Al-imad Journal of Humanities and Applied Sciences (AJHAS)
مجلة العماد للعلوم الإنسانية والتطبيقية

ISSN: 3106-0323
Volume 2 – Issue 1 – 2026
Pages 467-489

Forecasting the Future: Economic Projections and Strategic Decision-Making in Libya

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التنبؤ بالمستقبل: التوقعات الاقتصادية وصنع القرار الاستراتيجي في ليبيا

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Received: 01-02-2026; Accepted: 13-03-2026; Published: 29-03-2026

Abstract:
This study analyzes Libya's economic growth and inflation rates from 2000 to 2024 and develops forecasts for 2024–2032 using time-series econometric models. The Box–Jenkins methodology was applied, employing ARMA (4,1) for economic growth and ARIMA (2,1,1) for inflation, following stationarity confirmation via unit root tests. Model selection was based on the Akaike Information Criterion (AIC), adjusted R^2, and parameter significance, while diagnostic tests ensured residuals were stationary, normally distributed, homoscedastic, and free from autocorrelation. The Theil inequality test further validated the predictive accuracy of the models. Forecast results indicate moderate fluctuations in economic growth, with alternating periods of slight contraction and modest recovery, while inflation is projected to rise steadily, reaching approximately 7.8% by 2032. These findings highlight the effectiveness of ARMA and ARIMA models in capturing Libya's macroeconomic dynamics and demonstrate their utility as evidence-based tools for strategic economic planning in contexts characterized by volatility and uncertainty.

Keywords: Libya, Economic Growth, Inflation, ARIMA, Time-Series Forecasting.

الملخص
تحلل هذه الدراسة معدلات النمو الاقتصادي والتضخم في ليبيا للفترة من 2000 إلى 2024، وتعمل على تطوير تنبؤات للفترة 2024-2032 باستخدام نماذج السلاسل الزمنية القياسية. تم تطبيق منهجية "بوكس-جينكينز" عبر استخدام نموذج *ARMA* (4,1) للنمو الاقتصادي ونموذج *ARIMA* (2,1,1) للتضخم، وذلك بعد التأكد من استقرار السلاسل عبر اختبارات جذر الوحدة. اعتمد اختيار النماذج على معيار "أكايكي" للمعلومات (*AIC*)، ومعامل التحديد المعدل R^2، ومعنوية المعلمات، بينما ضمنت الاختبارات التشخيصية أن البواقي كانت مستقرة، وتتبع التوزيع الطبيعي، وتتمتع بتجانس التباين وخالية من الارتباط الذاتي. كما أكد اختبار "ثيل" لعدم المساواة دقة التنبؤ للنماذج المستخدمة. تشير نتائج التنبؤ إلى تقلبات متوسطة في النمو الاقتصادي مع فترات متبادلة من الانكماش الطفيف والتعافي المتواضع، بينما يتوقع أن يرتفع التضخم بشكل مطرد ليصل إلى حوالي 7.8% بحلول عام 2032. تسلط هذه النتائج الضوء على فعالية نماذج *ARMA* و*ARIMA* في استيعاب الديناميكيات الاقتصادية الكلية في ليبيا، وتبرز فائدتها كأدوات قائمة على الأدلة للتخطيط الاقتصادي الاستراتيجي في السياقات التي تتسم بالتقلب وعدم اليقين.

الكلمات المفتاحية: ليبيا، النمو الاقتصادي، التضخم، *ARIMA*، التنبؤ بالسلاسل الزمنية.

1. Introduction:

Economic forecasting is considered one of the essential tools relied upon by policymakers in shaping public policies and planning long-term growth and development strategies, especially in economies characterized by volatility and instability (Armstrong, 2001). Through quantitative models and analytical techniques, economic forecasting provides a knowledge base that enables anticipation of future trends in key macroeconomic indicators such as GDP, inflation rates, and exchange rates. This, in turn, facilitates early responses to potential challenges and promotes efficient allocation of resources (Gujarati & Porter, 2009).

The importance of economic forecasting is closely tied to the formulation of national strategies. The absence of a forward-looking vision supported by data often leads to a reduced ability to adapt to shocks or capitalize on emerging opportunities (OECD, 2019). Economic literature has shown that the effectiveness of economic policy is largely dependent on the accuracy of forecasts and their ability to simulate future scenarios within reasonable margins of error (Makridakis et al., 1998).

In the Libyan context, the relevance of this subject becomes particularly evident due to the complex economic and political conditions the country is experiencing. These include fluctuations in macroeconomic indicators such as economic growth and the inflation rates, as well as structural weaknesses in the productive and institutional sectors (World Bank, 2023; CMI, 2022). Such circumstances make forecasting tools an indispensable necessity for formulating more adaptive and forward-looking economic strategies.

This study aims to develop a forecasting model based on the Autoregressive Integrated Moving Average (ARIMA) framework (Box & Jenkins, 1976) to analyze the time series of Libya's economic growth rate and inflation rates over the period from 2000 to 2024, and to generate quantitative forecasts extending to 2032.

The ARIMA model is one of the most widely used tools in economic forecasting due to its capacity to capture different time-series patterns, including trends, seasonality, and short-term fluctuations (Hyndman & Athanasopoulos, 2018).

Through this analysis, the paper seeks to demonstrate how forecasting outputs can be used to inform future strategies in the Libyan economy, particularly in light of the growing need for evidence-based economic planning and enhanced institutional capacity to adapt to both regional and global transformations.

2. Problem Statement:

Libya has faced deep-rooted structural economic challenges for years, compounded by persistent political and security tensions. These conditions have led to sharp fluctuations in key macroeconomic indicators, particularly in the inflation rates and economic growth rates. A core issue lies in the absence of reliable quantitative forecasting tools based on time-series data, which undermines the country's capacity to design effective, forward-looking development strategies (World Bank, 2023).

In the economic literature, quantitative forecasting, especially through time-series models such as ARIMA, is widely recognized as a robust method for anticipating the future trajectories of economic indicators (Box & Jenkins, 1976; Hyndman & Athanasopoulos, 2018). However, Libya's academic and research environments still lack empirical studies that apply such models to develop realistic future scenarios.

Accordingly, this study seeks to address the following core research problem:
To what extent can the ARIMA model produce accurate forecasts for Libya's economic growth rate and inflation rates, and how valid are these forecasts as a tool for guiding future economic strategies in a context marked by uncertainty?

3. Research Questions:

This study seeks to address the following research questions:

1. What are the historical time trends of Libya's economic growth rate and inflation rates during the period 2000–2024?
2. How effective is the ARIMA model in representing and estimating these time series?
3. What are the projected values of economic growth and the inflation rates through 2032 based on the model?
4. To what extent can these forecasts be utilized to support and shape future economic strategies in Libya?

4. Research Objectives:

This study aims to achieve the following objectives:

1. To analyze the historical time trends of Libya's economic growth rate and inflation rates from 2000 to 2024.
2. To assess the efficiency of the ARIMA model in modeling and estimating the selected macroeconomic time series.
3. To develop reliable forecasts for Libya's economic growth and inflation rates up to the year 2032 using the ARIMA model.
4. To explore the potential of applying these forecasts as inputs for evidence-based strategic economic planning in Libya's context of volatility and uncertainty.

5.Research Hypotheses:

Based on a study of Hyndman & Athanasopoulos (2018) and the quantitative nature of the study and the adoption of the ARIMA model, the main hypotheses are as follows:

H1: The ARIMA model can effectively capture the dynamic patterns of Libya's economic growth rate and inflation rates during the study period.

H2: Forecasts generated using the ARIMA model for the period 2025–2032 will demonstrate acceptable levels of accuracy and reliability for use in policy planning.

H3: Quantitative forecasts derived from time-series modeling can serve as a valuable tool for supporting the design of forward-looking economic strategies in Libya.

6.Significance of the Study:

The significance of this study lies in its provision of an applied quantitative model based on real-world time-series data within an economic environment marked by political and institutional instability. By focusing on economic growth and the inflation rates, the study helps address a research gap in the economic literature concerning fragile economies, where forecasting studies are often absent or narrowly scoped (Armstrong, 2001).

Furthermore, the findings of this study may serve as a valuable tool for policymakers by supporting the development of economic plans grounded in potential future scenarios. This, in turn, can strengthen strategic capacity to adapt to crises and market volatility.

7. Research Gap:

Despite the growing body of global literature emphasizing the importance of quantitative economic forecasting, particularly through time-series models such as ARIMA, there remains a notable absence of such applications within the Libyan economic context. While countries with volatile macroeconomic conditions have increasingly adopted these models to inform economic policy and mitigate uncertainty (Hyndman & Athanasopoulos, 2018; Makridakis et al., 1998), Libya continues to lack a systematic and data-driven forecasting framework grounded in empirical modeling.

Most existing economic research in Libya has either relied on descriptive or theoretical analyses, or has been limited in scope and timeframe. The few studies that have employed time-series models, such as the work by Al-Warflli (2021), have not extended their forecasts into the medium or long term, nor have they explicitly connected their findings to policy formulation or national strategic planning. Furthermore, these studies have tended to focus on single indicators (GDP), without considering the broader interaction between key macroeconomic variables such as inflation and economic growth.

Additionally, while international and regional studies have demonstrated the robustness of ARIMA models in capturing economic trends under conditions of uncertainty, including in fragile and transition economies (Bangladesh, Egypt, Algeria), there is currently no comprehensive forecasting study in Libya that integrates ARIMA methodology with strategic economic decision-making.

