

Using the Box-Jenkins Methodology to Forecast Carbon Dioxide Emissions from Energy in Algeria up to the 2030 Horizon

استخدام منهجية بوكس جينكز للتنبؤ بالانبعاثات غاز ثاني أكسيد الكربون الناتجة عن الطاقة في الجزائر

حتى آفاق 2030

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Abstract:

This study aimed to analyze the time series of carbon dioxide (CO₂) emissions from energy in Algeria during the period 1980–2023 and forecast them using the Box-Jenkins methodology. To achieve this objective, a descriptive-analytical approach and an econometric approach were employed, with the assistance of the statistical program EViews-10. The results revealed that the time series under study became stationary at the second difference. The best model among the selected models was identified as ARIMA model (0,2,1), which was used to forecasting future CO₂ emissions for the period 2024–2030. The forecasting results indicated that the expected volume of emissions would range between approximately 351.9064 and 389.9539 million tons during the forecast period. Furthermore, the results showed that CO₂ emissions in Algeria are projected to follow an upward trend during the forecast period (2024–2030), driven by the ongoing increase in investment projects and economic expansion. This, in turn, leads to excessive use of energy resources, resulting in higher levels of toxic emissions, particularly CO₂.

Keywords: Carbon Dioxide Emissions from Energy; Time Series Analysis; Box-Jenkins Methodology; Forecasting; ARIMA Model.

JEL Classification Codes: Q54; C22; C53; C22.

ملخص:

هدفت هذه الدراسة إلى تحليل السلسلة الزمنية لانبعاثات غاز ثاني أكسيد الكربون الناتجة عن الطاقة في الجزائر خلال الفترة 1980–2023 والتنبؤ بها باستخدام منهجية *Box-Jenkins*، ولتحقيق هذا الهدف، تم استخدام المنهج الوصفي التحليلي والمنهج القياسي، وبالمساعدة البرنامج الإحصائي *EViews-10*. أظهرت النتائج أن السلسلة الزمنية قيد الدراسة مستقرة عند الفرق الثاني، وتم التوصل إلى أن أفضل نموذج من بين النماذج المختارة هو النموذج: *ARIMA(0,2,1)* والذي تم استخدامه للتنبؤ المستقبلي بحجم انبعاثات غاز ثاني أكسيد الكربون للفترة من 2024 إلى 2030، وأظهرت نتائج التنبؤ أن حجم الانبعاثات المتوقع سيتراوح بين 351.9064 و 389.9539 مليون طن تقريباً خلال فترة التنبؤ. وأن انبعاثات غاز ثاني أكسيد الكربون في الجزائر ستسلك اتجاهها تصاعدياً خلال فترة التنبؤ (2024–2030) وذلك بسبب الاستمرار في زيادة المشاريع

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الاستثمارية والتوسع في النشاط الاقتصادي مما يؤدي إلى الإفراط في استخدام موارد الطاقة التي تؤدي بدورها إلى زيادة حجم الانبعاثات السامة خاصة انبعاثات غاز CO_2 .

كلمات مفتاحية: انبعاثات غاز ثاني أكسيد الكربون من الطاقة، تحليل السلاسل الزمنية، منهجية بوكس جينكرز، التنبؤ، نموذج ARIMA.
تصنيفات JEL: Q54، C22، C53، C22.

INTRODUCTION:

The process of forecasting macroeconomic variables such as inflation, growth, unemployment, energy, carbon dioxide (CO_2) emissions, and others, is critical. It requires the use of specific statistical methods, as well as the continuous development of forecasting tools and techniques to improve accuracy in an ever-changing economic environment. Like all economic phenomena, forecasting CO_2 emissions is of great importance in combating climate change, promoting innovation in clean energy, and directing investments toward sustainable solutions. Additionally, it can be an essential tool for planning and controlling these emissions, reducing future environmental and economic risks.

Forecasting of carbon dioxide (CO_2) emissions from energy in Algeria is of great importance, especially in light of the environmental and economic challenges it faces, as well as its international commitment to achieving climate change goals and reducing environmental pollution. This is particularly relevant as Algeria is one of the countries producing oil and gas, with a heavy reliance on fossil fuels. Therefore, CO_2 emissions from various sectors such as energy, transportation, and industry represent a significant part of the environmental challenges that require continuous monitoring and analysis.

Moreover, Algeria's CO_2 emissions index has witnessed a continuous increase the period from 1990 to 2022, which led the Algerian government to comply with international agreements and implement future development plans while considering the reduction of negative environmental impacts and contributing to the reduction of these emissions, especially in recent years. Based on the predictions of CO_2 emissions, the government can make decisions to improve energy efficiency and develop renewable energy sources such as solar and wind.

In this context, most economic studies have turned to the use of econometric models and time series models to forecast the future trajectory of economic phenomena. One of the most important time series methodologies is **the Box-Jenkins methodology**, which relies on using sequentially **collected** time series data over a specific period and analyzing its components for forecasting.

Research Problem :

This research paper addresses the construction of an accurate econometric model that can predict and forecast the behavior and trends of the time series for CO_2 emissions up to 2030 horizon using **the Box-Jenkins methodology**. Therefore, the following problem statement is formulated :

How can the Box-Jenkins methodology be used to forecast carbon dioxide (CO_2) emissions from energy in Algeria up to 2030 horizon ?

Based on this, the following hypotheses are formulated to answer the research question:
Hypothesis 1: The time series of carbon dioxide (CO_2) emissions from energy in Algeria (ECO_2) during the period 1990 to 2023 is considered a non-stationary (unstable) time series.

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Hypothesis 2: The Autoregressive Integrated Moving Average (ARIMA) model is the most suitable model among the **Box-Jenkins models** to describe the data of carbon dioxide (CO₂) emissions from energy time series.

The study aimed to explore the Box-Jenkins methodology and utilize it to predict carbon dioxide (CO₂) emissions in Algeria up to the year 2030. To achieve this objective and address this topic, a descriptive-analytical approach was used to study the development of carbon dioxide (CO₂) emissions from energy in Algeria. Additionally, the econometric approach was applied through the implementation of the Box-Jenkins methodology to forecast the volume of carbon dioxide emissions up to 2030 horizon, relying on annual data from 1980 to 2023 and utilizing the statistical programs EViews-10.

Although the topic is not new, studies addressing it in Algeria using the proposed Box-Jenkins methodology remain limited. Among these studies is research conducted by **HADJ Khelifa (2021)**, where the researcher employed the Box-Jenkins methodology and proposed the construction of a hybrid econometric model in the form of **ARIMA(1,1,7)-GARCH(1,1)** to forecast carbon dioxide (CO₂) emissions in Algeria. Additionally, the researcher estimated the annual forecast of carbon dioxide emissions for the period spanning **2019-2025**, which showed a continuous increase. (HADJ , 2021)

We also find a study conducted by **AYAD Hicham and CHENINI Moussa (2019)**, in which the researchers attempted to analyze the relationship between energy consumption, economic growth, and carbon dioxide emissions in Algeria during the period from **1970 to 2017**, using the **VAR model**. The researchers concluded that there is no cointegration between the study variables, and it was found that carbon dioxide emissions are primarily driven by economic growth and energy consumption. (AYAD & CHENINI , 2019)

The study conducted by **Tingxin Wen** and his colleagues (2023) aimed to identify the factors influencing carbon dioxide emissions in China and to predict future trends based on these factors. The results of the study showed that the **ARIMA + LSTM** model was more accurate in predicting the trends of carbon dioxide emissions and in classifying the factors affecting these emissions in each of the specified regions of China. Additionally, the **ARIMA + LSTM** model was used to forecast future carbon dioxide emission trends in the eastern, central, and western regions of China, with the aim of enabling China to take the necessary measures to reduce carbon dioxide emissions (Tingxin , Yazhou, Yun , & Haoyuan, 2023, p. 2)

1- Theoretical framework of the study:

