

Combining SARIMA and EGARCH Models for Modeling and Analyzing Real GDP Data in Albania

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Abstract: - Gross domestic product (GDP) is an important measure that reflects the development of the national economy and supports relevant sectors in formulating informed policies and strategic decisions. The purpose of this study is to analyze the trend and volatility of the real GDP time series from 2000 to 2024 in Albania. The

model incorporates both a **SARIMA (2,1,2)(0,0,1)₄** (Seasonal Autoregressive Integrated Moving Average) process to capture the conditional mean and a GARCH (1,1) process to model the conditional volatility.

The results indicate that the real GDP series exhibits strong autoregressive behavior, characterized by very persistent volatility. By capturing precise economic outcomes, such as real GDP growth rates and the shift of this research provides a framework for decision makers.

From the forecasting findings, it is evident that Albania's GDP will continue to expand steadily. The following suggestions are made to support Albania's economic development: (1) optimizing and improving the economic structure; (2) strengthening competition in the market.

Key-Words: - Real GDP, SARIMA Model, GARCH Model, Time Series Analysis, Forecasting, Volatility persistence, Economic structure.

Received: June 25, 2026. Revised: July 27, 2026. Accepted: August 18, 2026. Published: October 1, 2026.

1 Introduction

A macroeconomic measure used to evaluate a nation's economic performance and capabilities over time is the gross domestic product, or GDP. Its analysis is crucial for government policy-making and economic forecasting, [1], [2]. While various models exist to forecast economic variables, such as VAR [3], LSTM [4], [5], and ARMA [6], the SARIMA model is often considered highly suitable for forecasting GDP [7], [8], [9]. This paper, using quarterly real GDP data from 2000 to 2024, aims to build a SARIMA (2,1,2) (0,0,1)₄ model. Specialized models are necessary because economic time series, such as GDP, frequently show volatility and non-linear dependence. Consequently, the volatility component of the GDP time series is examined

using the GARCH (1,1) (Generalized Autoregressive Conditional Heteroscedasticity) model, EGARCH type. Prior research on financial and economic time series data has shown how well GARCH models capture time-varying volatility [10], [11], [12], which is a crucial feature of stylized economic phenomena like volatility clustering. This method will yield a more accurate and dependable analysis by accounting for the volatility of the data.

"Stylized facts" like volatility clustering—the tendency for periods of high volatility to be followed by additional high volatility and vice versa—are revealed by the examination of economic time series. Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models are utilized to precisely capture and model such volatility in order

to address this. This paper focuses on quarterly real GDP time series data in Albania from 2000 to 2024, a variable that has previously been investigated using the SARIMA (2,1,2) (0,0,1)₄ model. However, an unresolved question remains regarding the model's accuracy for the current data. This study, therefore, aims to re-evaluate the GARCH (1,1) model's predictive power by applying it to quarterly real GDP time series data in Albania.

The paper is organized into five sections as follows. Section 1 presents the research problem and the study's significance. The theoretical and empirical literature is presented in Section 2. The subsequent section 3 provides a brief description of SARIMA and EGARCH models. The fourth section presents the results and discussion of the SARIMA and EGARCH models as applied to quarterly real GDP time series data in Albania. Section 5 discusses the research findings and policy implications.

2 Literature Review

Analyzing macroeconomic time series, like GDP, frequently calls for complex econometric models that can take into consideration both the data's average behavior and its varying volatility. An established and popular technique for evaluating and predicting time series containing autoregressive and moving average components is the SARIMA (Seasonal Autoregressive Integrated Moving Average) model. However, volatility clustering—the tendency for significant changes to be followed by significant changes and vice versa—is seen in several economic measures, including GDP, [13]. Traditional SARIMA models do not capture this characteristic.

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model and its variations have emerged as a key tool in financial and economic research as a solution to this problem. Bollerslev [10] developed the GARCH model, which expands on Engle's ARCH model [11] by permitting the conditional variance to depend on both prior squared residuals and its own historical values. This method works especially well for simulating volatility's time-varying character.

Research has frequently combined SARIMA and GARCH models to create a robust framework for analyzing economic data, [14], [15], [16]. This SARIMA-GARCH approach simultaneously models the conditional mean of the series using the SARIMA process and the conditional variance using the GARCH process. The applicability of these models for predicting financial exchange rates and

other economic variables has also been shown by other research, [17], [18], and [19]. Researchers generally agree that GARCH models—especially the GARCH (1,1) specification—are resilient and straightforward, which makes them ideal for capturing volatility clustering in a variety of economic data, [20], [21].

Econometrics has traditionally placed a strong emphasis on the examination and prediction of macroeconomic and time-series data. Traditional linear models, such as SARIMA, have been a standard for capturing the mean behavior of a series. These models—including the SARIMA form described in the text—assume homoskedasticity, meaning the variance of the error term is constant over time.

Nevertheless, a plethora of empirical evidence has shown that this assumption is frequently broken, beginning with the groundbreaking work of [11] and [22]. Real GDP and commodity prices are examples of financial and economic data that frequently display heteroskedasticity, particularly in the form of volatility clustering. This is a "stylized fact" in which periods of low volatility are followed by periods of low volatility and periods of high volatility are followed by periods of high volatility, [23]. Models that can represent time-varying volatility are required to account for this occurrence. This idea was first formalized by [11] in the ARCH model, which permits the conditional variance to be a function of previous squared error terms. By adding lagged conditional variances, Bollerslev's GARCH model [10] expanded on this methodology.