This gap highlights the need for an applied, evidence-based study that develops accurate, long-term forecasts for Libya's economic growth and inflation rates. Such a study would not only fill a significant void in the academic literature but also provide policymakers with essential tools to support economic planning in a highly uncertain environment. By bridging the divide between quantitative modeling and strategic policy development, this research aims to contribute both theoretically and practically to Libya’s economic transformation efforts.

8. Theoretical Framework:

Economic forecasting is a fundamental branch of quantitative economic analysis, employed to anticipate future trends in key macroeconomic variables such as Gross Domestic Product (GDP), unemployment rates, inflation, and exchange rates (Makridakis et al., 1998). This forecasting relies on mathematical and statistical assumptions based on historical data and is used to develop economic scenarios that aid decision-making at governmental and institutional levels (Armstrong, 2001).

The theoretical significance of economic forecasting arises from its foundation in the modern neoclassical school, which emphasizes how individuals and governments adapt to future expectations, particularly under the concept of rational expectations (Muth, 1961; Lucas, 1972). Research indicates that effective quantitative models enable policymakers to take proactive measures that mitigate the effects of economic shocks and promote sustainable economic growth (OECD, 2019).

Among empirical forecasting models, the Autoregressive Integrated Moving Average (ARIMA) model, developed by Box and Jenkins in the 1970s, is one of the most widely used for economic time series. The model is distinguished by its capability to handle long-term temporal trends and non-stationary data without requiring independent variables within the model structure (Box & Jenkins, 1976).

9. Literature Review:

In recent decades, there has been a notable increase in the use of quantitative models, particularly time-series models, for analyzing and forecasting economic indicators. Among these, the Autoregressive Integrated Moving Average (ARIMA) model stands out as a widely utilized tool due to its flexibility and ability to adapt to the characteristics of non-stationary time series data.

In a seminal study, Box and Jenkins (1976) demonstrated the effectiveness of the ARIMA model in analyzing the behavior of macroeconomic variables, highlighting its practical application for short- and medium-term forecasting when sufficient historical data are available. This was further supported by the work of Makridakis et al. (1998), who conducted extensive tests on the accuracy of forecasting models and concluded that ARIMA remains one of the most stable models, especially when the relationships between variables are unknown or non-linear.

Hyndman and Athanasopoulos (2018) also noted that the ARIMA model is well-suited for cases involving long time-series data, even when affected by seasonal fluctuations or external shocks, making it appropriate for studying economies experiencing instability.

Within the Arab context, Abdullah (2014) applied the ARIMA model to estimate unemployment rates in Egypt during the first decade of the millennium, finding that the model produced forecasts closely aligned with observed outcomes despite limitations in the statistical quality of the data. Similarly, in Algeria, Aziz Ben Masoud (2017) employed the same model to forecast the Algerian dinar’s exchange rate against the U.S. dollar, concluding that ARIMA outperformed alternative models like Vector Autoregression (VAR) in terms of accuracy.

Internationally, Hossain (2014) applied the ARIMA model to Bangladesh’s GDP data and successfully built an accurate forecasting model despite the country’s sharp political and economic changes. Singh et al. (2021) used ARIMA to analyze inflation data in India, demonstrating its ability to capture seasonal effects amid complex economic structures.

Some researchers have compared ARIMA’s performance with hybrid models, such as ARIMA combined with Artificial Neural Networks (ARIMA-ANN) or Generalized Autoregressive Conditional Heteroskedasticity models (ARIMA-GARCH), especially for exchange rate forecasting. For example, Kim and Kim (2019) found that integrating ARIMA with other models sometimes improves forecasting performance, though ARIMA remains the fundamental quantitative tool for time-series analysis.

Regarding Libya, empirical studies employing the ARIMA model for forecasting remain limited, with most existing research taking a descriptive or general analytical approach. One exception is a study by Abdel Moneim Al-Warfali (2021), which focused on GDP forecasting using time-series models but did not extend into long-term forecasts or link findings explicitly to national economic strategies.

In Libya, Abdullah (2025) analyzed the behavior of the time series of the real GDP variable in Libya using the Box-Jenkins methodology, based on annual data for the period from 1980 to 2023. He also forecasted future values for the period (2024–2030). The forecasting results for the real GDP variable in Libya during the period (2024–2030) indicated that the estimated GDP values were very close to the actual values. Moreover, the expected values of the variable during the forecast period showed an increasing trend with some fluctuations between the beginning and the end of the period, suggesting that developments in Libya’s GDP are largely linked to external factors related to global markets.

Therefore, this study aims to fill a knowledge gap in the economic literature on Libya by presenting an applied ARIMA model focused on two key variables: economic growth and the real effective exchange rate. Moreover, it seeks to connect the quantitative outputs with strategic economic planning for the country.

10.Methodology:

10.1. Type and Design of the Study:

This study is classified as a quantitative descriptive and analytical research. It relies on analyzing Libya’s economic time-series data from 2000 to 2024 with the objective of constructing a forecasting model using time series analysis. The focus is on predicting two key variables: economic growth and the inflation rate, extending forecasts through 2032. The time series design was chosen due to its proven ability to uncover temporal patterns, volatility, and to analyze future trends (Box & Jenkins, 1976).

10.2 Data Sources:

Historical data for the economic growth rate (GDP growth rate) and the inflation rate were collected from reliable sources, The World Bank.

10.3.Data Analysis Steps and Use of the ARIMA Model:

10.3.1. Exploratory Data Analysis (EDA):

Time series plots for the two variables (economic growth and inflation rate) will be created to identify any evident trends, seasonality, or volatility.

10.3.2. Stationarity Testing:

- Stationarity is a fundamental requirement for applying the ARIMA model; therefore, the Augmented Dickey-Fuller (ADF) test will be conducted to detect the presence of a unit root in the time series data.
- If non-stationarity was identified, differencing techniques will be applied to transform the series into a stationary form (Box & Jenkins, 1976; Hyndman & Athanasopoulos, 2018).

10.3.3. Model Identification:

- The orders of the autoregressive (p), differencing (d), and moving average (q) components will be determined using plots of the autocorrelation function (ACF) and partial autocorrelation function (PACF).
- Several ARIMA models will be tested, and the best-fitting model will be selected based on criteria such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) (Makridakis et al., 1998).

10.3.4. Estimation of ARIMA (p, d, q) Model Parameters:

The estimation of parameters in an ARIMA (p, d, q) model is typically performed using statistical techniques such as Maximum Likelihood Estimation (MLE) or the Least Squares Method. These methods aim to obtain the most accurate parameter values that best fit the observed time series data.

10.4. General Mathematical Form of the ARIMA Model:

10.4.1. Autoregressive Models AR(p):

In autoregressive models, the current value of the time series is explained as a linear function of its own past values up to a specified lag (p). The general form of the AR(p) model is given by:

$$X_t = \theta_0 + \theta_1 Xt_{-1} + \theta_2 Xt_{-2} + \cdots + \theta_p Xt_{-p} + \varepsilon_t \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where:

- Xt: the value of the time series at time t
- θ_0 to θ_p: the model parameters
- Xt_{-1} to Xt_{-p}: lagged values of the time series
- ε_t: the random error term at time t

A key feature of the AR(p) model is that its autocorrelation function (ACF) declines gradually, often exponentially, as the number of lags increases, while the partial autocorrelation function (PACF) typically cuts off sharply after lag p. This behavior is crucial for identifying the appropriate order of the autoregressive component.

10.4.2. Moving Average Models MA(q):

In moving average models, the current value of the series depends on a linear combination of past forecast errors. Specifically, the model captures the influence of random shocks from the present and previous time periods. The general form is:

$$X_t = \theta_0 + \theta_1 \varepsilon t_{-1} + \theta_2 \varepsilon t_{-2} + \cdots + \theta q \varepsilon t_{-}q \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Where:

- Xt: the value of the time series at time t
- θ_0 to θq: the model parameters
- $\varepsilon_t t_{-1}$ to $\varepsilon_t t_{-}q$: past values of the random error term

This model is characterized by a rapidly declining PACF and a distinct cutoff in the ACF after lag q, aiding in the identification of the moving average order.

10.4.3. Mixed Models ARMA (p, q):

ARMA models combine both autoregressive and moving average components. This allows the model to capture a wider range of patterns in time series data. The general form of the ARMA (p, q) model is:

$$X_t = \theta_0 + \theta_1 Xt_{-1} + \cdots + \theta_p Xt_{-p} + \varepsilon_t + \varphi_1 \varepsilon t_{-1} + \cdots + \varphi\_q \varepsilon t_{-q} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Where the model incorporates both:

- Autoregressive terms (Xt_{-1} to Xt_{-p})
- Moving average terms (εt_{-1} to εt_{-q})
- θ and φ represent model coefficients
- ε_t is the current error term

This hybrid structure allows ARMA models to flexibly account for autocorrelations and stochastic fluctuations in time series data.

10.5 Model Diagnostics:

Diagnostic tests such as the Ljung-Box test will be conducted to verify the independence of the residuals.

The distribution of the residuals will be also analyzed to assess their conformity to a normal distribution.

10.6.Forecasting:

Once the model has been identified, its parameters estimated, and it has been validated and tested, it can be employed to forecast future values of the time series. The aim is to understand the pattern and behavior of the series by relying on the current and past values of the dependent variable (X_t), as well as the residuals (ε_t), which are treated as estimates of the random error term.