In the era of economic globalization and rapid technological advancement, issues related to carbon dioxide (CO₂) emissions and climate change have emerged as critically important topics, attracting the attention of both researchers and governments due to their severity. Massive carbon dioxide emissions exacerbate the greenhouse effect, necessitating strong and effective measures to ensure the achievement of sustainable global development. According to the Intergovernmental Panel on Climate Change (IPCC), the concentration of carbon dioxide in the atmosphere is increasing at a rate of 2% annually (Tingxin , Yazhou, Yun , & Haoyuan, 2023, pp. 2-3). In this context, the evolution of carbon dioxide emissions from energy in Algeria will be analyzed, addressing the following points :

1-1 Definition of Carbon Dioxide Emissions

Carbon dioxide is a natural gas that plays a crucial role in regulating Earth's temperature. However, the increase in its concentration in the atmosphere due to human activities is causing adverse climate changes. Therefore, effective measures must be taken to reduce carbon dioxide emissions and transition to more sustainable energy sources. It is a colorless and odorless gas and is considered one of the trace gases present in Earth's atmosphere. This gas is characterized by being approximately 53% heavier than air, which means it tends to accumulate in the lower layers of the atmosphere. Among its sources are the respiration of living organisms, the combustion of fossil fuels, industrial processes, organic decomposition, and more. (Galina , 2016, pp. 1-2)

Carbon dioxide (CO₂), or carbon gas, also known as: "A chemical compound and one of the components of the atmosphere, composed of one carbon atom bound to two oxygen atoms. It is in a gaseous state under normal conditions, but it is also used in its solid state and plays a significant role in the carbon cycle in nature" (<https://gml.noaa.gov>, s.d.)

According to the U.S. Environmental Protection Agency (EPA), carbon dioxide (CO₂) is considered one of the primary greenhouse gases contributing to climate change. It enters the atmosphere mainly through the burning of fossil fuels (such as coal, oil, and natural gas), as well as emissions from solid waste, decomposing biological materials (like trees), and certain industrial processes such as cement production. On the other hand, plants absorb carbon dioxide as part of the photosynthesis process, which helps remove it from the atmosphere and store it in biomass. (Overview of Greenhouse Gases, s.d.)

1-2 The Harmful Effects of Carbon Dioxide:

Carbon dioxide is considered a natural and essential gas for life on Earth. However, the increase in its concentration in the atmosphere due to human activities leads to serious negative effects, the most important of which are : (Leonel, 2023, pp. 2-4)

- **Impact on Climate and Global Warming :** The increase in the gas leads to widespread climate changes and exacerbates the greenhouse effect, causing a rise in global temperatures.
- **Impact on Ecosystems and Biodiversity :** The rise in carbon dioxide concentration negatively affects ecological balance, threatening biodiversity.
- **Impact on Human Health and Quality of Life :** Air pollution resulting from increased emissions contributes to the aggravation of respiratory diseases and the deterioration of quality of life.
- **Impact on the Economy :** Governments bear significant costs to address the effects of climate change, such as building dams to protect coastal areas from flooding.
- **Impact on Food Security :** Climate change leads to a reduction in agricultural crops in some regions due to drought or floods, threatening food security.
- **Impact on Industries :** Industries that rely on natural resources, such as fishing and tourism, are significantly affected by changes in ecosystems.

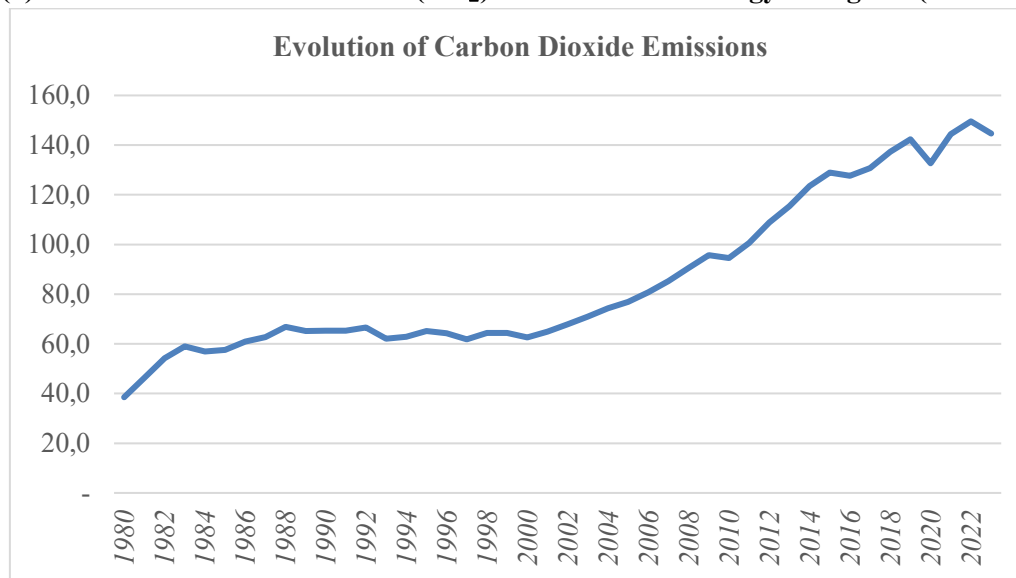
In this context, a study conducted by researchers from the United States showed that the "thermosphere," the outer layer of the atmosphere, is at risk of shrinking due to increased carbon dioxide emissions resulting from the burning of fossil fuels (Kakha , Nino, & Inga, 2021, p. 17). Therefore, it has become imperative to take urgent measures to reduce carbon dioxide emissions and transition to clean and sustainable energy sources.

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1-3 The Evolution of Carbon Dioxide Emissions in Algeria :

The following figure illustrates the key stages in the development of carbon dioxide emissions from energy in the Algerian economy. The figure below shows this:

Figure(1) : Evolution of carbon dioxide (CO₂) emissions from energy in Algeria (1980-2023)



Source: Prepared by the researchers based on Annex 1

We observe from **Figure 1** that the development of carbon dioxide emissions from energy during the study period is characterized by three main phases :

Starting from 1980-1989, emissions increased at a moderate pace, reaching 65.1 million tons in 1989, compared to 38.5 million tons in 1980. This was due to the limited investments at that time and the low use of energy resources in industry.

Carbon dioxide emissions continued to increase, but at a slow pace tending toward stabilization. Emissions went from 65.4 million tons in 1990 to 64.9 million tons in 2001, as a result of the policies implemented by the state and the investment programs at the time, which led to the start of industrialization and the broader use of energy sources, ultimately increasing emissions.

The third phase, from 2002 to 2023, witnessed a rapid rise in CO₂ emissions, reaching their peak in 2019 at 142.4 million tons. This was due to the recovery of the oil market, which led to increased consumption of fossil fuels and all types of primary energy, in addition to the investment trends that Algeria experienced during that period as a result of the economic revival programs. In 2020, emissions dropped to 132.7 million tons due to the COVID-19 pandemic, only to rise again starting in 2021 after the pandemic subsided.

2- Econometric study:

After conducting the theoretical study, we will attempt to adopt the Box-Jenkins methodology to predict the carbon dioxide (CO₂) emissions from energy in Algeria up to the 2030 horizon.

2-1 Box-Jenkins Methodology

The Box-Jenkins method involves modeling time series and forecasting the predicted movements from observable data through a series of iterations. This methodology is univariate and is essentially a forecasting tool. It does not provide explanations for the reasons behind

changes due to the absence of explanatory variables in the model (Abdulkader & Motasam , 2018, p. 111) .

The Box-Jenkins models are well known for being **Autoregressive Integrated Moving Average (ARIMA) models**. The methodologies used to solve **ARIMA model** equations require extensive computational operations; therefore, statistical software programs will be used to describe and diagnose **ARIMA models** (Damodar , 2003, p. 837) such as the **EViews** program.

2-1-1 The concept of the Box-Jenkins method

The ARIMA methodology is applied to stationary data, where the symbol Z_t represents stationary data at time t , while Y_t represents the value of non-stationary data at that time t . Accordingly, the **ARIMA** process takes into account linear models of the following form : (Abdulkader & Motasam , 2018, p. 113)

$$Z_t = \mu_t + \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \dots - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \dots + e_t$$

where Z_t and Z_{t-1} represent stationary data points, while e_t and e_{t-1} represent the predicted error values at the present and past times, respectively.

As for μ_t , ϕ_1 , $\phi_2 \dots$, and θ_1 , $\theta_2 \dots$, they are the parameters of the model to be estimated.