This addition makes the GARCH model particularly effective at modeling the persistence of volatility, as seen in the high GARCH coefficient in the provided analysis.

These models have been used on a wide range of financial and economic time series in numerous studies. GARCH models are excellent at capturing volatility and increasing forecasting accuracy, according to research on commodities like rubber, oil, and electricity [24], [25] and [26]. Moreover, it is standard procedure to combine the SARIMA and GARCH procedures into a single SARIMA-GARCH framework. The conditional mean and volatility of the series can be modeled simultaneously using this method. For example, research on the Chinese stock market has shown that ARMA-GARCH models predict volatility better than other models, [27], [28]. Similar to this, this combined technique is frequently used in the analysis of real GDP time series to account for both persistent volatility and autoregressive trends. Some researchers have also investigated the presence of

structural breaks in the volatility of GDP, suggesting that neglecting such breaks can bias GARCH estimates of persistence, [29].

For data with volatility clustering, typical time series models are inadequate, according to the literature. A reliable method for simulating the dynamic behavior and time-varying volatility present in real-world data is the SARIMA-GARCH framework, which has been extensively used and verified across various markets and economic variables. In the context of our study, the SARIMA and EGARCH models aid in the policy forecasting process and enhance the estimation of GDP data in Albania. Given the structure of the Albanian economy, which is strongly influenced by seasonal factors such as tourism, agriculture, and remittances, SARIMA offers reliable short- and medium-term forecasts. On the other side, EGARCH models allow for the assessment of volatility and asymmetric responses in GDP growth. This study is particularly important for Albania as it addresses a clear research gap by applying advanced time series models (SARIMA-EGARCH) to estimate and analyze the real GDP, capturing both seasonality and volatility in real GDP dynamics.

3 Materials and Methods

3.1 Data

In this section, 96 quarterly real GDP data are used. These data consist of the period from 1 January 2000 to 31 December 2024. All observations were taken from published World Bank Data for Albania, [30].

3.2 SARIMA Model Specification

In 1976, the authors [31], proposed ARIMA (p,d,q) models where (p) is the number of autocorrelation terms, (d) is the number of differencing elements, and (q) is the number of moving average terms. The letter "I" in ARIMA is used to differentiate when the series is not stationary. However, when the time series is stationary, we can model it using three classes of time series processes: autoregressive (AR), moving-average (MA), seasonal moving-average (SMA), and mixed Seasonal Autoregressive Integrated Moving Average (SARIMA), [32]. An autoregressive model of order (p), denoted as AR(p), can be expressed as [33]:

$$\text{Log}(Y_t) = \mu + c_1 \log(Y_{t-1}) + \varepsilon_t \quad (1)$$

The moving average of order (q), which is denoted as MA(q), can be expressed as follows:

$$\text{Log}(Y_t) = \mu + \varepsilon_t + \varepsilon_{t-i} \quad (2)$$

where ε_t , is a white noise disturbance term with E

$$(\varepsilon_t) = 0 \text{ and } \text{var}(\varepsilon_t) = \sigma^2$$

whereas the term (I) represents the number of times the raw time series has been differenced to achieve stationarity. The combination of the AR(p), I(d), MA(q) and SMA(Q) models of the SARIMA (2,1,2)

(0,0,1)₄ type transforms the data series from non-stationary to stationary as follows:

$$\text{Log}(Y_t) = \mu + c_1 d[\text{Log}(Y_{t-1})] + c_j \varepsilon_{t-1} + \varepsilon_t \quad (3)$$

or in sigma notation:

d[

$$\text{Log}(Y_t) = C + \sum_{i=1}^m c_i d[\log(Y_{t-i})] + \sum_{j=1}^n c_j (\varepsilon_{t-i}) \quad (4)$$

where $d[\text{Log}(Y_t)]$ is the first difference of quarterly

log(real GDP) data, C is a constant term, c_i are the parameters of the autoregressive component of order

(p), c_j are the parameters of the moving average

component of order (q), and ε_j is the error term at time (t). The order (p, q, n) are non-negative integer.

3.3 EGARCH Model Specification

Two time-varying volatility models are popular among researchers: the ARCH model and the EGARCH model, [32]. The ARCH model aims to predict the conditional variance of return series. This equation is a form of a GARCH model, specifically an asymmetric GARCH model, often used in time series data to model the volatility of the data. It shows how the logarithm of the conditional

variance $\log(\sigma_t^2)$ at time t is determined by past information. Written as follows, [34]:

$$\begin{aligned} \text{Log}(\sigma_t^2) = & C + C_{i1} \sum_{i=1}^p \left(\frac{|\text{ARCH}_{t-i}|}{\text{GARCH}_{t-i}} \right) + \\ & C_{i2} \sum_{i=1}^p \frac{\text{ARCH}_{t-i}}{\text{GARCH}_{t-i}} + \\ & C_j \sum_{j=1}^q \text{Log}(\text{GARCH}_{t-1}^2) \text{Log}(\text{GARCH}_t^2) \end{aligned} \quad (5)$$

or

$$\log(\sigma_t^2) = C + C_{i1} \sum_{i=1}^p \frac{|\varepsilon_{t-i}|}{\sigma_{t-i}} + C_{i2} \sum_{i=1}^p \frac{\varepsilon_{t-i}}{\sigma_{t-i}} + C_j \sum_{j=1}^q \log(\sigma_{t-j}^2) \log \sigma_i^2 \quad (6)$$

In order to account for volatility clustering and asymmetric effects in a time series, the equation offers the general version of the EGARCH (Exponential Generalized Autoregressive Conditional Heteroskedasticity) variance model.