The first forecasted value (X_{t+1}) is obtained using these observed values, a process known as one-step-ahead forecasting. To predict the next future value (X_{t+2}), the previously forecasted value (X_{t+1}) is substituted into the prediction equation, assuming that the out-of-sample error term is zero. This recursive process continues until the desired forecasting horizon is reached (Cleveland and Devlin, 1980).

10.6.1. Applied Aspect of the Study:

Most economic time series exhibit non-stationarity due to structural changes, policy shifts, and evolving market conditions over time. This lack of stationarity can lead to spurious regression results if not addressed properly (Granger & Newbold, 1974). Therefore, it is essential to test the stationarity of the time series before proceeding with econometric modeling. A key step in this process involves determining the presence of a unit root, which indicates whether the series is stationary at level (integrated of order zero, I(0)) or becomes stationary only after differencing (first or second difference, implying I(1) or I(2)).

To formally assess this, the following hypotheses are typically tested:

- Null Hypothesis (H_0): The time series contains a unit root (it is non-stationary).
- Alternative Hypothesis (H_1): The time series does not contain a unit root (it is stationary).

In this study, we adopt one of the most widely used methods for unit root testing: the Augmented Dickey-Fuller (ADF) test, which allows for the detection of unit roots while accounting for possible autocorrelation in the error terms (Dickey & Fuller, 1979; Said & Dickey, 1984). The results of this test will guide the appropriate transformations of the data before estimating the production function or productivity models.

10.6.2. Assessment of Time Series Stationarity:

This study conducted unit root tests to examine the stationarity of two key macroeconomic time series: the real economic growth rate and the inflation rate. The Augmented Dickey-Fuller (ADF) test was employed to determine the order of integration for each series, which is a necessary step to ensure the validity of econometric modeling and to avoid spurious regression results.

10.6.2.1.Economic Growth Rate:

The results of the ADF test indicate that the real economic growth rate series is stationary at level. The null hypothesis of a unit root was rejected at the 5% significance level, suggesting that the series does not exhibit a stochastic trend and is integrated of order zero, I(0). Therefore, it can be used in its original form in further econometric analysis without the need for differencing.

Table (1): results of ADF Test for Economic Growth

Null Hypothesis: GDPG has a unit root				
Exogenous: Constant, Linear Trend				
Lag Length: 3 (Automatic - based on SIC, maxlag=5)				
			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			-5.058920	0.0030
Test critical values:	1% level		-4.467895	
	5% level		-3.644963	
	10% level		-3.261452	

Source: Based on the results of the Augmented Dickey-Fuller (ADF) Test.

10.6.2.2.Inflation Rate:

In contrast, the inflation rate series was found to be non-stationary at level. The ADF test failed to reject the null hypothesis of a unit root, indicating the presence of a stochastic trend. However, after applying the first difference to the series, stationarity was achieved, and the null hypothesis was rejected at the 5% significance level. This implies that the inflation series is integrated of order one, I(1), and must be differenced once before it can be included in any regression model to ensure statistical validity. Table (1) provides the results of the test. Table (2) shows the results of the test.

Table (2): results of ADF Test for Inflation Rates

Null Hypothesis: INF has a unit root				
Exogenous: Constant, Linear Trend				
Lag Length: 1 (Automatic - based on SIC, maxlag=5)				
			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			-3.241743	0.1012
Test critical values:	1% level		-4.416345	
	5% level		-3.622033	
	10% level		-3.248592	
Null Hypothesis: D(INF) has a unit root				
Exogenous: Constant, Linear Trend				

Lag Length: 1 (Automatic - based on SIC, maxlag=5)				
			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			-4.867577	0.0041
Test critical values:	1% level		-4.440739	
	5% level		-3.632896	
	10% level		-3.254671	

Source: Based on the results of the Augmented Dickey-Fuller (ADF) Test.

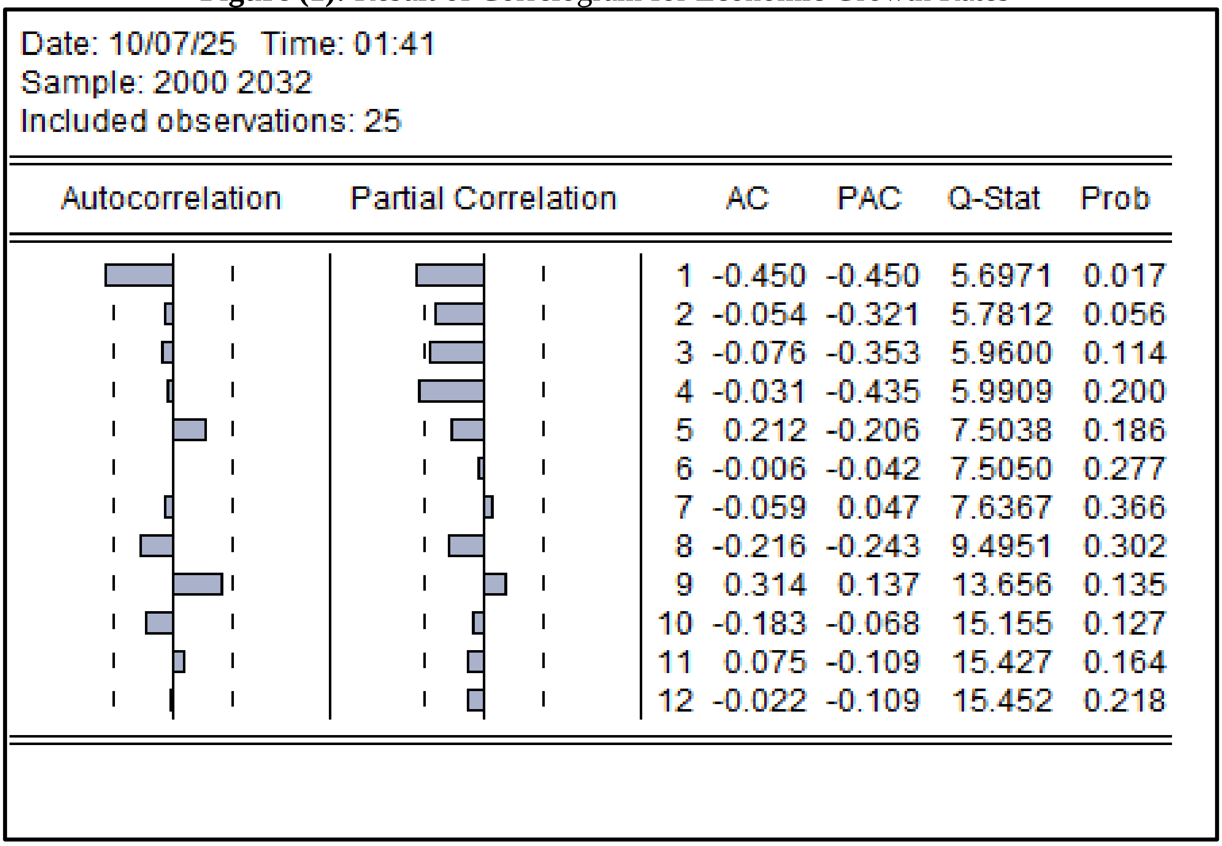
These results underscore the differing statistical properties of the two variables, highlighting the need to appropriately transform each series before incorporating them into a joint econometric framework. After confirming the stationarity of the time series, the analysis can now proceed to the Box–Jenkins methodology for time series modeling.

10.6.3.Model Specification:

Based on the order of integration and the stationarity properties of the time series, as indicated by the results of unit root tests, the appropriate model for estimating economic growth rates is the ARMA (p, q) model, since the series is stationary at level. In contrast, the inflation rate, which became stationary only after first differencing, is best modeled using an ARIMA (p, d, q) specification.

The specific lag orders of both models are determined through the analysis of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). Figures (1) and (2) illustrate the components of the autoregressive (AR) and moving average (MA) terms in each model respectively, providing a visual guide for identifying suitable lag structures.

Figure (1): Result of Correlogram for Economic Growth Rates



Date: 10/07/25 Time: 01:41
Sample: 2000 2032
Included observations: 25

	AC	PAC	Q-Stat	Prob
1	-0.450	-0.450	5.6971	0.017
2	-0.054	-0.321	5.7812	0.056
3	-0.076	-0.353	5.9600	0.114
4	-0.031	-0.435	5.9909	0.200
5	0.212	-0.206	7.5038	0.186
6	-0.006	-0.042	7.5050	0.277
7	-0.059	0.047	7.6367	0.366
8	-0.216	-0.243	9.4951	0.302
9	0.314	0.137	13.656	0.135
10	-0.183	-0.068	15.155	0.127
11	0.075	-0.109	15.427	0.164
12	-0.022	-0.109	15.452	0.218

Source: Based on the results of Correlogram Test.