2-1-2 ARIMA modeling of time series data (the carbon dioxide emissions from energy in Algeria)

The Box-Jenkins methodology includes several methods for forecasting time series, assuming that the time series under study are stationary rics (Damodar , 2003, p. 840) .By applying **the Box-Jenkins methodology**, we can determine the type of model, whether it follows an AR (Autoregressive) model, an MA (Moving Average) process, an ARMA (Autoregressive Moving Average) process, or an ARIMA (Autoregressive Integrated Moving Average) process,by knowing the values of **(p, d, q)** and following the steps outlined in **the Box-Jenkins methodology**:

First: Identification:

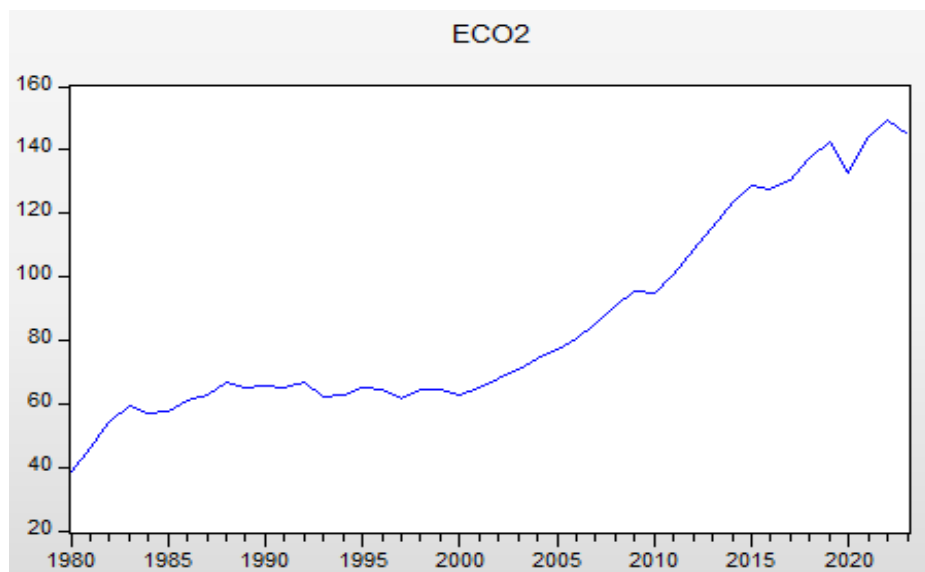
In this phase, the model most compatible with the time series is identified. This phase includes a series of steps, as follows:

A- Graphical Representation of the Series Under Study

The graphical representation The graph gives us an initial idea about the stability of the time series. Therefore, a descriptive study of the data in the time series under study is required. The series represents the carbon dioxide (CO₂) emissions from energy, and we denote the series as **ECO2**, which consists of observations from 1980 to 2023, as shown in **Appendix 1**. The data for this series were obtained from the reports, publications, and statistics of the Energy Institute available on the following website: <https://www.energyinst.org/statistical-review/resources-and-data-downloads> from the years (1980-2023). The following figure provides the initial impression formed by the time series.

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Figure(2) : Evolution of carbon dioxide (CO₂) emissions from energy in Algeria (1980-2023)



Source: Prepared by the researchers based on the output of the Eviews-10 program.

It can be observed from the figure that the volume of carbon dioxide emissions in Algeria has shown a continuous increase throughout the study period. Therefore, it can be said that the series of carbon dioxide emissions contains a general **trend component**, meaning that the carbon dioxide emissions from energy (**ECO2**) series is **non-stationary** (unstable).

B- Checking the stationarity of the Time Series :

It can be difficult to determine the nature of the time series—whether stationary or non-stationary—just from the graph(graphical representation). Thus, we need to confirm it using other **statistical tests**, such as **Unit Root Tests**. Among these tests the **Augmented Dickey-Fuller (ADF) test**, which examines the stationarity or non-stationarity of a time series by identifying the presence of a trend componen (Damodar & Dawn C, 2009, p. 758) t. In this step, we will test the stationarity of the time series under study using **the Augmented Dickey-Fuller test**.

The process involves transitioning from the first model, which contains both the **trend** and the **intercept**, to the second model, which includes only the **intercept** without the trend, and finally to the third model, which **excludes both the intercept and the trend**, based on the following hypotheses:

- Null Hypothesis (H_0): The series carbon dioxide emissions from energy (ECO2) contains a unit root. (non-stationary).
- Alternative Hypothesis (H_1): The series carbon dioxide emissions from energy (ECO2) does not contain a unit root. (stationary).

The following table shows us the results of the Augmented Dickey-Fuller test:

Table(1) : Augmented Dickey-Fuller Unit Root Test for (ECO2) Series

	<i>At Level</i>		
	<i>Model 1</i>	<i>Model 2</i>	<i>Model 3</i>
<i>Energy Emissions Series (ECO2)</i>	<i>With Trend and intercept</i>	<i>With Intercept</i>	<i>Without Trend and Intercept</i>
<i>Test Statistic</i>	-2.083554	0.372728	3.802604
<i>P-Value</i>	0.5385	0.9794	0.9999
	<i>At 1st Difference</i>		
	<i>Model 1</i>	<i>Model 2</i>	<i>Model 3</i>
<i>Energy Emissions Series (ECO2)</i>	<i>With Trend and Intercept</i>	<i>With Intercept</i>	<i>Without Trend and Intercept</i>
<i>Test Statistic</i>	-3.781896	-1.807642	-1.365497
<i>P-Value</i>	0.0281	0.3714	0.1569
	<i>At 2nd Difference</i>		
	<i>Model 1</i>	<i>Model 2</i>	<i>Model 3</i>
<i>Energy Emissions Series (ECO2)</i>	<i>With Trend and Intercept</i>	<i>With Intercept</i>	<i>Without Trend and Intercept</i>
<i>Test Statistic</i>	-6.98509	-7.100264	-7.206037
<i>P-Value</i>	0.000	0.0000	0.0000

Source : Prepared by the authors based on EViews-10 program output

The carbon dioxide emissions from energy series (ECO2) is non-stationary at the level, as the p-value is greater than 5% in all models. Therefore, we accept the initial hypothesis indicating the presence of a unit root, and the series is of the **Difference Stationary (DS)** type. The third model shows that the trend is not significant at the 5% level. Hence, we need to take the first difference of the series. When we examined the variable at the first difference, we found that the p-value is still greater than 5% in all models, so we accept the initial hypothesis indicating the presence of a unit root, thus requiring the second difference of the series. However, when examining the variable at the second difference, we found that the p-value is less than 5% in all models, which indicates that the series has become stationary. Therefore, the carbon dioxide emissions from energy (ECO2) series is **stationary at the second difference**, and we denoted as $ECO2 \sim I(2)$.

C- Analysis of Simple and Partial Autocorrelation Functions :

After describing the time series and confirming its stationarity, we proceed to determine the appropriate values for (p, d, q), the degree of lag for the **Autoregressive (AR)** model (p) and the degree of lag for the **Moving Average(MA)** model (q). The main tools used for this are the **Autocorrelation function (ACF)**, **Partial Autocorrelation Function (PACF)**, and the **Correlogram**, which is a graphical representation of the **Autoregressive Coefficients** and **Partial Autoregressive Coefficients** at different lag periods (Damodar , 2003, p. 840) . These tools help in proposing a set of candidate models that might fit the time series data under study. The EViews program aids in extracting these coefficients, as shown in the figure below :

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Figure (4) : Correlogram of ACF and PACF for the ECO2 Series at the 2nd Difference