In the variance equation, the ARCH_(t-i) term represents the residual from the previous period

(ε_{t-i}), GARCH_(t-i) represents the variance from

the previous period σ_{t-i} and $GARCH_{t-i}^2$ represents the variance from the previous period to the second

power (σ_{t-1}^2); $GARCH_t^2$ represents the variance of the current period, and C is the constant term.

Below is a thorough explanation of each element::

$\log(\sigma_t^2)$ - is the logarithm of the conditional variance at time t. The real GDP growth volatility is

represented by the variable σ_t^2 . One important feature for this kind of model is that taking the logarithm guarantees that the variance will always be positive. The constant term is denoted by C. It shows the starting point of log-volatility when every

other factor is zero. The term $\sum_{i=1}^p \frac{|\varepsilon_{t-i}|}{\sigma_{t-i}}$, captures the effect of past volatility shocks on current volatility, which measures the size of the shock without considering its sign. The absolute value,

$|\varepsilon_{t-i}|$, means that both positive and negative shocks of the same size have the same effect on future volatility. This is a common feature in many

GARCH models. C_{i1} is the coefficient that measures the impact of these past shocks. The summation from i=1 to p indicates that the model considers the shocks from the previous p time periods. The term

$\sum_{i=1}^p \frac{\varepsilon_{t-i}}{\sigma_{t-i}}$ accounts for the asymmetric effect of

shocks. The variable ε_{t-i} is not in absolute value here. This indicates that the effects of positive and

negative shocks on volatility are different; that is, a negative shock frequently causes a larger increase in volatility than a positive shock of the same magnitude. This is referred to as the leverage effect.

This term specifically captures that effect, where C_{i2} is the coefficient for the asymmetric

effect. $\log(\sigma_{t-j}^2) \log(\sigma_t^2)$, measures the persistence or clustering of volatility. It shows how the logarithm of past conditional variances

$\log(\sigma_{t-1}^2)$ influences the current logarithm of the

conditional variance $[\log(\sigma_t^2)]$. This term indicates that high volatility tends to be. Overall, the model posits that the log of current volatility depends on:

- ✓ A constant baseline level.
- ✓ The magnitude of recent unexpected GDP fluctuations, regardless of whether they were positive or negative.
- ✓ The direction of those recent unexpected changes, specifically accounting for the fact that bad news (negative fluctuations) can have a larger impact on volatility than good news (positive fluctuations).
- ✓ The level of volatility in the recent past.

Simply put, it is a model that forecasts future volatility by utilizing historical data on growth and volatility.

3.4 Diagnostic Checking

In order to verify that all assumptions are satisfied and the model is sufficient, testing a combined SARIMA (2,1,2) (0,0,1)₄ and EGARCH (1,1) model entails examining both the mean and variance components of the model. This multi-step procedure expands upon the model's diagnostic testing. The following procedures are used to validate the model:

(1) Normality of residuals (Jarque-Bera test).

One essential diagnostic step for an ARIMA-EGARCH model is testing the residuals. An ARIMA-EGARCH model's main objective is to effectively capture the volatility clustering and serial correlation while leaving behind residuals that are identically and independently distributed.

(2) Heteroskedasticity test (The ARCH test).

A time series' time-varying volatility can be ascertained using this technique. This test determines if the variance of the residuals relies on the squared values of previous residuals, a phenomenon known as conditional heteroskedasticity.

(3) Autocorrelation test (Ljung-Box test). This test determines whether a time series has autocorrelation, showing that the residuals in a time series model are independently distributed. It proves that the model has successfully accounted for all the serial correlation and volatility clustering in the data.

4 Results and Discussion

4.1 Descriptive Statistics of GDP Series

Table 1 provides the descriptive statistics for the real GDP growth rate each quarter, offering a basic grasp of the specific characteristics of the data. This large value indicates a wide spread of data points around the mean.

The large degree of dispersion is confirmed by the standard deviation. The data points deviate from the mean by an average of 1,183 units.

Kurtosis: indicates that compared to a normal distribution, the data distribution has "fat tails" and a more peaked center. This suggests that extreme values are more likely. This is a significant discovery since it validates the application of a GARCH model, which is intended to deal with this kind of "heavy-tailed" behavior.

Skewness: denotes a small rightward skew in the data, with a longer right tail and more values above than below the mean.

Table 1. Quarterly real GDP data descriptive statistics from 2000 to 2024 in \$(million)

N	Mean	Var.	St. d	Kurtosis	Skewness
96	2,983.13	1,400,052	1,1183,238	3.063	0.157

Source: Author's calculation

4.2 In-Sample Analysis

4.2.1 Graphical Analysis

As shown in Figure 1 (left panel), there is a clear trend of 96 quarterly observations of real GDP in Albania from 1st January 2000 to 31th December 2024. When quarterly real GDP is converted to growth rates, the plot in Figure 1 (right panel) illustrates that there exists volatility clustering in quarterly rates of real GDP.