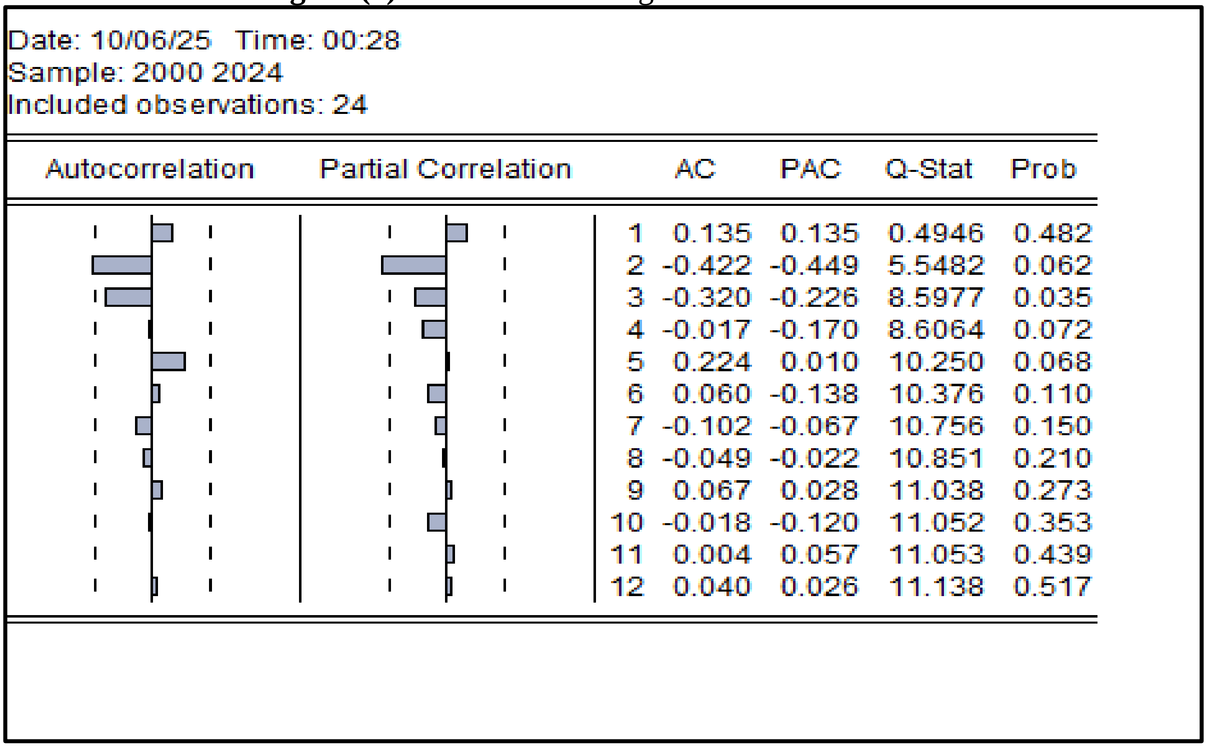
Regarding Figure (1), which presents the correlogram results of the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) for the time series of economic growth rates, the findings suggest that the appropriate orders for the ARMA model are as follows:

- The autoregressive (AR) component appears significant at lags p = 1 and p = 4,
- While the moving average (MA) component shows significance at lag q = 1.

These results indicate that the ARMA(1,1), ARMA(4,1), or potentially a mixed specification such as ARMA(1,4,1), may be suitable for modeling the dynamics of economic growth, subject to further diagnostic testing.

Figure (2) shows the correlogram for the inflation rate series reveals statistically significant autocorrelation up to lag three, with negative correlations observed at some of the initial lags. This pattern indicates the necessity of incorporating autoregressive (AR) and/or moving average (MA) components within an ARIMA model to adequately capture the dynamic structure of the series. Based on these findings, initial model specifications such as ARIMA(1,1,1) or ARIMA(2,1,1) are recommended, with subsequent diagnostic checks performed after estimation to validate the model fit.

Figure (2): Result of Correlogram for Inflation Rates



Date: 10/06/25 Time: 00:28
Sample: 2000 2024
Included observations: 24

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.135	0.135	0.4946	0.482
		2	-0.422	-0.449	5.5482	0.062
		3	-0.320	-0.226	8.5977	0.035
		4	-0.017	-0.170	8.6064	0.072
		5	0.224	0.010	10.250	0.068
		6	0.060	-0.138	10.376	0.110
		7	-0.102	-0.067	10.756	0.150
		8	-0.049	-0.022	10.851	0.210
		9	0.067	0.028	11.038	0.273
		10	-0.018	-0.120	11.052	0.353
		11	0.004	0.057	11.053	0.439
		12	0.040	0.026	11.138	0.517

Source: Based on the results of Correlogram Test.

10.6.4.Optimal Model Selection Stage:

Following the identification of candidate ARMA and ARIMA models, the next step involves estimating and comparing these models to determine the most suitable one for forecasting. This selection is based on several key criteria, including: a higher number of statistically significant estimated parameters, the highest value of the adjusted coefficient of determination (Adjusted R^2), the lowest values for the Akaike Information Criterion (AIC), and the smallest variance estimate ($Sigma^2$). Estimation was carried out using the Ordinary Least Squares (OLS) method. Based on the evaluation results, the optimal models identified were ARMA(4,1) and ARIMA(2,1,1). Other candidate models were excluded as they did not satisfy the conditions required for optimal model performance. Table (3) presents a summary of the comparative results.

Table (3): Results of ARMA and ARIMA Models

Models	**Results of ARMA Models**		
ARMA	(1,1)	**(4,1)**	(1,4,1)
sig	0	**1**	0
SIGMASQ	400.8866	**397.5956**	397.5406
Adj-R2	0.236288	**0.242557**	0.206598
AIC	9.092353	**9.085293**	9.164960
Models	**Results of ARIMA Models**		
ARIMA	(1,1,1)	**(2,1,1)**	
sig	0	**2**	
SIGMASQ	43.29991	**36.97893**	
Adj-R2	0.080712	**0.175657**	
AIC	6.925176	**6.809992**	

Source: Prepared by the researcher

10.6.5.Model Estimation:

After estimating the two models using the Ordinary Least Squares (OLS) method, the corresponding regression equations were obtained. By comparing the results and evaluating the models based on the lowest values of the Akaike Information Criterion (AIC), the ARMA(4,1) and ARIMA(2,1,1) models emerged as the most suitable. These models demonstrate strong predictive capabilities for the time series of economic growth rates and inflation rates. Their forecasting accuracy will be further validated through a series of diagnostic tests in the subsequent step. Accordingly, the regression equation results are presented as follows:

ARMA (4,1)….. GDP= 2.591775 + 0.087566 AR(4) - 0.650581 MA(1)

ARIMA (2,1,1)… GDP= 0.325023 - 0. 478828 AR(2) + 0. 631422 AR(1) - 0.585940 MA(1)

Diagnostic Testing:

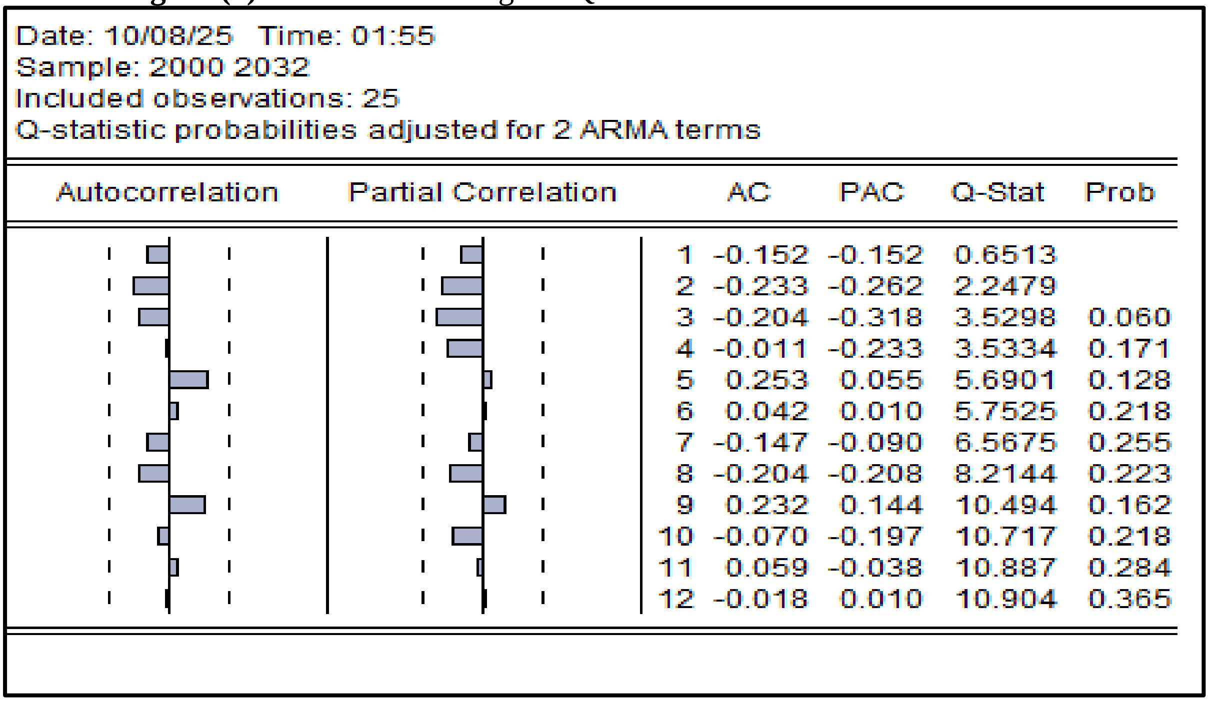
Prior to conducting the forecasting process, it is essential to subject the selected optimal models, ARMA(4,1) and ARIMA(2,1,1), to a series of diagnostic tests. These tests aim to verify that the models are free from econometric issues and meet the necessary statistical assumptions. Ensuring model adequacy is a prerequisite for reliable forecasting of future values of Libya's economic growth and inflation rates. The validity of the models will therefore be assessed through these diagnostic procedures before proceeding to the prediction stage.

