA(1,0,0) was selected as the best ARIMA model because it had significant parameters, the lowest AIC and SC values among the compared models, and the highest R-squared value. The Durbin-Watson statistic of 1.986755, which is close to two, also indicates that the model adequately reduced autocorrelation in the residuals.

Diagnostic Tests of the ARIMA(1,0,0) Model

Table 2

Test	Result	Decision
Jarque-Bera Normality Test	JB = 164.4099; Prob. = 0.0000	Residuals are not normally distributed
Residual Autocorrelation Test	Prob. > 0.05	No significant autocorrelation
Centered VIF	1.020315	No multicollinearity
ARCH-LM Test	Prob. F = 0.0246	ARCH effect exists
ARCH-LM Test	Prob. Chi-Square = 0.0247	ARCH effect exists

Source:EViews10, processed data2026

The residuals of the selected ARIMA(1,0,0) model were further examined through several diagnostic tests, including normality, autocorrelation, multicollinearity, and heteroskedasticity tests.

The normality test based on the Jarque-Bera statistic produced a value of 164.4099 with a probability value of 0.000000. The result indicates that the residuals are not normally distributed. This condition is associated with the extreme economic shock that occurred

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during the COVID-19 pandemic in 2020, which contributed to a high kurtosis value of 9.91.

The autocorrelation test using the residual correlogram and Q-statistic showed that most probability values across the examined lags were above the 5% significance level. This indicates that the residuals no longer contain significant autocorrelation and can therefore be considered to satisfy the white-noise condition.

The multicollinearity test produced a Centered VIF value of 1.020315, which is considerably below the commonly used threshold of 10. This result indicates that the model does not suffer from multicollinearity.

The ARCH-LM test was conducted to examine the presence of conditional heteroskedasticity. The test produced a Prob. F value of 0.0246 and a Prob. Chi-Square value of 0.0247. Both values are below the 5% significance level, indicating the presence of an ARCH effect in the residuals. This result shows that the residual variance is not constant over time and that the ARIMA model does not fully capture the volatility characteristics of the economic growth series.

ARIMA(1,0,0)-ARCH(1) Model Estimation

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	5.166866	0.429941	12.01761	0.0000
AR(1)	0.676475	0.159656	4.237072	0.0000
Variance Equation				
C	0.536139	0.060326	8.887358	0.0000
RESID(-1)^2	0.637697	0.313773	2.032348	0.0421

Source:EViews10, processed data2026

Following the identification of an ARCH effect, the ARIMA(1,0,0) model was combined with an ARCH(1) model. The resulting model was ARIMA(1,0,0)-ARCH(1).
In the mean equation, the constant coefficient was 5.166866 and the AR(1) coefficient was 0.676475, with both parameters having probability values of 0.0000. These results indicate that the previous period's economic growth has a significant positive relationship with current economic growth.

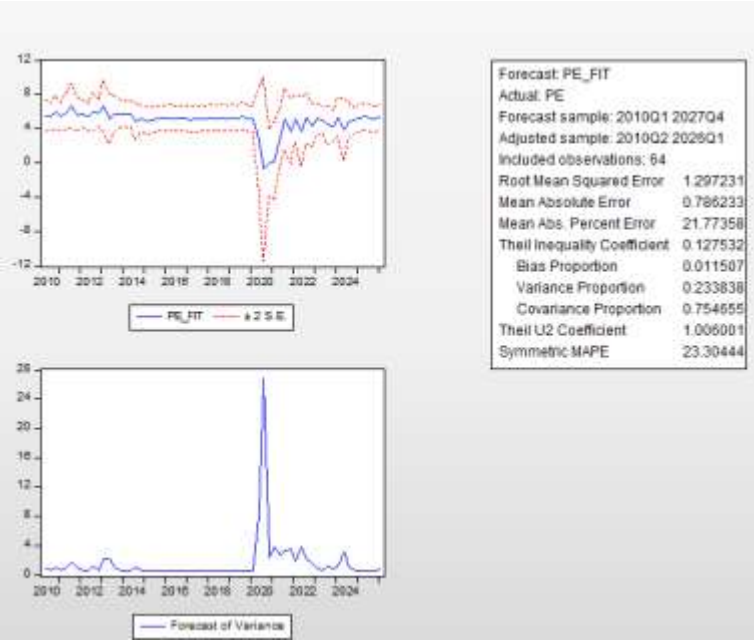
In the variance equation, the ARCH(1) coefficient was 0.637697 with a probability value of 0.0421. The significant ARCH coefficient indicates that the magnitude of shocks in the previous period significantly affects the conditional variance of the current period.
These results demonstrate that the ARIMA(1,0,0)-ARCH(1) model is able to represent both the conditional mean and the time-varying conditional variance of economic growth. The

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ARCH component therefore provides additional information regarding the volatility characteristics that were not captured by the ARIMA model alone.