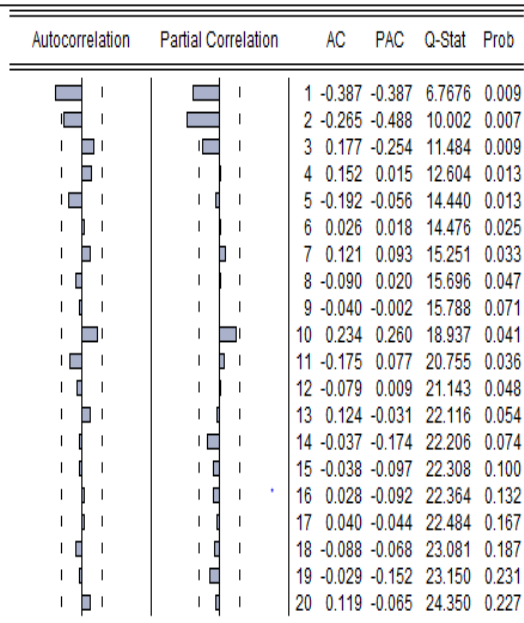
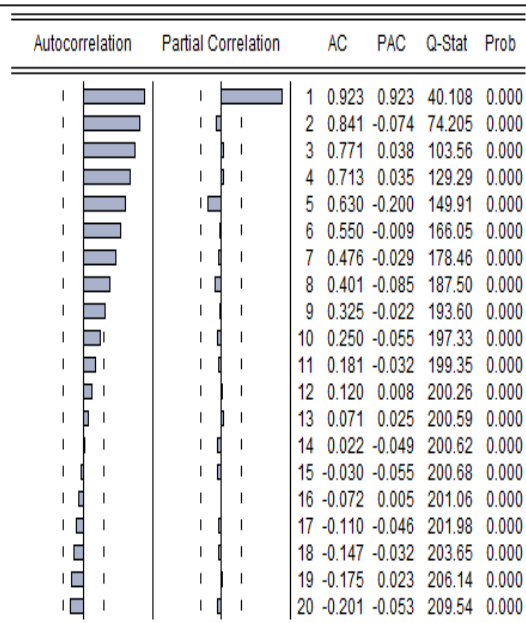


Figure (3) : Correlogram of ACF and PACF for the ECO2 series at the Level



Source : Prepared by the authors based on EViews-10 program output.

It can be observed from Figure 3 and by examining the **Correlogram** and **Partial Correlogram** of the carbon dioxide emissions from energy (ECO2) in Algeria from 1980-2023 that the series is non-stationary. We find that it stabilizes at the second difference, which is evident from the **Correlogram** of the estimated **ACF** and **PACF** values for the second differences of the carbon dioxide emissions from energy (ECO2) series, as shown in Figure 4. Now we have a completely different shape for the **ACF** and **PACF**. The values of the **Partial Autocorrelation Coefficients (PAC's)** at the first and second lag periods are outside the confidence interval, with values of 0.378 and 0.488, both negative and statistically significant. Thus, we set the value (**p=1**) and (**p=2**). We also propose (**p=3**), as it is approximately on the edge of the confidence interval. We also observe the **Autocorrelation Coefficients (AC's)** at the first and second lag periods, which are also outside the confidence interval, with values of 0.378 and 0.265, both negative and statistically significant. Therefore, we set the value (**q=1**) and (**q=2**), as they approach the confidence interval.

Since the selection process is an approximation, we propose the best possible suggestions, and later tests are conducted. We can also include (**q=0**) and (**p=0**) to estimate the non-negative trend (Ma, 2018, p. 5). Accordingly, the following models can be proposed to select the appropriate model :

Table (2) : Proposed Models for ARIMA Methodology

Model Number	Models	Model Number	Models
Model 1	ARIMA(1,2,1)	Model 6	ARIMA(1,2,0)
Model 2	ARIMA(2,2,1)	Model 7	ARIMA(2,2,0)
Model 3	ARIMA(3,2,1)	Model 8	ARIMA(3,2,0)
Model 4	ARIMA(1,2,2)	Model 9	ARIMA(0,2,1)
Model 5	ARIMA(2,2,2)	Model 10	ARIMA(0,2,2)

Source : Prepared by the authors based on Appendix 2

Second : Estimation

After identifying the appropriate model by selecting the suitable values for (p, d, q), i.e., determining the lags for both the **Autoregressive (AR)** and **Moving Average (MA)** components, the next step is to estimate the parameters in the model (Damodar , 2003, p. 840) . In some cases, it is appropriate to use the **Ordinary Least Squares (OLS) method**, and in other cases, non-linear estimation models are employed for model estimation. Statistical Programs dedicated to this task can be used.

Let **D(D(ECO2))** represent the second differences of the carbon dioxide emissions from energy(ECO2) series in Algeria, as it is stationary of the second degree. Using the EViews program, we estimate the first **model AR(1)**, which represents the variable with a first-order lag (lagged by one period), up to the fifth model **ARIMA(2,1,1)** by entering the model into the dialogue box after selecting **Quick** → **Estimate equation** with the following formulas:

D(D(ECO2)) c AR(1)
D(D(ECO2)) c AR(2)
D(D(ECO2)) c AR(3)
D(D(ECO2)) c Ma(1)
D(D(ECO2)) c Ma(2)
D(D(ECO2)) c AR(1) Ma(1)
D(D(ECO2)) c AR(1) Ma(2)
D(D(ECO2)) c AR(2) Ma(1)
D(D(ECO2)) c AR(2) Ma(2)
D(D(ECO2)) c AR(3) Ma(1)
D(D(ECO2)) c AR(3) Ma(2)

We obtain the results shown in **Appendix 2**

Excluding the **ARIMA(2,2,0)**, **ARIMA(3,2,0)**, and **ARIMA(0,2,2)** model, in addition to the following models: **ARIMA(1,2,1)**, **ARIMA(2,2,1)**, **ARIMA(3,2,2)**, and **ARIMA(2,2,2)** due to the insignificance of the models. The best models are then selected from the previous ones based on the Akaike and Schwarz criteria, where we choose the model with the lowest value of these criteria, as shown in the following table :

Table (3) : Selection of the Best Models

Proposed Models	Schwarz Criterion	Akaike info Criterion
<i>ARIMA(1,2,0)</i>	6.3314	6.20281
<i>ARIMA(0,2,1)</i>	5.994643	5.870523
<i>ARIMA(1,2,2)</i>	6.067465	5.901973

Source : Prepared by the authors based on the outputs of the EViews-10 program.

Based on the Akaike and Schwarz criteria, the best model is found to be: **ARIMA(0,2,1)**, with the estimation results shown as follows:

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Figure (5): Estimation Results of the Model: D(D(ECO2)) c MA(1)

Sample: 1982 2023
Included observations: 42
Convergence achieved after 18 iterations
Coefficient covariance computed using outer product of gradients

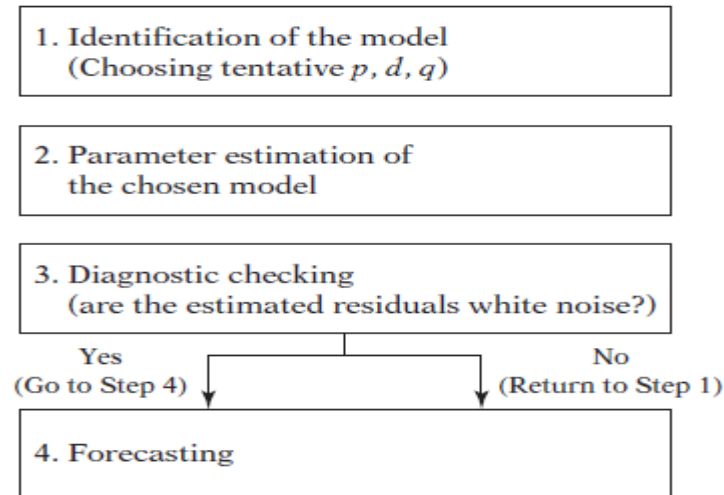
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.031250	0.142229	-0.219718	0.8272
MA(1)	-0.824742	0.125419	-6.575879	0.0000
SIGMASQ	17.50777	3.845165	4.553192	0.0001
R-squared	0.415425	Mean dependent var	-0.302193	
Adjusted R-squared	0.385447	S.D. dependent var	5.538960	
S.E. of regression	4.342180	Akaike info criterion	5.870523	
Sum squared resid	735.3265	Schwarz criterion	5.994643	
Log likelihood	-120.2810	Hannan-Quinn criter.	5.916018	
F-statistic	13.85760	Durbin-Watson stat	2.009858	
Prob(F-statistic)	0.000028			
Inverted MA Roots	.82			

Source : Prepared by the authors based on the outputs of the EViews-10 program.