10.6.6.Residual Stationarity Testing:

To assess the adequacy of the estimated models and to verify the absence of autocorrelation in the residuals, a residual stationarity test was conducted using both the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF). The analysis began with the ARMA(4,1) model, and the corresponding results are presented in Figure (3). As observed, all autocorrelation and partial autocorrelation coefficients fall within the confidence bounds, indicating that the residuals are stationary and free from systematic patterns or temporal dependencies.

This observation is further supported by the Ljung–Box Q-test, which evaluates the statistical significance of autocorrelations within the residuals. The test yielded a Q-statistic of approximately 10.904 and an associated p-value of 0.365. Since the p-value exceeds the 5% significance threshold, the null hypothesis, which posits that autocorrelation coefficients are not significantly different from zero, cannot be rejected. Consequently, it can be concluded that the ARMA(4,1) model does not suffer from autocorrelation issues and is statistically valid for forecasting and interpretation purposes.

Figure (3): Result of Correlogram Q-Statistics for Economic Growth Rat**es**



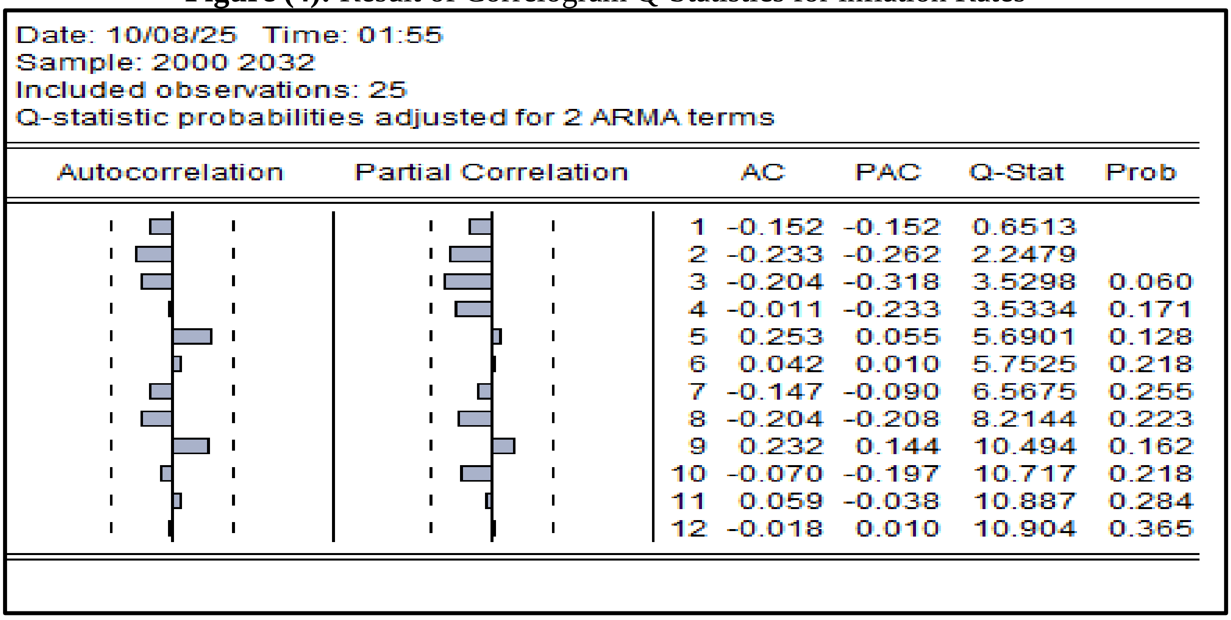
Date: 10/08/25 Time: 01:55
Sample: 2000 2032
Included observations: 25
Q-statistic probabilities adjusted for 2 ARMA terms

	AC	PAC	Q-Stat	Prob
1	-0.152	-0.152	0.6513	
2	-0.233	-0.262	2.2479	
3	-0.204	-0.318	3.5298	0.060
4	-0.011	-0.233	3.5334	0.171
5	0.253	0.055	5.6901	0.128
6	0.042	0.010	5.7525	0.218
7	-0.147	-0.090	6.5675	0.255
8	-0.204	-0.208	8.2144	0.223
9	0.232	0.144	10.494	0.162
10	-0.070	-0.197	10.717	0.218
11	0.059	-0.038	10.887	0.284
12	-0.018	0.010	10.904	0.365

Source: Based on the results of Correlogram Q-Statistics Test.

Similarly, for the ARIMA(2,1,1) model, the residual stationarity test results are displayed in Figure (4). Again, all ACF and PACF coefficients lie within the confidence intervals, confirming that the residuals exhibit stationarity. The Ljung–Box test reinforces this result, reporting a Q-statistic of about 5.242 and a p-value of 0.949, which is far above the 5% significance level. Therefore, the null hypothesis cannot be rejected, suggesting that the residuals are uncorrelated and that the model is well-specified.

Figure (4): Result of Correlogram Q-Statistics for inflation Rates



Date: 10/08/25 Time: 01:55
Sample: 2000 2032
Included observations: 25
Q-statistic probabilities adjusted for 2 ARMA terms

	AC	PAC	Q-Stat	Prob
1	-0.152	-0.152	0.6513	
2	-0.233	-0.262	2.2479	
3	-0.204	-0.318	3.5298	0.060
4	-0.011	-0.233	3.5334	0.171
5	0.253	0.055	5.6901	0.128
6	0.042	0.010	5.7525	0.218
7	-0.147	-0.090	6.5675	0.255
8	-0.204	-0.208	8.2144	0.223
9	0.232	0.144	10.494	0.162
10	-0.070	-0.197	10.717	0.218
11	0.059	-0.038	10.887	0.284
12	-0.018	0.010	10.904	0.365

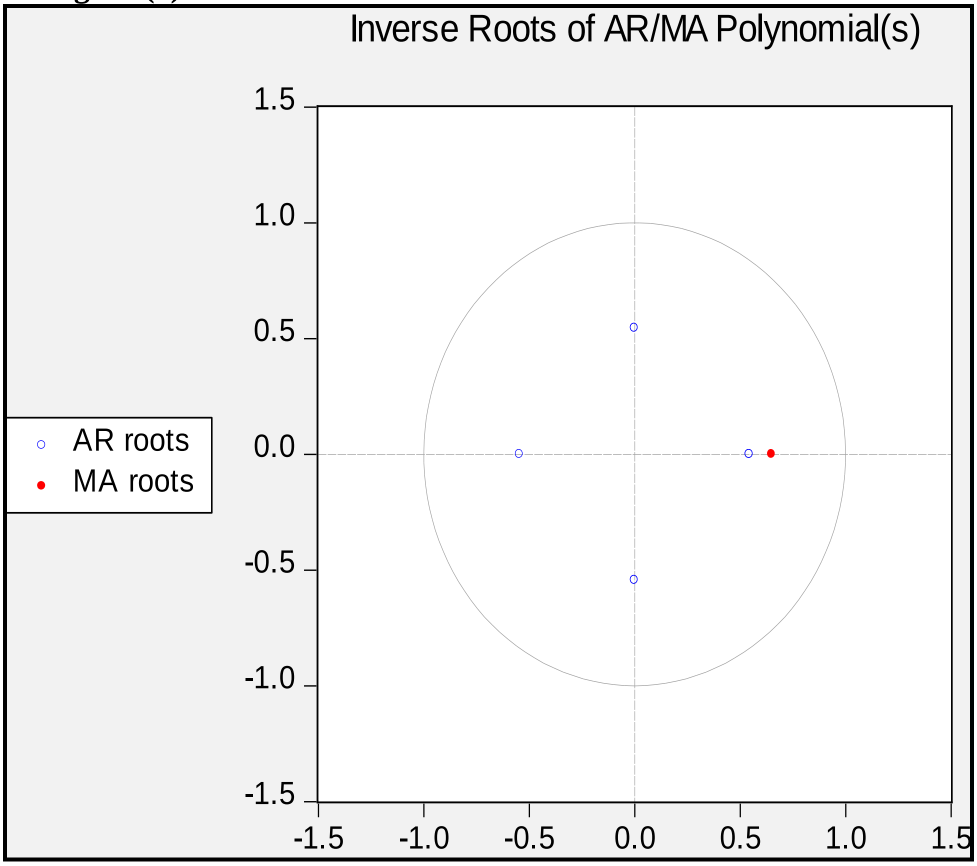
Source: Based on the results of Correlogram Q-Statistics Test.

Overall, the findings indicate that both the ARMA(4,1) and ARIMA(2,1,1) models exhibit desirable statistical properties in terms of residual behavior, thereby supporting their reliability for estimation and forecasting purposes.

10.6.7.Stability Test:

The inverse roots analysis was employed as a key tool to assess the stability of the residual series derived from the estimated model. As illustrated in Figure (5), all inverse roots lie outside the unit circle (i.e., their absolute values exceed one), indicating that the model satisfies the condition of stationarity. This requirement is fundamental for the validity of time series models and their reliability in forecasting economic growth rates. This evaluation aligns with the quantitative economic literature, which asserts that the stationarity of ARMA models is ensured when the inverse roots of the autoregressive (AR) polynomial lie outside the unit circle—thereby guaranteeing the convergence and boundedness of the time series over time (Hamilton, 1994).