Forecast Evaluation



Source:EViews10, processed data2026

The forecasting performance of the ARIMA(1,0,0)-ARCH(1) model was evaluated using RMSE, MAE, MAPE, SMAPE, and the Theil Inequality Coefficient.

The model produced an RMSE value of 1.297231 and an MAE value of 0.786233. The RMSE represents the magnitude of forecasting errors while giving greater weight to larger errors, whereas the MAE indicates that the average absolute difference between actual and predicted values was less than one percentage point.

The MAPE value was 21.77%, indicating that the average forecasting error was approximately 22%. The SMAPE value was 23.30%, suggesting a moderate level of deviation between actual and predicted values. The MAPE and SMAPE results should be interpreted in the context of the economic growth data, particularly because the series experienced a substantial negative shock during the COVID-19 pandemic.

The Theil Inequality Coefficient was 0.127532. The relatively low value indicates a relatively small difference between the forecast and actual values. The Bias Proportion was 0.011507, indicating a relatively small systematic bias in the forecasts. Meanwhile, the Covariance Proportion was 0.754655, representing the largest component of the Theil

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decomposition and indicating that a substantial proportion of the forecast error was associated with unsystematic variation.

Overall, the evaluation results indicate that the ARIMA(1,0,0)-ARCH(1) model provides adequate forecasting performance and can be used to forecast the economic growth of Lampung Province.

Forecasting Economic Growth of Lampung Province

2026Q1	5.419282
2026Q2	5.337619
2026Q3	5.282376
2026Q4	5.245006
2027Q1	5.219725
2027Q2	5.202624
2027Q3	5.191055
2027Q4	5.183229

Source:EViews10, processed data2026

The ARIMA(1,0,0)-ARCH(1) model was subsequently used to forecast economic growth for eight quarters ahead, covering 2026Q1 to 2027Q4. The forecasting results indicate that economic growth is expected to remain around 5% throughout the forecast period, with a gradual decline toward a more stable long-term level.

The forecast begins at approximately 5.42% in 2026Q1 and gradually decreases to approximately 5.18% by 2027Q4. This gradual decline does not indicate a negative economic slowdown but rather reflects the mean-reverting characteristic of the autoregressive process. Following the substantial fluctuations experienced during previous periods, particularly the COVID-19 shock, economic growth is projected to gradually move toward its long-term average.

The forecasting results do not indicate a projected economic contraction or an unusually high growth surge during the forecast period. Therefore, assuming no major external economic shocks occur, the economic activity of Lampung Province is expected to remain relatively stable during 2026–2027.

Overall, the forecast indicates a relatively stable economic outlook for Lampung Province during the 2026–2027 period. Although the projected growth rate is expected to decline slightly from the beginning to the end of the forecast period, it remains within a range consistent with relatively stable economic conditions. The forecasting results may

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therefore serve as supporting information for regional economic planning, investment planning, and the formulation of future economic growth targets.

DISCUSSION

The results indicate that the economic growth of Lampung Province experienced relatively stable growth during 2010–2019, followed by a sharp contraction during the COVID-19 pandemic in 2020. The contraction in the second quarter of 2020 represents an external economic shock that significantly altered the movement of the economic growth series. However, the subsequent recovery and stabilization of economic growth during 2021–2025 indicate that the series gradually returned toward its long-term average. This pattern suggests that economic growth in Lampung Province has a mean-reverting tendency, in which substantial deviations caused by external shocks are followed by gradual movements toward the long-term average.

The selection of ARIMA(1,0,0) as the best mean model indicates that current economic growth is significantly influenced by its previous-period value. The significant AR(1) coefficient suggests the existence of temporal dependence in the economic growth series, meaning that economic conditions in the previous quarter provide important information for explaining current economic conditions. The selection of ARIMA(1,0,0) over ARIMA(0,0,1) and ARIMA(1,0,1) also indicates that the autoregressive component is sufficient to represent the linear temporal dependence in the observed series, while the addition of a moving average component does not provide a significant improvement.

However, the diagnostic results show that the ARIMA(1,0,0) model alone is not sufficient to fully capture the characteristics of the data. The ARCH-LM test confirms the presence of an ARCH effect, indicating that the variance of the residuals changes over time. This finding demonstrates that the economic growth series contains time-varying volatility that cannot be adequately represented by the conditional mean equation alone. The application of an ARCH model as an extension of the ARIMA framework is consistent with previous research showing that ARIMA-ARCH models can be applied when ARIMA residuals exhibit heteroskedasticity and can be used to model both the time-series pattern and changing variance of the data.