Third : Diagnostic Checking

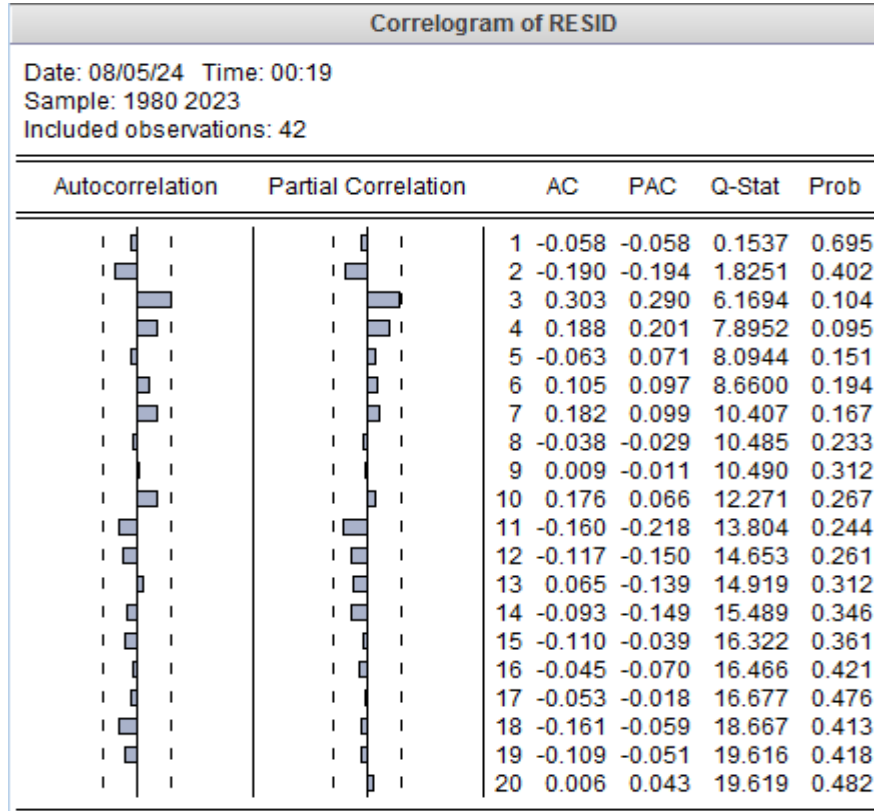
After selecting the previous ARIMA model and estimating its parameters, we verify whether the model fits the data well—i.e., whether it is appropriate. This is done through a simple test to ensure that the model residuals are purely random (**white noise**) (Bourbonnais, 2015, p. 262) and that the series is stationary. Therefore, the Box-Jenkins methodology is an iterative process, as illustrated in the following figure : (Damodar , 2003, p. 841)

Figure (6) : Steps for Building a Model According to the Box-Jenkins Methodology



One of the simplest diagnostic methods is obtaining the model residuals and calculating the **ACF** and **PACF** of these **residuals** up to the 20th lag period, as shown in the following figure :

Figure (7) : Correlogram and Partial Correlogram of the Residuals

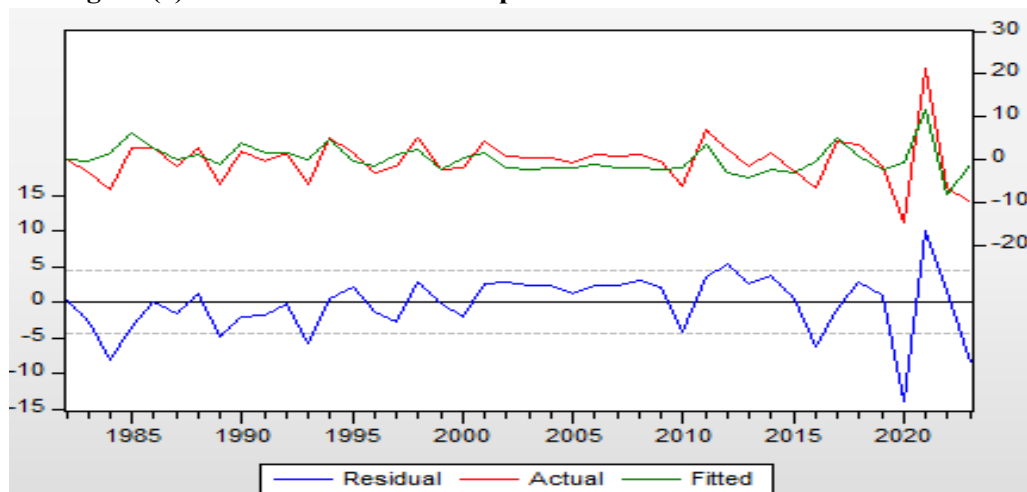


Source : Prepared by the researchers based on EViews-10 output.

It is observed that the **Correlogram**, whether for **Autocorrelation** or **Partial Correlation**, gives the impression that the estimated residuals are **purely random**. Therefore, there is no need to search for another ARIMA model.

Additionally, the residual values can be plotted, and the actual values can be compared with the estimated values, as illustrated in the following figure :

Figure (8) : Residual Plot and Comparison of Actual vs. Estimated Values



Source : Prepared by the researchers based on EViews-10 output.

The residual plot indicates that the estimated values are very close to the actual values, which also demonstrates the efficiency of the selected model.

Using the Box-Jenkins Methodology to Forecast Carbon Dioxide Emissions from Energy in Algeria up to the 2030 Horizon

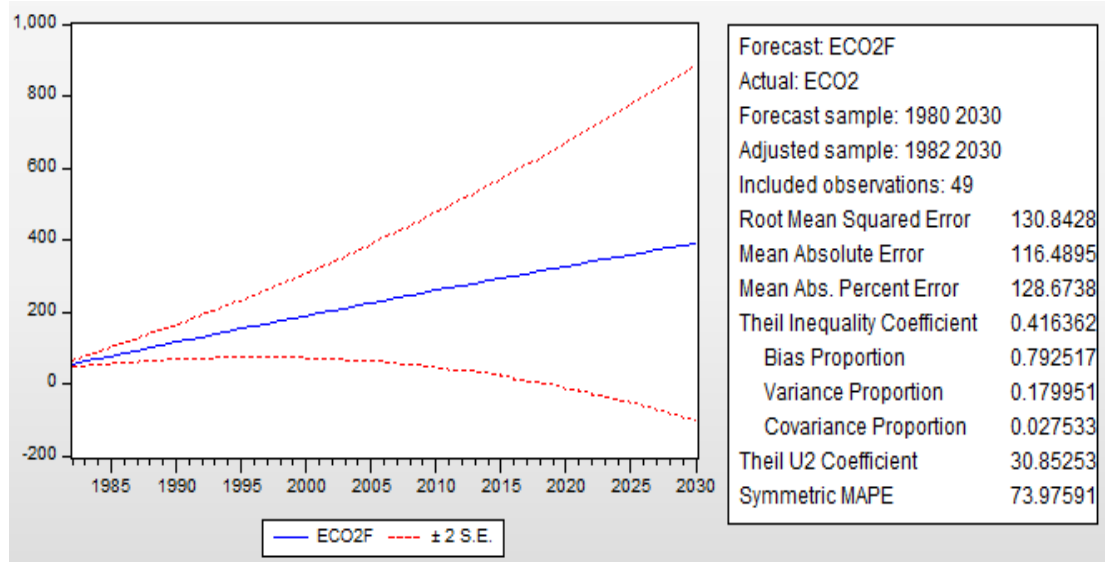
Fourth : Forecasting

The final test for a successful **ARIMA** model is to evaluate its predictive performance both within the sample period and beyond (Damodar , 2003, p. 840). Forecasting is one of the main reasons for the popularity of the **ARIMA** model.

Referring to the previous example and using **EViews**, we will extend the time series to predict the next seven periods. To do this, we enter the command **Expand** in the command bar. After pressing **Enter**, a dialog box appears to expand the time series for forecasting future values. In the **End date** field, we enter the year **2030**, assuming an extended period of seven years, and then click OK.