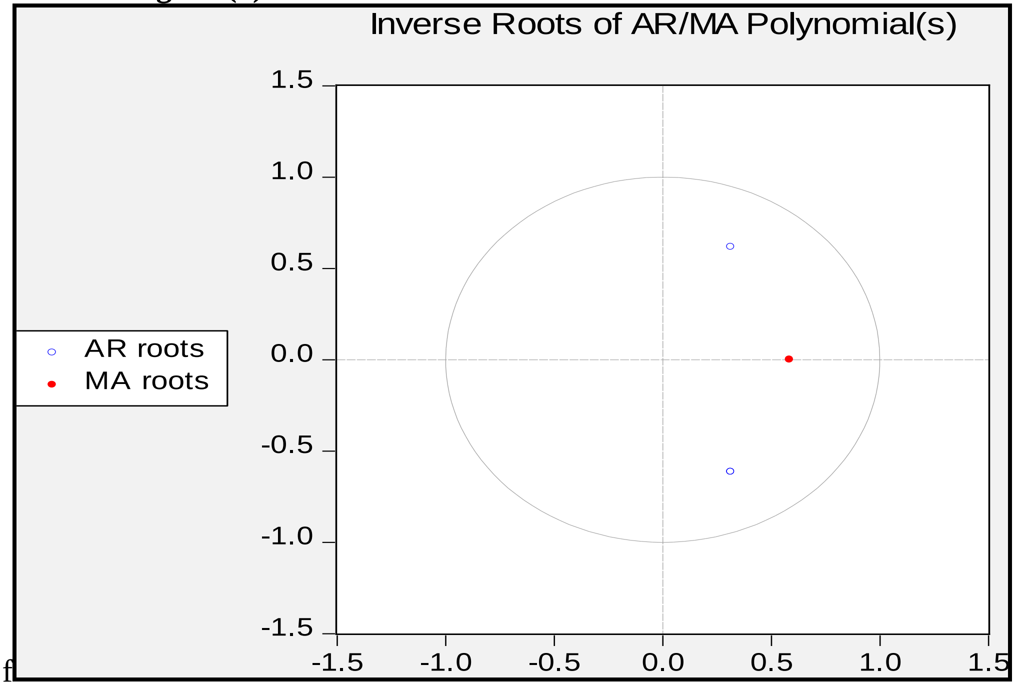
Figure (5): Result of Inverse Roots Test for Economic Growth Rates



Source: Based on The Results of Inverse Roots Test.

Similarly, the stationarity test results for the ARIMA model applied to inflation rates, as presented in Figure (6), confirm the same condition. All inverse roots are located outside the unit circle, reflecting the structural stability of the model. This, in turn, enhances its credibility in capturing the dynamic behavior of inflation, supporting its use for time series analysis and for anticipating future economic trends.

Figure (6): Result of Inverse Roots Test for inflation Rates

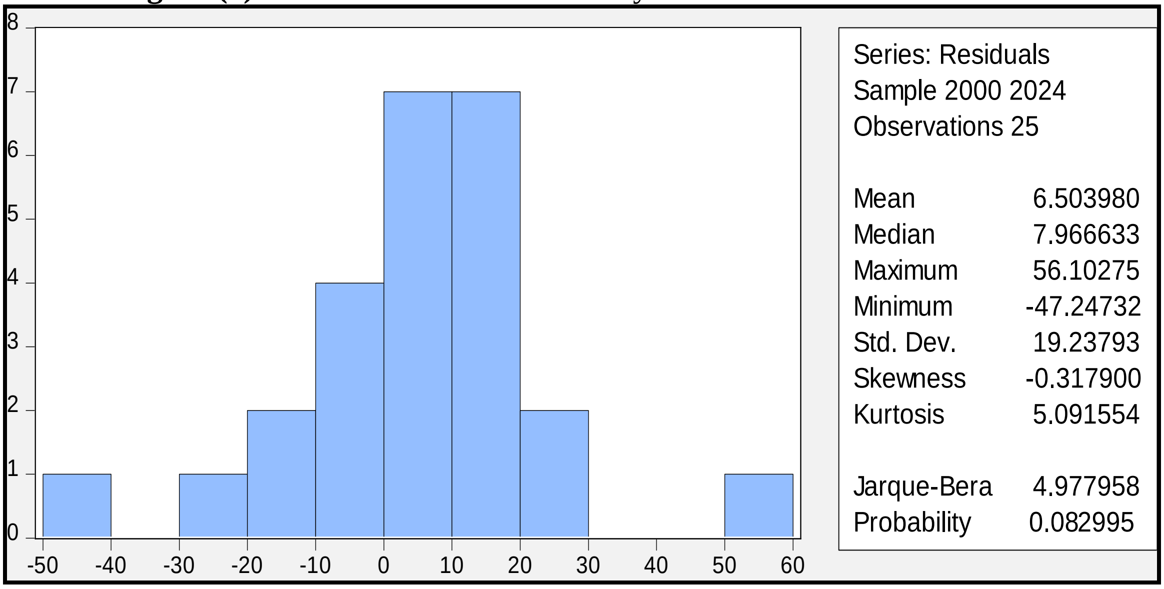


Source: Based on The Results of Inverse Roots Test.

10.6.8.Normality Test of Residuals:

The Jarque–Bera test was employed to examine whether the residuals from the estimated models follow a normal distribution. For the ARMA model related to economic growth rates, the results presented in Figure (7) indicate a p-value of 0.0820, which exceeds the conventional significance level of 0.05. Accordingly, the null hypothesis—stating that the residuals are normally distributed—cannot be rejected. This conclusion is further supported by the fact that the computed test statistic is lower than the critical value, indicating that the residuals possess appropriate distributional properties. Such normality is essential to ensure the reliability of the estimated parameters and the predictive performance of the model.

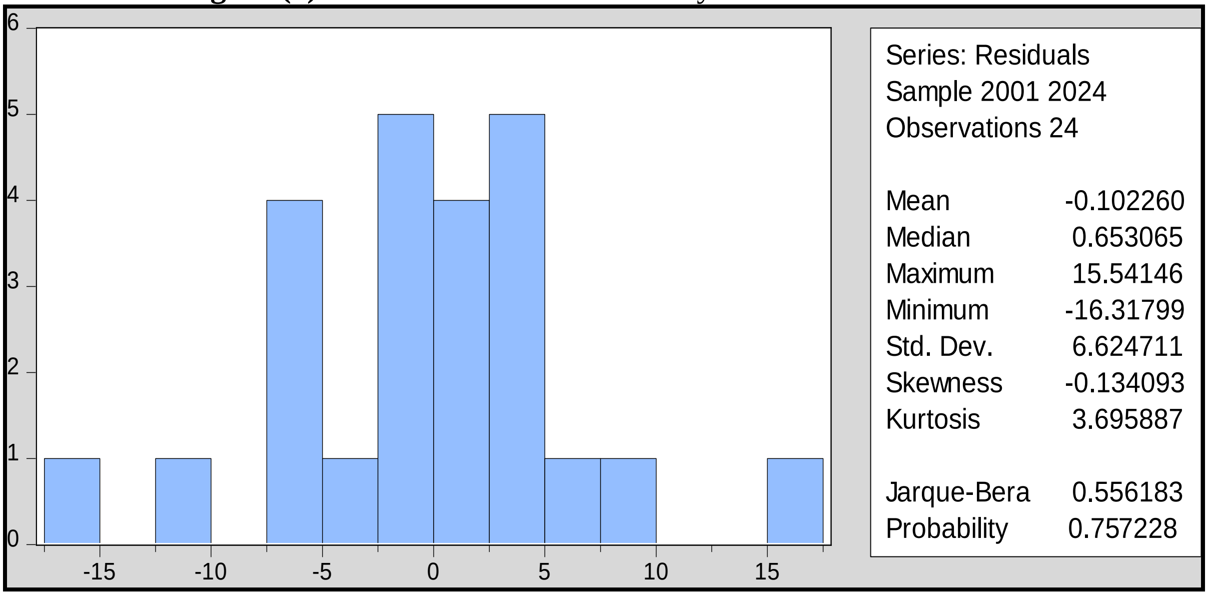
Figure (7): Result of Residual Normality Tests for Economic Growth Rates



Source: Based on The Results of Residual Normality Tests.

Similarly, for the ARIMA model applied to inflation rates, the Jarque–Bera test yielded a p-value of 0.757, as shown in Figure (8), which is well above the 0.05 threshold. Consequently, the null hypothesis of normality cannot be rejected. The alignment between the test statistic and the critical value further confirms that the model's residuals conform to the assumption of normality. This reinforces the model's statistical soundness and its suitability for dynamic forecasting and analysis of the economic variables under investigation.

Figure (8): Result of Residual Normality Tests for inflation Rates



Source: Based on The Results of Residual Normality Tests.

10.6.9. Heteroscedasticity (ARCH Test):

For the ARMA model of economic growth rates, the results of the ARCH test reported in Table (4) indicate that the p-values associated with both the F-statistic and the Chi-Square statistic are 0.0979, which exceed the conventional 0.05 level of significance. This suggests that there is no sufficient statistical evidence to reject the null hypothesis of homoscedastic residuals, implying the absence of heteroscedasticity over the period 2003–2024. However, the statistical significance of the lagged squared residual (RESID²(-1)) may signal a marginal effect that warrants additional attention, although it does not constitute conclusive evidence of a heteroskedastic pattern. Overall, the model may be considered reliable in terms of residual variance stability, indicating that the assumption of constant variance is not violated.

Table (4): Results of Heteroscedasticity Test for ARMA and ARIMA Models

Heteroscedasticity Test: ARCH		**ARMA (4,1)**	
F-statistic	2.408102	Prob. F(3,18)	0.1008
Obs*R-squared	6.300856	Prob. Chi-Square(3)	**0.0979**
Heteroscedasticity Test: ARCH		**ARIMA (2,1,1)**	
F-statistic	0.182998	Prob. F(1,21)	0.6732
Obs*R-squared	0.198695	Prob. Chi-Square(1)	**0.6558**

Source: Based on the results of the Heteroscedasticity Test (ARCH).