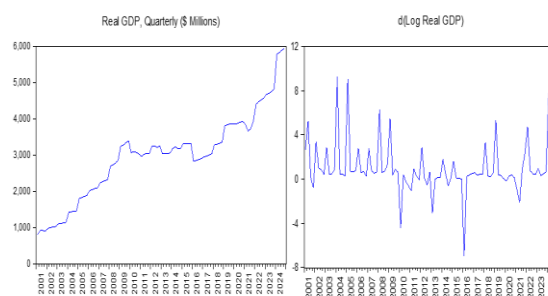


Fig. 1: Quarterly real GDP data (left panel) and quarterly growth rate data of real GDP (right panel)

Source: Author's results

The Impulse Response Function (IRF) and its Accumulated Response, which are common instruments in econometric and time-series analysis, are shown in Figure 2 to clarify the dynamics represented by the ARMA model. At the Impulse Response Graph, the solid blue line shows the impulse response (the effect of the shock) and the dashed red lines show confidence bands at ± 2 standard errors (uncertainty range). The blue line starts with a large positive response at time 0, which is expected as it's the period of the shock itself. The effect then quickly decays towards zero, and after approximately period 4, it becomes statistically insignificant because the blue line falls within the dashed red lines. This indicates that the shock has a short-lived effect on the variable, which essentially dissipates within the first few periods.

Whereas, the accumulated response ± 2 S.E. (Bottom Graph) shows the cumulative effect of the shock over time, where the blue line shows the accumulated response and the dashed red lines show ± 2 standard errors. It essentially tracks the total impact of the shock as it accumulates. The accumulated reaction is positive from the beginning and rises until it reaches a stable level, as indicated by the blue line. Even though there are occasional brief swings, the general pattern is unaffected. The fact that the cumulative response remains significantly above the lower confidence interval indicates that the effect is statistically significant during a course of the analysis. Overall, this shows that even while the initial shock weakens very rapidly, its cumulative impact on the variable is long-lasting and beneficial. In short, the bottom graph indicates the overall, long-term influence, whereas the top graph indicates the time and duration of the immediate effect. In this instance, the shock causes a long-lasting, positive cumulative change in the variable after having a brief but significant instantaneous influence.

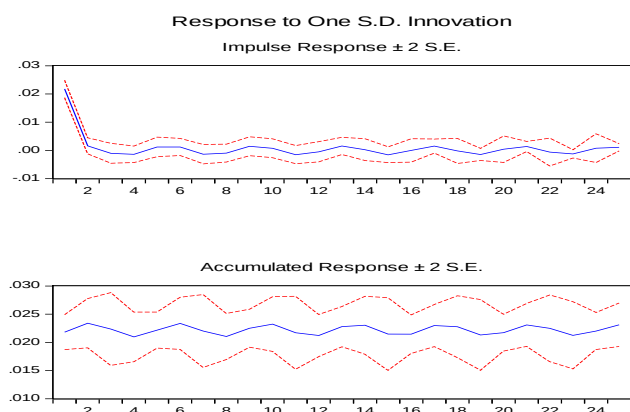


Fig. 2: Impulse and accumulated responses ± 2 S.E for quarterly real GDP data from 2000 to 2024
Source: Author's calculation

4.2.2 Unit Root and Stationarity Results

Quarterly Real GDP data is a non-stationary series, while quarterly d (Log.Real GDP data) enables the transformation of the series from non-stationary to stationary. According to the findings of Dickey–Fuller (ADF) tests [35], the Phillips–Perron (PP) [36], and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) [37], the stationarity criterion is satisfied by the first difference of the logarithm of real GDP. The results are summarized in Table 2.

Table 2. The stationary test's summary results

Stat. test	Deterministic terms included	Results (in level)	Conclusion
ADF	Intercept/ Trend & Intercept/ None	p-value=0.0000< 0.05	Stationary
PP	Intercept/ Trend & Intercept/ None	p-value=0.0000< 0.05	Stationary
KPPS	Intercept/ Trend & Intercept/ None	p-value=0.0000< 0.05	Stationary

Source: Author's own calculations based on a quarterly real GDP series using the log-difference method

The next test of statistical independence is conducted when the series are stationary. After testing the AR(1) and MA(2) models, it was discovered that the $Pr > ChiSq$ values were higher than 0.05 for all lag orders, suggesting that the models were successful in passing the diagnostic test.

4.2.3 ARMA Frequency Spectrum Analysis

ARMA Frequency Spectrum analysis is applied to capture temporal dependencies and spectral features of the time series. The time series' spectral density is displayed in Figure 3, with power on the vertical axis and frequency (ω) on the horizontal, showing how various frequencies affect the total variance. The frequencies that contribute most to the variability of the series are indicated as peaks in the spectrum. Values around π indicate very short cycles, whereas low frequencies represent long-term changes. The following describes how frequency (ω) and cycle length $T = 2\pi / \omega$ are related. For the dominant frequency at $1/2\pi$, we can calculate the period:

$$T = 2\pi / 1/2\pi = 4 \quad (7)$$

The prominent peak at $1/2\pi$ indicates that the most influential component of the time series is a cycle with a period of approximately 4 time units. This could represent a quarterly cycle in a business context or a 4-year cycle in a demographic study, for example. The ARMA model has identified and captured this strong periodic behavior.