Returning to the estimation window of the selected model **ARIMA(0,2,1)** and selecting Forecast, a dialog box appears with several sections. One section is for naming the forecast equation, and the next section allows selecting whether to forecast the original series (**ECO2**) or its first difference (**DECO2**) or second difference. The original values **ECO2** are selected, and after clicking OK, the following results appear :

Figure (9) : Results of Theil's Test



Source : Prepared by the researchers based on Eviews-10- output.

The figure above presents some key indicators used to assess the accuracy of the selected forecasting model. One of these indicators is **Theil's Inequality Coefficient**, which has a value of **Theil Inequality Coefficient = 0.4163**, less than one. This suggests that the model is suitable and valid for forecasting.

To display the forecasted values for the next seven periods, we click on the forecast file in the workfile. The forecasted values for **ECO2** over the years 2024–2030 are presented in the following table :

Table (4) : Forecasted ECO2 Values for the Period 2024–2030

Years	2024	2025	2026	2027	2028	2029	2030
ECO2	351.9064	358.3258	364.7139	371.0708	377.3964	383.6908	389.9539

Source : Prepared by the researchers based on Figure (9).

The results indicate a continuous increase in the carbon dioxide emissions from energy (ECO2) consumption, according to the proposed forecasting model. Emissions are expected to range between 351.9064 and 389.9539 million tons during the period 2024–2030.

Conclusion:

This study sought to address the research question posed at the beginning, which revolves around forecasting and analyzing the trends the time series of carbon dioxide (CO₂) emissions from energy in Algeria up to the 2030 horizon using the **Box-Jenkins methodology**. Given that Algeria heavily relies on the petroleum industry as a fundamental pillar, the study also considered its environmental, health, social, and economic impacts.

Through theoretical and empirical analysis of Algeria's energy-related gas emissions until 2030, the study reached the following findings :

- Carbon dioxide emissions (CO₂) have become one of the most critical macroeconomic indicators in recent years due to their rapid increase, global warming, and their negative environmental impacts. This is particularly relevant for Algeria, a major energy-producing country.
- **The Box-Jenkins methodology** is designed to forecast and analyze the stochastic or probabilistic characteristics of an economic time series. It allows the dependent variable Y_t to be explained by its past values (lags) and the current and lagged values of residuals U_t .
- **The Box-Jenkins methodology** includes various time series forecasting techniques and assumes that the studied time series is stationary.
- The analysis confirmed that the CO₂ emissions time series (ECO2) is non-stationary at level but becomes stationary after taking the second difference, validating the first hypothesis.
- The **ARIMA(0,2,1)** moving average model was found to be the most suitable for the data under study. However, this result does not support the second hypothesis.
- There is a strong alignment between actual and forecasted values, as indicated by the **ARIMA(0,2,1) model**. The forecast suggests a continuous increase in energy-related gas emissions in Algeria, with emissions expected to range between **351.9064 and 389.9539 million tons** during the period **2024–2030**.

Recommendations :

Based on the findings, the following recommendations are proposed :

- Greater emphasis should be placed on econometric studies that analyze time series of macroeconomic variables.
- Researchers should be encouraged to use time series models and various forecasting methods, given their significance in future economic analysis and planning.

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-Appendices:

Appendix 1 :

Carbon dioxide emissions from energy.

Unit : million tons.

Years	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990
The carbon dioxide emissions from energy	38,5	46,3	54,3	59,0	57,0	57,6	61,0	62,7	66,9	65,1	65,4
Years	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001
The carbon dioxide emissions from energy	65,3	66,6	62,1	62,8	65,2	64,3	61,8	64,4	64,4	62,6	64,9
Years	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
The carbon dioxide emissions from energy	67,9	71,0	74,3	76,9	80,8	85,2	90,6	95,7	94,6	100,6	108,9
Years	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
The carbon dioxide emissions from energy	115,4	123,6	129,0	127,7	130,7	137,3	142,4	132,7	144,5	149,6	144,7

Source : Based on reports, publications, and statistics from the Energy Institute on the following website.
<https://www.energyinst.org/statistical-review/resources-and-data-downloads>

Appendix 2 :