The significant ARCH(1) coefficient in the variance equation further indicates that shocks occurring in the previous period significantly influence the magnitude of current-period volatility. This result implies that an economic shock does not only affect the level of economic growth but may also influence the uncertainty surrounding subsequent observations. The ARIMA(1,0,0)-ARCH(1) model therefore provides a more comprehensive representation of the economic growth series by modeling the temporal dependence in the

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conditional mean and the time-varying conditional variance simultaneously. Similar applications of combined ARIMA and ARCH/GARCH models have demonstrated the relevance of incorporating volatility models when the underlying time-series data exhibit heteroskedasticity and volatility clustering.

The forecasting evaluation indicates that the ARIMA(1,0,0)-ARCH(1) model provides adequate predictive performance. The RMSE and MAE values indicate that the average forecasting deviation is relatively limited, while the MAPE and SMAPE values suggest a moderate level of forecasting error. These results should be interpreted in the context of the substantial economic shock experienced in 2020, which may increase forecasting errors and make the economic growth series more difficult to predict. Nevertheless, the relatively low Theil Inequality Coefficient and low Bias Proportion indicate that the model does not produce substantial systematic forecasting bias. The dominant Covariance Proportion further suggests that a considerable share of the forecast error is associated with unsystematic variation rather than systematic model bias.

The forecasting results for 2026–2027 indicate that the economic growth of Lampung Province is expected to remain around 5%, declining gradually from approximately 5.42% in 2026Q1 to approximately 5.18% in 2027Q4. This gradual movement toward a stable level is consistent with the mean-reverting characteristics of the autoregressive process. The forecast does not indicate a projected economic contraction or an unusually high growth surge during the forecast period. Therefore, under the assumption that no major external shock occurs, economic activity in Lampung Province is expected to maintain relatively stable growth.

Overall, the findings demonstrate that incorporating the ARCH component into the ARIMA model is important for the analysis of Lampung Province's economic growth. The ARIMA(1,0,0)-ARCH(1) model not only captures temporal dependence in the conditional mean but also accounts for changes in residual volatility over time. This finding is in line with previous studies applying ARIMA-ARCH or ARIMA-GARCH frameworks, which emphasize the usefulness of combining a time-series model with a conditional variance model when the data exhibit heteroskedasticity. The resulting forecasts provide an indication of relatively stable economic growth in Lampung Province during 2026–2027 and can serve as supporting information for regional economic planning, investment planning, and the formulation of future economic development strategies.

CONCLUSION

This study analyzes the economic growth of Lampung Province and develops a forecasting model using the ARIMA-ARCH approach based on quarterly data from 2010Q1

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to 2025Q4. The results show that economic growth was stationary at the level and that the ARIMA(1,0,0) model was selected as the best mean model based on parameter significance and model selection criteria. However, the ARCH-LM test indicated the presence of conditional heteroskedasticity in the residuals. Therefore, the ARIMA(1,0,0) model was combined with an ARCH(1) specification, resulting in the ARIMA(1,0,0)-ARCH(1) model.

The results indicate that the ARIMA(1,0,0)-ARCH(1) model is capable of capturing both the temporal dependence in the mean and the time-varying volatility of economic growth. The forecasting evaluation also indicates that the model provides adequate predictive performance. The forecasting results for 2026–2027 suggest that economic growth in Lampung Province is expected to remain relatively stable at around 5%, with a gradual movement toward its long-term average.

These findings suggest that the ARIMA(1,0,0)-ARCH(1) model can be used as a supporting analytical tool for forecasting regional economic growth. The forecasting results may provide useful information for regional governments in formulating economic policies, investment planning, and future development strategies. Nevertheless, the forecast remains conditional on the absence of major external shocks that could significantly affect the regional economy.

Recommendations

This study has several limitations. First, the analysis uses quarterly economic growth data of Lampung Province covering the period from 2010Q1 to 2025Q4. Therefore, the forecasting results are limited to the characteristics and information contained within the observation period. Second, the observation period includes the COVID-19 pandemic, which caused an extraordinary economic shock and substantial fluctuations in economic growth. This condition may affect the stability of the time-series data and the accuracy of the forecasting results. Third, this study applies a univariate ARIMA(1,0,0)-ARCH(1) model, which primarily uses the historical pattern of economic growth and its conditional volatility. Consequently, other economic factors that may influence regional economic growth are not directly incorporated into the forecasting model.

Limitations and suggestions for further study

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