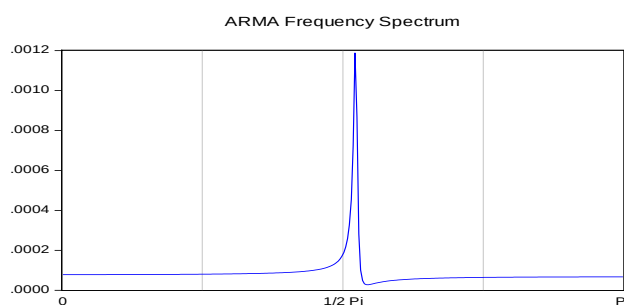


Fig. 3: Quarterly real GDP statistics from 2000 to 2024 using the ARMA Frequency Spectrum
Source: Author's calculation

4.2.4 Autocorrelation and Partial Autocorrelation

The most prominent characteristic is the cyclical, wavelike pattern in the blue bars, as shown in Figure 4. The relationships' magnitude gradually decreases as the bars alternate between being positive, negative, and positive once more. This suggests that the data has a significant seasonal or cyclical component. There is a positive correlation at lag 1, indicating a positive relationship between the current and prior values. The pattern repeats once the correlation at lag 2 is negative. A crucial feature of a non-stationary time series with a cyclical or seasonal trend is this kind of pattern, which decays gradually.

The bottom graph shows the PACF, which measures the correlation between the time series and

its own past values after removing the effect of the correlations at intermediate lags. It helps in identifying the direct relationship between a value and its past. The PACF also shows a significant, though decaying, cyclical pattern. Significant correlations are seen in the initial few lags, after which the pattern continues with weaker but still noticeable correlations. This pattern implies that there are substantial direct correlations between the data points at specific lags that cannot be accounted for by the lags in between. A more sophisticated cyclical pattern is suggested by the combination of slowly fading ACF and PACF, which probably means that an Autoregressive (AR) component is required to model the data. Therefore, it appears that this time series is not stationary and has a significant seasonal or cyclical component based on the cyclical and steadily declining trends in both the ACF and PACF.

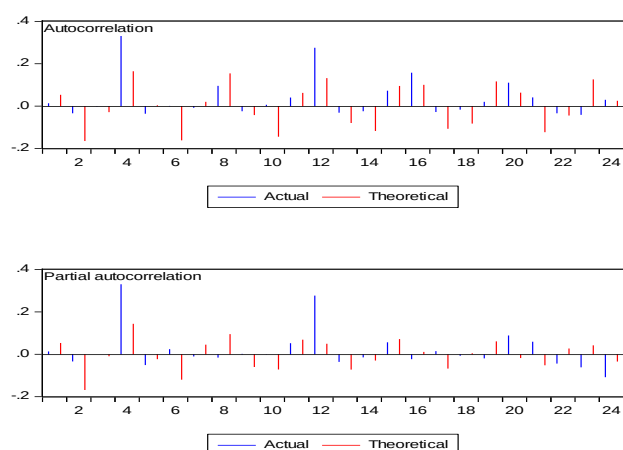


Fig. 4: Autocorrelation and partial autocorrelation between 2000 and 2024 in quarterly real GDP data.
Source: Author's calculation

4.3 Model Specification

The Schwarz Criterion (SC) and the Akaike Information Criterion (AIC) were used to determine the best model, with the specification with the lowest values of these criteria being preferred.

Table 3. Performance Comparison of SARIMA Models based on AIC and SC

Model Specification	AIC	SC (BIC)
SARIMA (2,1,2)(0,0,1) ₄ (Top row)	4.293428	4.536935
SARIMA (1,1,1)(1,0,0) ₄	3.591219	3.811953
SARIMA (1,1,1)(1,0,1) ₄	3.346198	3.594524
SARIMA (2,1,2)(0,0,1) ₄ (Bottom row)	3.289818	3.428542

Source: AIC and SC values are derived from the author's model estimations.

The best model was the SARIMA (2,1,2)(0,0,1)₄ (bottom row), which received the lowest AIC (3.2898) and BIC (3.4285) values. This particular configuration is the most dependable specification for forecasting and additional analysis because it provides the optimum balance between model complexity and goodness of fit.

4.3.1 Model Estimation Results

Table 3 illustrates the outcomes of a GARCH (1,1) type model along with a SARIMA (2,1,2) model, which is used to examine time series data that shows volatility clustering. Volatility clustering is when periods of high volatility are followed by periods of high volatility, and periods of low volatility are followed by periods of low volatility.

Table 4. Estimation Results: Mean and Variance Equations

Variable	Coef.	S.E	z-Stat	P.value
C	0.009096	0.000223	40.82975	0.0000
AR(1)	0.086382	1.39E-12	6.21E+10	0.0000
AR(2)	-0.533331	0.000759	-702.9013	0.0000
MA(1)	-0.022997	0.005662	-4.061763	0.0000
MA(2)	0.492640	0.003506	140.4940	0.0000
SMA(4)	0.220689	0.021367	10.32828	0.0000

Variable	Coef.	Std. Error	z-Statistic	Prob.
C(7)	-2.67283	0.015	-178.189	0.00
C(8)	-1.02438	0.145	-7.06469	0.00
C(9)	0.41068	0.048	8.55583	0.00
C(10)	0.59306	0.015	39.5373	0.00

Source: Author's model estimation using quarterly Log real GDP data

Particularly, the variance equation and the mean equation (Table 4) are distinct models that are calculated in Eviews results. The following are the derived equations and their implications.