Regarding the ARIMA model estimated for inflation rates, the ARCH test results presented in Table (4) reveal that the p-values for both the F-statistic and the Chi-Square statistic amount to 0.6558, which is substantially higher than the 0.05 significance threshold. As such, the null hypothesis of homoscedasticity cannot be rejected. This strongly suggests the absence of heteroscedasticity in the model's residuals, thereby confirming that one of the core assumptions of time series analysis—constant variance—is satisfied. Consequently, the model demonstrates statistical robustness and can be considered appropriate for analyzing inflation dynamics and producing reliable forecasts.

10.6.10.Forecasting Stage:

After identifying the optimal models capable of accurately and efficiently forecasting economic growth rates and inflation rates values, namely the Autoregressive Moving Average model ARMA (4,1) and the Autoregressive Integrated Moving Average model ARIMA (2,1,1), the next step involved ensuring that these models were free from econometric issues. The diagnostic test results for the residual series confirmed the adequacy of the selected models. As illustrated in Figures (9) and (10), there is a strong alignment between the actual values (Actual) and the fitted values (Fitted), indicating that the estimated models closely track the real behavior of the series. Moreover, most of the residuals remained within the confidence interval bounds, suggesting the absence of autocorrelation among the model errors and validating the reliability of the forecasting results.

Figure (9): Actual and Fitted Values of Economic Growth Rates

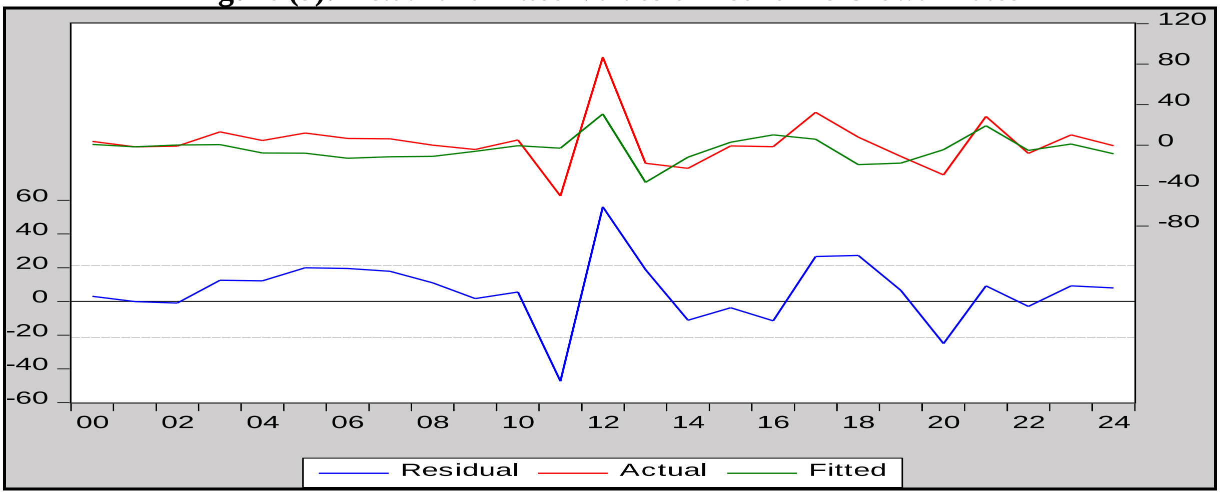
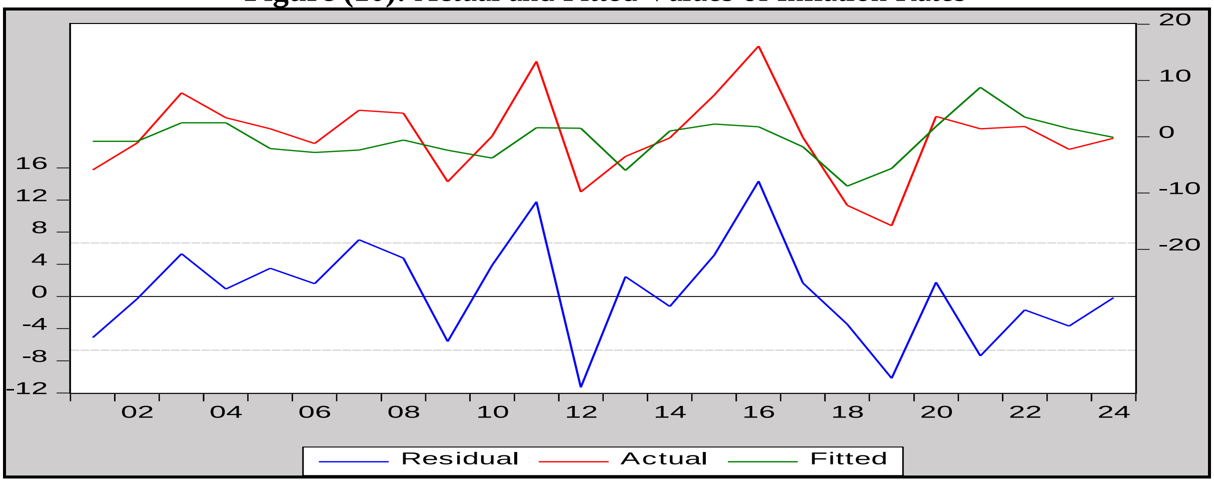


Figure (10): Actual and Fitted Values of Inflation Rates



Conversely, the results of the Theil inequality test, illustrated in Figures (11) and (12), show that the corresponding Theil coefficients are 0.7291 and 0.5539, respectively. Since these values are less than one, and all predicted values fall within the confidence intervals, this confirms the validity and reliability of the estimated models for forecasting future values of economic growth and inflation rates in Libya.

Figure (10): Results of Thiel Test for the validity and accuracy of the model in forecasting (Economic Growth)

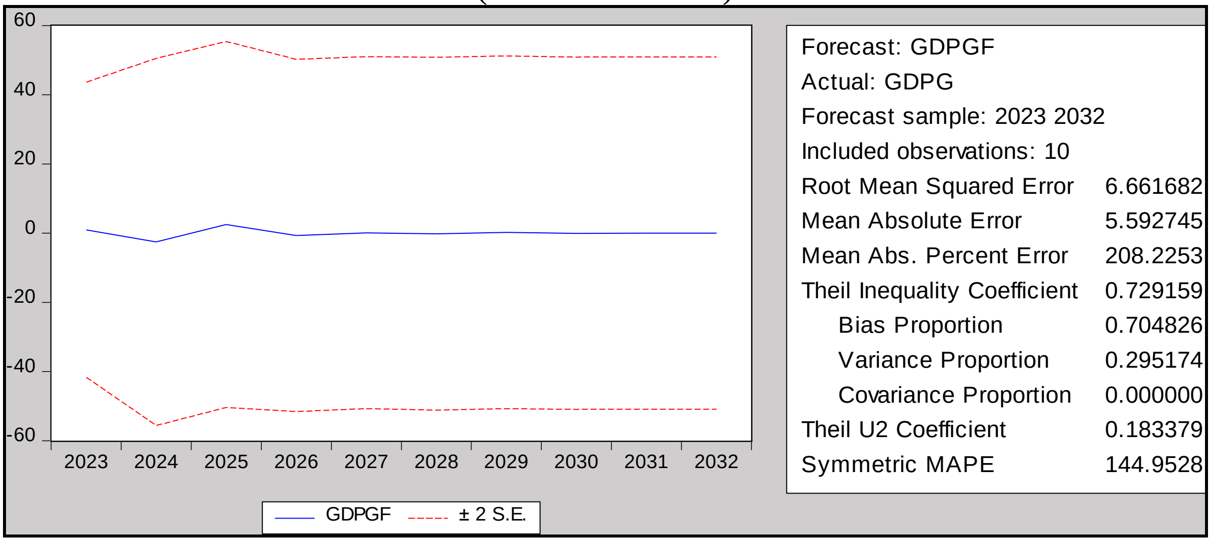
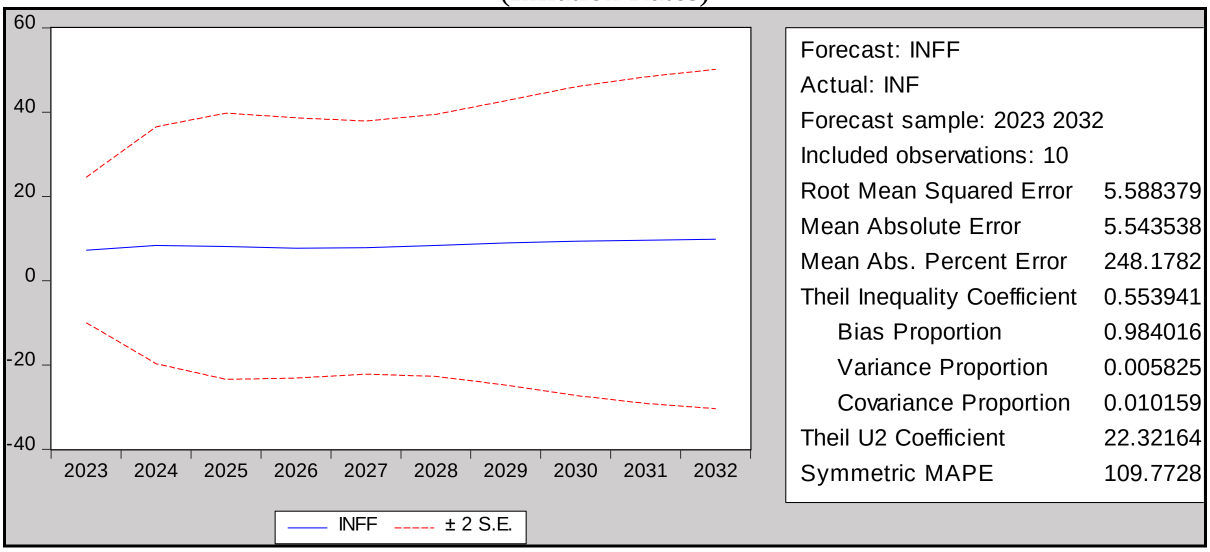


Figure (11): Results of Thiel Test for The validity and accuracy of the model in forecasting (Inflation Rates)



10.6.11.Forecasting:

The forecasting stage represents the primary objective of this study, aiming to identify the future trends and trajectories of economic growth and inflation rates. Relying on the optimal forecasting models, ARMA (4,1) and ARIMA (2,1,1), the projected values of the study variables for the future period (2024–2032) were obtained, as presented in Table (5).