Figure(3) : Model Estimation Results <u>$D(D(ECO2))$</u> c $Ar(3)$ Sample: 1982 2023 Included observations: 42 Convergence achieved after 7 iterations Coefficient covariance computed using outer product of gradients <table><tr><th>Variable</th><th>Coefficient</th><th>Std. Error</th><th>t-Statistic</th><th>Prob.</th></tr><tr><td>C</td><td>-0.336598</td><td>1.428656</td><td>-0.235605</td><td>0.8150</td></tr><tr><td>AR(3)</td><td>0.321717</td><td>0.241359</td><td>1.332942</td><td>0.1903</td></tr><tr><td>SIGMASQ</td><td>28.01425</td><td>3.425462</td><td>8.178240</td><td>0.0000</td></tr></table> R-squared 0.064620 Mean dependent var -0.302193 Adjusted R-squared 0.016652 S.D. dependent var 5.538960 S.E. of regression 5.492649 Akaike info criterion 6.321252 Sum squared resid 1176.599 Schwarz criterion 6.445371 Log likelihood -129.1475 Hannan-Quinn criter. 6.366746 F-statistic 1.347147 Durbin-Watson stat 2.862599 Prob(F-statistic) 0.271810 Inverted AR Roots .69 -34+ 59i -34- 59i	Variable	Coefficient	Std. Error	t-Statistic	Prob.	C	-0.336598	1.428656	-0.235605	0.8150	AR(3)	0.321717	0.241359	1.332942	0.1903	SIGMASQ	28.01425	3.425462	8.178240	0.0000	Figure(2) : Model Estimation Results <u>$D(D(ECO2))$</u> c $Ar(2)$ Sample: 1982 2023 Included observations: 42 Convergence achieved after 7 iterations Coefficient covariance computed using outer product of gradients <table><tr><th>Variable</th><th>Coefficient</th><th>Std. Error</th><th>t-Statistic</th><th>Prob.</th></tr><tr><td>C</td><td>-0.202431</td><td>0.685752</td><td>-0.295195</td><td>0.7694</td></tr><tr><td>AR(2)</td><td>-0.285304</td><td>0.150212</td><td>-1.899337</td><td>0.0649</td></tr><tr><td>SIGMASQ</td><td>27.57258</td><td>3.358631</td><td>8.209469</td><td>0.0000</td></tr></table> R-squared 0.079368 Mean dependent var -0.302193 Adjusted R-squared 0.032156 S.D. dependent var 5.538960 S.E. of regression 5.449178 Akaike info criterion 6.301599 Sum squared resid 1158.048 Schwarz criterion 6.425718 Log likelihood -129.3336 Hannan-Quinn criter. 6.347093 F-statistic 1.681090 Durbin-Watson stat 3.052291 Prob(F-statistic) 0.199381 Inverted AR Roots -.00+ 53i -.00- 53i	Variable	Coefficient	Std. Error	t-Statistic	Prob.	C	-0.202431	0.685752	-0.295195	0.7694	AR(2)	-0.285304	0.150212	-1.899337	0.0649	SIGMASQ	27.57258	3.358631	8.209469	0.0000	Figure(1) : Model Estimation Results <u>$D(D(ECO2))$</u> c $Ar(1)$ Sample: 1982 2023 Included observations: 42 Convergence achieved after 23 iterations Coefficient covariance computed using outer product of gradients <table><tr><th>Variable</th><th>Coefficient</th><th>Std. Error</th><th>t-Statistic</th><th>Prob.</th></tr><tr><td>C</td><td>-0.237415</td><td>0.772364</td><td>-0.307388</td><td>0.7602</td></tr><tr><td>AR(1)</td><td>-0.409022</td><td>0.145610</td><td>-2.809024</td><td>0.0077</td></tr><tr><td>SIGMASQ</td><td>25.08293</td><td>4.569112</td><td>5.489673</td><td>0.0000</td></tr></table> R-squared 0.162495 Mean dependent var -0.302193 Adjusted R-squared 0.119547 S.D. dependent var 5.538960 S.E. of regression 5.197344 Akaike info criterion 6.207281 Sum squared resid 1053.483 Schwarz criterion 6.331400 Log likelihood -127.3529 Hannan-Quinn criter. 6.252775 F-statistic 3.783457 Durbin-Watson stat 2.311304 Prob(F-statistic) 0.031496 Inverted AR Roots -.41	Variable	Coefficient	Std. Error	t-Statistic	Prob.	C	-0.237415	0.772364	-0.307388	0.7602	AR(1)	-0.409022	0.145610	-2.809024	0.0077	SIGMASQ	25.08293	4.569112	5.489673	0.0000					
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Figure(5) : Model Estimation Results <u>$D(D(ECO2))$</u> c $Ar(1)$ $Ma(1)$ Dependent Variable: D(DENR) Method: ARMA Maximum Likelihood (OPG - BHHH) Date: 08/04/24 Time: 19:34 Sample: 1982 2023 Included observations: 42 Convergence achieved after 34 iterations Coefficient covariance computed using outer product of gradients <table><tr><th>Variable</th><th>Coefficient</th><th>Std. Error</th><th>t-Statistic</th><th>Prob.</th></tr><tr><td>C</td><td>-0.046121</td><td>0.196195</td><td>-0.235078</td><td>0.8154</td></tr><tr><td>AR(1)</td><td>-0.103899</td><td>0.212317</td><td>-0.489357</td><td>0.6274</td></tr><tr><td>MA(1)</td><td>-0.781264</td><td>0.179569</td><td>-4.350761</td><td>0.0001</td></tr><tr><td>SIGMASQ</td><td>17.40950</td><td>4.051570</td><td>4.296976</td><td>0.0001</td></tr></table> R-squared 0.418707 Mean dependent var -0.302193 Adjusted R-squared 0.372815 S.D. dependent var 5.538960 S.E. of regression 4.386579 Akaike info criterion 5.911786 Sum squared resid 731.1989 Schwarz criterion 6.077278 Log likelihood -120.1475 Hannan-Quinn criter. 5.972446 F-statistic 9.123832 Durbin-Watson stat 1.952327 Prob(F-statistic) 0.000112 Inverted AR Roots -.10 Inverted MA Roots .78	Variable	Coefficient	Std. Error	t-Statistic	Prob.	C	-0.046121	0.196195	-0.235078	0.8154	AR(1)	-0.103899	0.212317	-0.489357	0.6274	MA(1)	-0.781264	0.179569	-4.350761	0.0001	SIGMASQ	17.40950	4.051570	4.296976	0.0001	Figure(4) : Model Estimation Results <u>$D(D(ECO2))$</u> c $MA(2)$ Sample: 1982 2023 Included observations: 42 Convergence achieved after 13 iterations Coefficient covariance computed using outer product of gradients <table><tr><th>Variable</th><th>Coefficient</th><th>Std. Error</th><th>t-Statistic</th><th>Prob.</th></tr><tr><td>C</td><td>-0.206935</td><td>0.687151</td><td>-0.301149</td><td>0.7649</td></tr><tr><td>MA(2)</td><td>-0.222680</td><td>0.160347</td><td>-1.388736</td><td>0.1728</td></tr><tr><td>SIGMASQ</td><td>28.12181</td><td>3.462958</td><td>8.120748</td><td>0.0000</td></tr></table> R-squared 0.061029 Mean dependent var -0.302193 Adjusted R-squared 0.012877 S.D. dependent var 5.538960 S.E. of regression 5.503183 Akaike info criterion 6.319701 Sum squared resid 1181.116 Schwarz criterion 6.443821 Log likelihood -129.7137 Hannan-Quinn criter. 6.365196 F-statistic 1.267413 Durbin-Watson stat 2.980870 Prob(F-statistic) 0.292899 Inverted MA Roots .47 -.47	Variable	Coefficient	Std. Error	t-Statistic	Prob.	C	-0.206935	0.687151	-0.301149	0.7649	MA(2)	-0.222680	0.160347	-1.388736	0.1728	SIGMASQ	28.12181	3.462958	8.120748	0.0000	Figure(3) : Model Estimation Results <u>$D(D(ECO2))$</u> c $Ma(1)$ Sample: 1982 2023 Included observations: 42 Convergence achieved after 18 iterations Coefficient covariance computed using outer product of gradients <table><tr><th>Variable</th><th>Coefficient</th><th>Std. Error</th><th>t-Statistic</th><th>Prob.</th></tr><tr><td>C</td><td>-0.031250</td><td>0.142229</td><td>-0.219718</td><td>0.8272</td></tr><tr><td>MA(1)</td><td>-0.824742</td><td>0.125419</td><td>-6.575879</td><td>0.0000</td></tr><tr><td>SIGMASQ</td><td>17.50777</td><td>3.845165</td><td>4.553192</td><td>0.0000</td></tr></table> R-squared 0.415425 Mean dependent var -0.302193 Adjusted R-squared 0.385447 S.D. dependent var 5.538960 S.E. of regression 4.342180 Akaike info criterion 5.870523 Sum squared resid 735.3265 Schwarz criterion 5.994643 Log likelihood -120.2810 Hannan-Quinn criter. 5.916018 F-statistic 13.85760 Durbin-Watson stat 2.009858 Prob(F-statistic) 0.000028 Inverted MA Roots .82	Variable	Coefficient	Std. Error	t-Statistic	Prob.	C	-0.031250	0.142229	-0.219718	0.8272	MA(1)	-0.824742	0.125419	-6.575879	0.0000	SIGMASQ	17.50777	3.845165	4.553192	0.0000
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SIGMASQ	17.50777	3.845165	4.553192	0.0000																																																															

Source : Prepared by the researchers based on Eviews-10- output.