4.3.2 Mean Equation SARIMA (2,1,2)

The mean equation describes how the average value of the dependent variable d(Log Real GDP) using a combination of autoregressive (AR) and moving average (MA) terms is modeled over time, written as follows:

$$Y_t = C + C_1 Y_{t-1} + C_2 Y_{t-2} + C_3 \varepsilon_{t-1} + C_4 \varepsilon_{t-2} + C_5 \varepsilon_{t-4} + \varepsilon_t \quad (8)$$

Y_t is the dependent variable, $d(\text{Log Real GDP})$, and ε_t the error term. Using the table's coefficient values as input, we get:

$$Y_t = 0.009 + 0.086Y_{t-1} + -0.533Y_{t-2} - 0.0237\varepsilon_{t-1} + 0.492\varepsilon_{t-2} + 0.220\varepsilon_{t-4} + e_t \quad (9)$$

According to the positive and significant constant, the average real GDP growth is approximately 0.90%. The growth from the prior era is positively persistent, as indicated by the positive AR(1) coefficient (0.086). A mean-reverting, oscillating pattern is suggested by the negative AR(2) coefficient (-0.533), where a high growth rate two times prior tends to be followed by a lower growth rate in the present period, and vice versa. Both are highly statistically significant. MA(1), MA(2), and SMA(4) show that shocks to the series affect future values. The MA(1) coefficient is negative and significant (-0.0229), while the MA(2) (0.492640) and SMA(4) (0.220689) coefficients are positive and significant. This implies that past unexpected shocks from one, two, and four periods earlier all have a significant impact on the current value of real GDP growth. The model does not include MA(3) since its coefficients are not statistically significant. According to the model, the time series has a substantial autoregressive component, a significant moving average component, and is stationary. All of these correlations are statistically significant, according to the p-values.

4.3.3 GARCH Estimates (Variance Equation)

Equation (10) is a form of a GARCH model, specifically an asymmetric GARCH model, often used in time series data to model the volatility of the data. It shows how the logarithm of the conditional

variance $\log(\sigma_t^2)$ at time t is determined by the past information, written as follows:

$$\log(\sigma_t^2) = C_7 + C_8 \left(\frac{|\text{ARCH}_{t-1}|}{\text{GARCH}_{t-1}} \right) + C_9 \left(\frac{\text{ARCH}_{t-1}}{\text{GARCH}_{t-1}} \right) + C_{10} \text{Log}(\text{GARCH}_{t-1}^2) \text{Log}(\text{GARCH}_{t-1}) \quad (10)$$

The ARCH_{t-1} term corresponds to the residual from the previous period (ε_{t-1}), and GARCH_{t-1} corresponds to the variance from the previous

period, σ_{t-1} and GARCH_{t-1}^2 corresponds to the variance from the previous period to the second

power, (σ_{t-1}^2) and $C(5)$ is the constant term in the variance equation. Summing up the variance equation will take the form:

$$\ln(\sigma_t^2) = C_7 + C_8 \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + C_9 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + C_{10} \ln(\sigma_{t-1}^2) \ln(\sigma_t^2) \quad (11)$$

Applying the output's coefficients, we obtain:

$$\ln(\sigma_t^2) = -2.67 - 1.02 \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + 0.41 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + 0.59 \ln(\sigma_{t-1}^2) \quad (12)$$

The constant Term (-2.67) represents the base level of volatility for the series. A negative value suggests that, without the influence of past shocks or volatility, the logarithm of the conditional variance would be negative, which is not an issue since it's a log-transform and the actual variance will be positive. The coefficient (-1.02) is associated

with the term $\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}}$, which measures the magnitude of the standardized shock from the previous period. A significant coefficient indicates that larger shocks, regardless of whether they are positive or negative, have a significant impact on future volatility. The negative sign is a structural property of the EGARCH model. The magnitude of this coefficient, 1.02, suggests a strong response of volatility to the size of a shock.

The coefficient (0.41) is the asymmetric effect of shocks. This is the coefficient for the term $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$, which captures the asymmetric effect of shocks. Future volatility is affected differently by positive and negative shocks of the same magnitude, according to a substantial value for this coefficient. Positive shocks tend to raise volatility more than negative shocks, according to a positive coefficient of 0.41. The positive sign here is an interesting finding, as the leverage effect is more common in time series data, and a 0.59 (Volatility Clustering) is

associated with the term $\ln(\sigma_{t-1}^2)$, which is the logarithm of the previous period's conditional variance. Times of high volatility are typically

followed by more high volatility, while times of low volatility are typically followed by low volatility, according to a positive and significant value of 0.59. The coefficient's value (0.59) also suggests that past volatility has a strong, persistent effect on current volatility.

4.3.4 Tests for Model Fit and Stability

Table 5 provides key statistics to evaluate the overall model fit. R-squared (0.099243) and Adjusted R-squared (0.047475), are very low, suggesting that the model for the mean d(Log Real GDP) explains only a small fraction of the series' variance.

Table 5. Model Fit Statistics

R-squared	0.099243
Adjusted R-squared	0.047475
S.D. dependent var	0.022052
Durbin-Watson stat	2.022

Source: Author's model estimation

This is typical for financial and economic time series and is not a major concern for a volatility model. Other diagnostic procedures ought to be considered as well. There is no discernible serial correlation in the residuals, as indicated by the Durbin-Watson statistic of 2.022. This implies that the linear dependence structure of the series is sufficiently captured by the model.

Inverted AR Roots and Inverted MA Roots are developed to improve the model's stability even more. All of a model's inverted roots must fall inside the unit circle in order for it to be stationary and invertible, which means that their modulus must be smaller than 1.

The Inverted AR Roots: The roots are 0.48

$\pm 0.73i$. Their modulus equals

$\sqrt{0.48^2 + 0.73^2} \approx 0.87$. This value is lower than 1, implying that the AR part of our model is stationary.