Table (5): The Projected Values of Economic Growth and Inflation Rates

Years	The projected values of Economic Growth Rates	The projected values of Inflation Rates
2024	-0.61	3.44
2025	2.48	5.46
2026	-0.72	6.57
2027	0.89	6.61
2028	-0.75	6.38
2029	0.22	6.48
2030	-0.06	6.92
2031	0.08	7.44
2032	-0.07	7.85

11.Findings and Conclusions:

This study set out to model and forecast Libya's economic growth and inflation rates for the period (2024–2032) using the Box–Jenkins methodology, specifically the Autoregressive Moving Average (ARMA) and Autoregressive Integrated Moving Average (ARIMA) models. Covering the historical period (2000–2024), the research aimed to evaluate the efficiency and predictive power of these time-series models in explaining the dynamics of key macroeconomic indicators within an environment characterized by volatility and structural instability.

The empirical results revealed several important findings. First, unit root tests showed that the economic growth rate series was stationary at level, while the inflation rate series required first differencing to achieve stationarity. Accordingly, the ARMA model was found suitable for modeling economic growth, whereas the ARIMA model was deemed more appropriate for modeling inflation.

Second, based on model selection criteria, including the Akaike Information Criterion (AIC), the adjusted coefficient of determination (Adjusted R^2), and the statistical significance of estimated parameters, the ARMA(4,1) and ARIMA(2,1,1) models were identified as the most efficient for forecasting. Diagnostic tests confirmed that both models satisfied essential econometric assumptions: the residuals were stationary, normally distributed, homoscedastic, and free from autocorrelation. The Ljung–Box Q-test and ARCH test supported these findings, while the inverse root analysis confirmed the dynamic stability of both models.

Third, the Theil inequality coefficients, which reached (0.7291) for economic growth and (0.5539) for inflation, were both less than one. In addition, all forecasted values were within their confidence intervals, confirming the models' validity and predictive accuracy. The strong alignment between actual and fitted values further demonstrated that the models successfully captured the underlying behavior of the time series.

Finally, the forecasts for the period (2024–2032) suggest moderate fluctuations in Libya's economic growth rates, alternating between slight contractions and modest recoveries, reflecting ongoing structural challenges and external vulnerabilities. In contrast, inflation is projected to remain elevated, following an upward trend that may reach approximately 7.8% by 2032.

Overall, these findings underscore the significance of quantitative forecasting tools such as the ARIMA model in supporting evidence-based economic policymaking. By providing data-driven projections, the study highlights the practical value of econometric modeling in guiding macroeconomic stabilization strategies, improving inflation management, and supporting long-term growth planning amid Libya's uncertain economic environment.

12. Recommendations:

1. Policymakers and institutions in Libya should adopt quantitative forecasting tools, such as ARMA and ARIMA models, to guide strategic economic decision-making under conditions of volatility.
2. Establish and maintain accurate, up-to-date databases for key indicators, including GDP, inflation, and exchange rates, to enhance the reliability of forecasts.
3. Implement fiscal and monetary policies aimed at controlling inflation, while supporting domestic production to meet demand.
4. Utilize growth forecasts to inform long-term development planning, focusing on productive sectors to boost competitiveness and reduce external dependence.
5. Encourage continuous research using time-series models to regularly update forecasts in response to structural economic changes and external shocks.
6. Integrate predictive insights into the policy-making process to improve responsiveness and strengthen economic stability.

Note: It is important to acknowledge that the artificial intelligence engine (ChatGPT) was utilized to assist in linking and interpreting the methods used to calculate the study variables, as well as to enhance the clarity and academic quality of the English language used in this paper. This support was provided for informational and linguistic purposes only.

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Appendix (1)

Dependent Variable: GDPG
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 10/07/25 Time: 02:22
Sample: 2000 2024
Included observations: 25
Convergence achieved after 35 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.586199	1.111480	2.326806	0.0301
AR(1)	-0.020779	0.268380	-0.077424	0.9390
MA(1)	-0.624222	0.309198	-2.018845	0.0559
SIGMASQ	400.8866	137.0612	2.924873	0.0078

R-squared	0.299930	Mean dependent var	2.641159
Adjusted R-squared	0.236288	S.D. dependent var	24.42331
S.E. of regression	21.34369	Akaike info criterion	9.092353
Sum squared resid	10022.16	Schwarz criterion	9.238618
Log likelihood	-110.6544	Hannan-Quinn criter.	9.132921
Durbin-Watson stat	2.046054		

Inverted AR Roots	-.02
Inverted MA Roots	.62

Dependent Variable: GDPG
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 10/07/25 Time: 02:21

Sample: 2000 2024
Included observations: 25
Convergence achieved after 18 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.591775	1.036514	2.500473	0.0208
AR(4)	0.087566	0.263678	0.332096	0.7430
MA(1)	-0.650581	0.214516	-3.032781	0.0061
SIGMASQ	397.5956	130.9915	3.035279	0.0061

R-squared	0.305677	Mean dependent var	2.641159
Adjusted R-squared	0.242557	S.D. dependent var	24.42331
S.E. of regression	21.25590	Akaike info criterion	9.085293
Sum squared resid	9939.891	Schwarz criterion	9.231559
Log likelihood	-110.5662	Hannan-Quinn criter.	9.125861
Durbin-Watson stat	2.075456		

Inverted AR Roots	.54	-.00+.54i	-.00-.54i	-.54
Inverted MA Roots	.65			

Dependent Variable: GDPG
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 10/07/25 Time: 02:21
Sample: 2000 2024
Included observations: 25
Convergence achieved after 33 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.591324	1.175472	2.204496	0.0394
AR(1)	0.026171	0.355165	0.073686	0.9420
AR(4)	0.096104	0.342144	0.280886	0.7815
MA(1)	-0.663446	0.347855	-1.907248	0.0703
SIGMASQ	397.5406	136.3986	2.914550	0.0083

R-squared	0.305773	Mean dependent var	2.641159
Adjusted R-squared	0.206598	S.D. dependent var	24.42331
S.E. of regression	21.75460	Akaike info criterion	9.164960
Sum squared resid	9938.516	Schwarz criterion	9.359980
Log likelihood	-110.5620	Hannan-Quinn criter.	9.219050
Durbin-Watson stat	2.103571		

Inverted AR Roots	.56	.01-.56i	.01+.56i	-.55
Inverted MA Roots	.66			

Appendix (2)

Dependent Variable: D(INF)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 10/07/25 Time: 02:39
Sample: 2001 2024
Included observations: 24
Failure to improve objective (non-zero gradients) after 14 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.368868	1.141920	0.323024	0.7500
AR(1)	0.698698	0.420041	1.663405	0.1111
MA(1)	-1.000000	4322.867	-0.000231	0.9998
SIGMASQ	43.29991	4149.447	0.010435	0.9918

R-squared	0.160651	Mean dependent var	0.209167
Adjusted R-squared	0.080712	S.D. dependent var	7.336920
S.E. of regression	7.034601	Akaike info criterion	6.925176
Sum squared resid	1039.198	Schwarz criterion	7.072432
Log likelihood	-80.10211	Hannan-Quinn criter.	6.964243
Durbin-Watson stat	1.512953		

Inverted AR Roots	.70
Inverted MA Roots	1.00

Dependent Variable: D(INF)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 10/07/25 Time: 02:37
Sample: 2001 2024
Included observations: 24
Convergence achieved after 37 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.325023	1.182836	0.274783	0.7863
AR(1)	0.631422	0.302265	2.088966	0.0497
AR(2)	-0.478828	0.176645	-2.710677	0.0135
MA(1)	-0.585940	0.288281	-2.032527	0.0556
SIGMASQ	36.97893	11.22894	3.293182	0.0036

R-squared	0.283180	Mean dependent var	0.209167
Adjusted R-squared	0.175657	S.D. dependent var	7.336920
S.E. of regression	6.661435	Akaike info criterion	6.809992
Sum squared resid	887.4943	Schwarz criterion	7.006334
Log likelihood	-77.71990	Hannan-Quinn criter.	6.862081

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Durbin-Watson stat	1.970727	
Inverted AR Roots	.32+.62i	.32-.62i
Inverted MA Roots	.59	

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