Figure(8) : Model Estimation Results <u>$D(D(ECO2)) \text{ c } Ar(2) \text{ MA}(2)$</u> Sample: 1982 2023 Included observations: 42 Convergence achieved after 20 iterations Coefficient covariance computed using outer product of gradients <table><tr><th>Variable</th><th>Coefficient</th><th>Std. Error</th><th>t-Statistic</th><th>Prob.</th></tr><tr><td>C</td><td>-0.218086</td><td>0.720429</td><td>-0.302717</td><td>0.7638</td></tr><tr><td>AR(2)</td><td>-0.525148</td><td>0.1034072</td><td>-0.507845</td><td>0.6145</td></tr><tr><td>MA(2)</td><td>0.246381</td><td>1.198986</td><td>0.205491</td><td>0.8383</td></tr><tr><td>SIGMASQ</td><td>27.30068</td><td>4.804651</td><td>5.682136</td><td>0.0000</td></tr></table> R-squared 0.088446 Mean dependent var -0.302193 Adjusted R-squared 0.016481 S.D. dependent var 5.538960 S.E. of regression 5.493126 Akaike info criterion 6.340416 Sum squared resid 1146.629 Schwarz criterion 6.505908 Log likelihood -129.1487 Hannan-Quinn criter. 6.401075 F-statistic 1.229017 Durbin-Watson stat 3.040483 Prob(F-statistic) 0.312504 Inverted AR Roots -.00+ .72i -.00- .72i Inverted MA Roots -.00+ .50i -.00- .50i	Variable	Coefficient	Std. Error	t-Statistic	Prob.	C	-0.218086	0.720429	-0.302717	0.7638	AR(2)	-0.525148	0.1034072	-0.507845	0.6145	MA(2)	0.246381	1.198986	0.205491	0.8383	SIGMASQ	27.30068	4.804651	5.682136	0.0000	Figure(7) : Model Estimation Results <u>$D(D(ECO2)) \text{ c } Ar(2) \text{ MA}(1)$</u> Sample: 1982 2023 Included observations: 42 Convergence achieved after 22 iterations Coefficient covariance computed using outer product of gradients <table><tr><th>Variable</th><th>Coefficient</th><th>Std. Error</th><th>t-Statistic</th><th>Prob.</th></tr><tr><td>C</td><td>-0.048669</td><td>0.171439</td><td>-0.283884</td><td>0.7780</td></tr><tr><td>AR(2)</td><td>-0.338616</td><td>0.191715</td><td>-1.766247</td><td>0.0854</td></tr><tr><td>MA(1)</td><td>-0.719337</td><td>0.121858</td><td>-5.903080</td><td>0.0000</td></tr><tr><td>SIGMASQ</td><td>16.01535</td><td>3.278310</td><td>4.885246</td><td>0.0000</td></tr></table> R-squared 0.465257 Mean dependent var -0.302193 Adjusted R-squared 0.423040 S.D. dependent var 5.538960 S.E. of regression 4.207276 Akaike info criterion 5.832737 Sum squared resid 672.6446 Schwarz criterion 5.998230 Log likelihood -118.4875 Hannan-Quinn criter. 5.893397 F-statistic 11.02071 Durbin-Watson stat 2.253665 Prob(F-statistic) 0.000024 Inverted AR Roots -.00+ .58i -.00- .58i Inverted MA Roots .72	Variable	Coefficient	Std. Error	t-Statistic	Prob.	C	-0.048669	0.171439	-0.283884	0.7780	AR(2)	-0.338616	0.191715	-1.766247	0.0854	MA(1)	-0.719337	0.121858	-5.903080	0.0000	SIGMASQ	16.01535	3.278310	4.885246	0.0000	Figure(6) : Model Estimation Results <u>$D(D(ECO2)) \text{ c } Ar(1) \text{ MA}(2)$</u> Sample: 1982 2023 Included observations: 42 Convergence achieved after 38 iterations Coefficient covariance computed using outer product of gradients <table><tr><th>Variable</th><th>Coefficient</th><th>Std. Error</th><th>t-Statistic</th><th>Prob.</th></tr><tr><td>C</td><td>-0.012806</td><td>0.151788</td><td>-0.084371</td><td>0.9332</td></tr><tr><td>AR(1)</td><td>-0.770266</td><td>0.145331</td><td>-5.300087</td><td>0.0000</td></tr><tr><td>MA(2)</td><td>-0.731796</td><td>0.207044</td><td>-3.534500</td><td>0.0011</td></tr><tr><td>SIGMASQ</td><td>17.16375</td><td>3.793957</td><td>4.523970</td><td>0.0001</td></tr></table> R-squared 0.426912 Mean dependent var -0.302193 Adjusted R-squared 0.381668 S.D. dependent var 5.538960 S.E. of regression 4.355509 Akaike info criterion 5.901973 Sum squared resid 720.8775 Schwarz criterion 6.067465 Log likelihood -119.9414 Hannan-Quinn criter. 5.962632 F-statistic 9.435824 Durbin-Watson stat 2.121302 Prob(F-statistic) 0.000086 Inverted AR Roots -.77 Inverted MA Roots .86 -.86	Variable	Coefficient	Std. Error	t-Statistic	Prob.	C	-0.012806	0.151788	-0.084371	0.9332	AR(1)	-0.770266	0.145331	-5.300087	0.0000	MA(2)	-0.731796	0.207044	-3.534500	0.0011	SIGMASQ	17.16375	3.793957	4.523970	0.0001
Variable	Coefficient	Std. Error	t-Statistic	Prob.																																																																									
C	-0.218086	0.720429	-0.302717	0.7638																																																																									
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SIGMASQ	17.16375	3.793957	4.523970	0.0001																																																																									
Figure(11) : Model Estimation Results <u>$D(ECO2) \text{ c } MA(1)$</u> Sample: 1982 2023 Included observations: 42 Convergence achieved after 18 iterations Coefficient covariance computed using outer product of gradients <table><tr><th>Variable</th><th>Coefficient</th><th>Std. Error</th><th>t-Statistic</th><th>Prob.</th></tr><tr><td>C</td><td>-0.031250</td><td>0.142229</td><td>-0.219718</td><td>0.8272</td></tr><tr><td>MA(1)</td><td>-0.824742</td><td>0.125419</td><td>-6.575879</td><td>0.0000</td></tr><tr><td>SIGMASQ</td><td>17.50777</td><td>3.845165</td><td>4.553192</td><td>0.0001</td></tr></table> R-squared 0.415425 Mean dependent var -0.302193 Adjusted R-squared 0.385447 S.D. dependent var 5.538960 S.E. of regression 4.342180 Akaike info criterion 5.870523 Sum squared resid 735.3265 Schwarz criterion 5.994643 Log likelihood -120.2810 Hannan-Quinn criter. 5.916018 F-statistic 13.85760 Durbin-Watson stat 2.009858 Prob(F-statistic) 0.000028 Inverted MA Roots .82	Variable	Coefficient	Std. Error	t-Statistic	Prob.	C	-0.031250	0.142229	-0.219718	0.8272	MA(1)	-0.824742	0.125419	-6.575879	0.0000	SIGMASQ	17.50777	3.845165	4.553192	0.0001	Figure(10) : Model Estimation Results <u>$D(D(ECO2)) \text{ c } Ar(3) \text{ MA}(2)$</u> Sample: 1982 2023 Included observations: 42 Convergence achieved after 25 iterations Coefficient covariance computed using outer product of gradients <table><tr><th>Variable</th><th>Coefficient</th><th>Std. Error</th><th>t-Statistic</th><th>Prob.</th></tr><tr><td>C</td><td>-0.257766</td><td>1.099554</td><td>-0.234427</td><td>0.8159</td></tr><tr><td>AR(3)</td><td>0.204611</td><td>0.303189</td><td>0.674862</td><td>0.5038</td></tr><tr><td>MA(2)</td><td>-0.134949</td><td>0.174391</td><td>-0.773828</td><td>0.4438</td></tr><tr><td>SIGMASQ</td><td>27.70374</td><td>3.368866</td><td>8.223460</td><td>0.0000</td></tr></table> R-squared 0.074988 Mean dependent var -0.302193 Adjusted R-squared 0.001961 S.D. dependent var 5.538960 S.E. of regression 5.533527 Akaike info criterion 6.353846 Sum squared resid 1163.557 Schwarz criterion 6.519338 Log likelihood -129.4308 Hannan-Quinn criter. 6.414505 F-statistic 1.026851 Durbin-Watson stat 2.985130 Prob(F-statistic) 0.391571 Inverted AR Roots .59 -.29- .51i -.29+ .51i Inverted MA Roots .37	Variable	Coefficient	Std. Error	t-Statistic	Prob.	C	-0.257766	1.099554	-0.234427	0.8159	AR(3)	0.204611	0.303189	0.674862	0.5038	MA(2)	-0.134949	0.174391	-0.773828	0.4438	SIGMASQ	27.70374	3.368866	8.223460	0.0000	Figure(9) : Model Estimation Results <u>$D(D(ECO2)) \text{ c } Ar(3) \text{ MA}(1)$</u> Sample: 1982 2023 Included observations: 42 Failure to improve objective (non-zero gradients) after 34 iterations Coefficient covariance computed using outer product of gradients <table><tr><th>Variable</th><th>Coefficient</th><th>Std. Error</th><th>t-Statistic</th><th>Prob.</th></tr><tr><td>C</td><td>0.011058</td><td>0.089648</td><td>0.123351</td><td>0.9025</td></tr><tr><td>AR(3)</td><td>0.420538</td><td>0.222480</td><td>1.890228</td><td>0.0664</td></tr><tr><td>MA(1)</td><td>-1.000000</td><td>1565.996</td><td>-0.000639</td><td>0.9995</td></tr><tr><td>SIGMASQ</td><td>14.67550</td><td>508.6168</td><td>0.028854</td><td>0.9771</td></tr></table> R-squared 0.509993 Mean dependent var -0.302193 Adjusted R-squared 0.471309 S.D. dependent var 5.538960 S.E. of regression 4.072442 Akaike info criterion 5.794300 Sum squared resid 616.3711 Schwarz criterion 5.959792 Log likelihood -117.6803 Hannan-Quinn criter. 5.854959 F-statistic 13.18332 Durbin-Watson stat 1.924390 Prob(F-statistic) 0.000005 Inverted AR Roots .75 -.37+ .65i -.37- .65i Inverted MA Roots 1.00	Variable	Coefficient	Std. Error	t-Statistic	Prob.	C	0.011058	0.089648	0.123351	0.9025	AR(3)	0.420538	0.222480	1.890228	0.0664	MA(1)	-1.000000	1565.996	-0.000639	0.9995	SIGMASQ	14.67550	508.6168	0.028854	0.9771					
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Source : Prepared by the researchers based on Eviews-10- output.