Inverted MA Roots: The roots are 0.01 $\pm 0.70i$ and

0.48 $\pm 0.48i$. For the first pair, the modulus is

$\sqrt{0.01^2 + 0.70^2} \approx 0.7$. This root is inside the unit circle, considering that this value is lower than 1.

For the second pair, the modulus is $\sqrt{0.48^2 + 0.48^2}$

≈ 0.68 . This root is likewise inside the unit circle since $0.68 < 1$. The fact that every inverted root

appears within the unit circle verifies the stability, stationarity, and invertibility of the estimated model.

4.4 Diagnostic Test of the Model

As emphasized earlier in this paper, to verify that all assumptions are satisfied and the model is sufficient, testing a combined SARIMA (2,1,2) (0,0,1)₄ and EGARCH (1,1) model entails examining both the mean and variance components of the model. To do this, we do a few diagnostic tests as proposed by [11], [31], [38], to determine whether the model has produced accurate and perceptive findings. The results are presented in the Appendix (Figure A1, Figure A2, Figure A3 in Appendix).

These diagnostic tests' findings show that the model offers a suitable specification for capturing Albania's real GDP dynamics and facilitates the creation of trustworthy and statistically sound projections.

4.5 Projections and Expectations for the Future (After 2024)

The growth rate's predicted trajectory (beyond 2024) indicates ongoing, moderately positive oscillations, indicating that analysts anticipate Albania's economy to continue expanding, albeit perhaps without periods of persistent high growth. For long-term development plans, investment choices, and government budgetary planning, this projection is essential.

5 Conclusions and Recommendations

This paper aimed to model quarterly real GDP Data in Albania from January 1, 2000, to December 31, 2024. The results of this paper show that the ARMA (2,1,3)- EGARCH (1,1) model is the best model for the period of the in-sample part and out-of-sample sections. This model provides a comprehensive economic interpretation. Figure 5 provides a graphic representation of Albania's economic cycle and illustrates the implications for the country's economy. Periods of economic expansion (growing GDP) are represented by peaks above the zero line, which suggest higher production, possibly more jobs, and higher consumer spending. Troughs below the zero-line signal economic contraction, or lowering GDP, which also increases the likelihood of job losses and lower corporate investment. Significant economic downturns are represented by the sharp negative spikes (e.g., 2009, 2014–15, 2020), which could result in technical recessions.

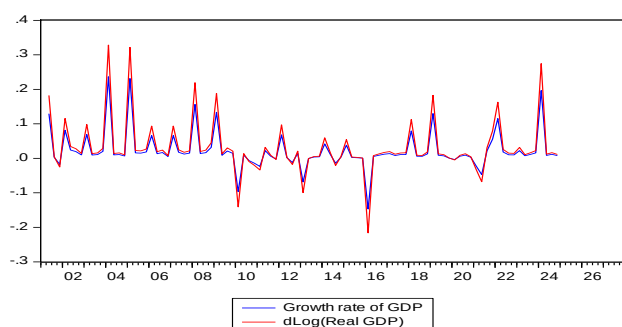


Fig. 5: Albania's GDP growth rate and dLog (real GDP) data from 2001 to 2024

Source: Author's evaluation

The ensuing positive spikes show times when the economy is recovering or making a significant comeback. The graph makes it abundantly evident that Albania's GDP growth rate is erratic rather than steady. This volatility suggests that the economy's performance is prone to regular and occasionally large fluctuations. Further studies [39], [40] support this conclusion as well. Businesses and politicians may find it difficult to plan economically when there is a lot of volatility. When the lines are flatter and nearer zero, the economy may be growing or stagnating more steadily, albeit perhaps more slowly.

Global Financial Crisis (2008-2009): Trade, remittances, and foreign investment were all impacted by the severe global economic downturn, as evidenced by the notable decline during this time [41], [42] and [43].

COVID-19 Pandemic (2020): The economic impact of the pandemic is evident in the deepest and most recent low in 2020, which was caused by significant supply chain disruptions and shutdowns. Once constraints are loosened, the subsequent sharp rebound likewise demonstrates a comparatively rapid recovery, typical following an abrupt, external shock.

2014-2015 Downturn: This significant period of negative growth warrants closer economic investigation. A regional crisis, structural problems, specific domestic policy blunders, or a persistent decline in important export prices or remittances that disproportionately impacted the Albanian economy could be the cause, [44]. After every major shock, growth rates return to positive territory, demonstrating the economy's ability to rebound even in the face of severe downturns. Even if the Albanian economy is vulnerable to foreign threats, this suggests that it is quite resilient.

Implications for Monetary and Fiscal Policy: Variations in GDP growth give economic policymakers important cues. In order to boost demand and aid in recovery during times of low or

negative growth (recessions), expansionary monetary (e.g., interest rate decreases, quantitative easing) or fiscal (e.g., increased government spending, tax cuts) measures are usually required. On the other hand, during times of extremely rapid, possibly overheated growth, policymakers may think about taking contractionary measures to stop inflation. Thus, the graph functions as a crucial indicator that directs macroeconomic management.

In conclusion, the graph is an essential tool for comprehending the dynamics and health of the Albanian economy, highlighting its cyclical character, shock sensitivity, recovery potential, and possibilities and difficulties for economic policy.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

The authors wrote, reviewed and edited the content as needed and they have not utilised artificial intelligence (AI) tools. The authors take full responsibility for the content of the publication.

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APPENDIX

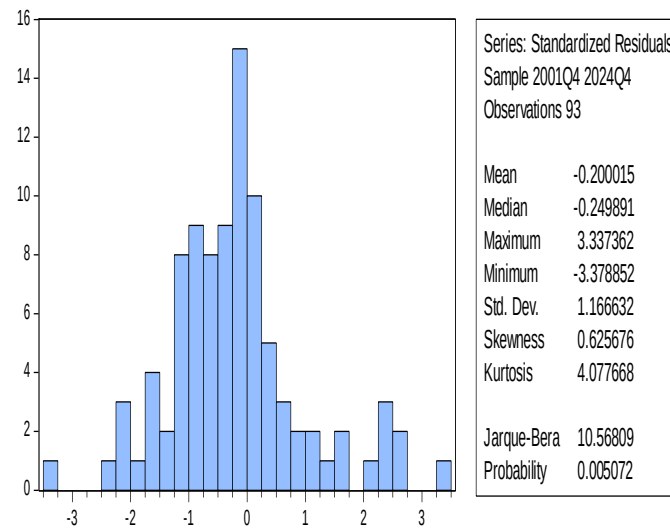


Fig. A1: Normality test using quarterly $\Delta \log$ real GDP data

Source: Author's residual diagnostics

Heteroskedasticity Test: ARCH

F-statistic	2.159635	Prob. F(2,88)	0.1214
Obs*R-squared	4.257547	Prob. Chi-Square(2)	0.1190

Test Equation:

Dependent Variable: WGT_RESID^2

Method: Least Squares

Date: 09/22/25 Time: 14:55

Sample (adjusted): 2002Q2 2024Q4

Included observations: 91 after adjustments

Variable	Coefficient	t	Std. Error	t-Statistic	Prob.
C	1.348484	0.304522	4.428192	0.0000	
WGT_RESID^2(-1)	0.186595	0.105605	1.766907	0.0807	
WGT_RESID^2(-2)	-0.144208	0.105648	-1.364984	0.1757	
R-squared	0.046786	Mean dependent var	1.408227		
Adjusted R-squared	0.025122	S.D. dependent var	2.270682		
S.E. of regression	2.241978	Akaike info criterion	4.485006		
Sum squared resid	442.3291	Schwarz criterion	4.567781		
Log likelihood	-201.0678	Hannan-Quinn criter.	4.518401		
F-statistic	2.159635	Durbin-Watson stat	1.976348		
Prob(F-statistic)	0.121443				

Fig. A2: ARCH Heteroskedasticity test using quarterly $\Delta \log$ real GDP data

Source: Author's residual diagnostics

Date: 09/22/25 Time: 15:11
Sample: 2001Q1 2027Q4
Included observations: 93
Q-statistic probabilities adjusted for 5 ARMA terms

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob*
. .	. .	1 -0.026	-0.026	0.0674	
. .	. .	2 0.017	0.016	0.0948	
.* .	.* .	3 -0.105	-0.105	1.1861	
. .	. .	4 0.043	0.038	1.3676	
.* .	.* .	5 -0.105	-0.101	2.4692	
. .	. .	6 0.031	0.015	2.5663	0.109
. .	. .	7 0.051	0.063	2.8342	0.242
. *	. .	8 0.076	0.056	3.4336	0.329
. .	. .	9 -0.044	-0.031	3.6401	0.457
. .	. .	10 0.033	0.031	3.7581	0.585
. .	. .	11 -0.059	-0.046	4.1354	0.658
. **	. **	12 0.259	0.264	11.440	0.121
. .	. .	13 -0.004	0.024	11.442	0.178
. .	. .	14 0.013	-0.016	11.461	0.245
. .	. .	15 -0.008	0.049	11.468	0.322
. *	. *	16 0.113	0.097	12.945	0.297
. .	. .	17 -0.050	0.007	13.235	0.352
. .	. * .	18 -0.058	-0.066	13.633	0.400
. .	. * .	19 -0.048	-0.070	13.910	0.456
. *	. *	20 0.182	0.163	17.939	0.266
. .	. *	21 0.034	0.076	18.082	0.319
. * .	. * .	22 -0.088	-0.152	19.047	0.326
. * .	. * .	23 -0.074	-0.068	19.733	0.348
. .	. * .	24 -0.032	-0.116	19.861	0.403
. * .	. * .	25 -0.099	-0.083	21.141	0.389
. .	. .	26 0.034	0.047	21.296	0.441
. .	. .	27 0.032	-0.043	21.436	0.494
. .	. .	28 0.073	-0.037	22.166	0.510
. * .	. * .	29 -0.106	-0.095	23.716	0.478
. * .	. * .	30 -0.073	-0.073	24.466	0.493
. .	. .	31 -0.015	0.061	24.500	0.547
. .	. * .	32 -0.059	-0.173	24.999	0.574
. .	. .	33 0.052	0.001	25.404	0.606
. * .	. .	34 -0.086	-0.026	26.505	0.598
. * .	. * .	35 -0.136	-0.175	29.314	0.501
. .	. .	36 -0.013	0.004	29.339	0.552

*Probabilities may not be valid for this equation specification.

Fig. A3: Ljung-Box test using quarterly $\Delta \log$ real GDP data.

Source: Author's residual diagnostics

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed to the present research, at all stages from the formulation of the problem to the final findings and solution.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

No funding was received for conducting this study.

Conflict of Interest

The authors have no conflicts of interest to declare.

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