pThe Impact of Electricity Consumption Efficiency on Climate Change Mitigation in Algeria: An ARDL Analysis (1990-2022)

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Abstract:

This study aims to investigate the impact of electricity consumption efficiency on climate change mitigation in Algeria during the period 1990- 2022. Electricity intensity is employed as a proxy for electricity efficiency, and its relationship with carbon dioxide (CO_2) emissions is empirically examined using the autoregressive distributed lag (ARDL) approach. The results reveal that electricity intensity has a statistically significant and positive effect on CO_2 emissions in both the short and long-run during the studied period, indicating that lower efficiency in electricity use contributes to higher carbon emissions. These findings highlight the importance of improving electricity efficiency as a key policy instrument for reducing emissions and supporting Algeria's climate change mitigation efforts.

Keywords: Electricity efficiency; electricity intensity; carbon emissions; climate change; ARDL.

Jel Classification Codes: P48, Q43, Q51, Q54.

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1. Introduction :

Climate change, of which global warming is a significant concern, is one of the most worrisome phenomena on the worldwide level, as it impacts all aspects of life. Therefore, global efforts have been consolidating for more than thirty years to collaborate in confronting this problem. This collaboration was shaped by various international agreements, which have defined the requirements for climate action, established unified objectives, and proposed applicable strategies to achieve the targeted outcomes, most notably mitigating global warming. Among the widely endorsed strategies for alleviating climate change effects is enhancing energy efficiency, which seeks to optimize energy use and minimize unnecessary consumption. In this context, electricity stands out as one of the most widely used forms of energy in modern life. Since electricity generation from non-renewable resources is associated with high levels of emissions due to the burning of fossil fuels, it is essential to promote energy-saving practices and consequently reduce electricity demand. This approach is expected to significantly contribute to reducing greenhouse gas emissions.

Similar to many other countries, Algeria is committed to reducing greenhouse gas emissions through various strategies, one of which is improving the efficiency of electricity consumption. This is particularly necessary given that electricity production in Algeria is based on non-renewable energy sources, resulting in a high rate of CO2 emissions.

— **Problem statement**: for examining the electricity efficiency impact on greenhouse gas emissions -specifically carbon emissions - in Algeria, the research adopts the following problem statement:

What is the impact of electricity consumption efficiency on reducing carbon dioxide emissions in Algeria?

— **Research hypothesis**: The study hypothesizes that improvements in electricity consumption efficiency significantly reduce carbon dioxide emissions in Algeria.

— **Previous studies:**

Many studies have been conducted to investigate the impact of energy efficiency on reducing greenhouse gas emissions, particularly carbon emissions:

— Li et al (2022) examined whether nations can lower CO_2 emissions through increased energy efficiency without impeding economic growth in the post-COVID-19 period. They examined labor, capital, and energy inputs as well as outputs like GDP and carbon emissions in 49 countries using a Data Envelopment Analysis (DEA) model. According to their findings, energy efficiency and NO_2, SO_2, and particulate matter emissions were found to be significantly inversely correlated.

— Mirza et al (2022) examined the energy efficiency impact on CO2 emissions in developing countries. They employed a second-generation panel data analysis. The study concluded that improving energy efficiency reduces CO2 emissions, while structural changes have a limited or even negative effect due to a shift toward more polluting industries.

— Hakan Altın (2024) explored the influence of renewable energy usage and energy efficiency on carbon emissions in the Group of Seven (G7). The study employed a cross-sectional panel data model. The main findings were the existence of a long-run cointegrating relationship that links renewable energy usage, energy efficiency, and CO2 emissions. Furthermore, a long-run relationship indicates that energy efficiency improvements reduce CO2 emissions.

— Liu et Al (2022) explored how energy efficiency can reduce CO2 emissions in the US while controlling trade, population, and economic growth. They employed the novel Fourier ARDL model. The study revealed that energy efficiency reduces emissions in the long and short run.

— Mecu et al (2023) analyzed the effect of renewable energy sources usage and energy efficiency on the economic growth and greenhouse gas emissions in the member countries of the EU. The study used a panel data regression model. The findings revealed that renewable energy production and energy efficiency reduce greenhouse gas emissions while positively influencing economic growth.

— **Position and objective of this study**: while the above studies have examined the impact of energy efficiency on the CO2 emissions in various global contexts, our study aims to investigate the role of electricity consumption efficiency in the specific context of Algeria. To achieve this objective, the study employs the ARDL model to capture both short- and long-run dynamics. This approach offers new insights specific to the Algerian case.

2. Conceptual framework

2. 1. Climate change and greenhouse gases:

Climate change refers to the long-term shifts in temperature and weather patterns that are caused by natural factors, such as solar activity changes or significant volcanic eruptions. However, since the 19th century, human activities have been the primary cause of climate change. This predominance of human influence on climate change is yielded mainly by the process of fossil fuels burning, such as coal, oil, and gas, used in industrial processes, electricity generation, transportation, and home heating, which produces greenhouse gas emissions that form a heat-trapping layer around the earth, trapping the sun's heat and raising temperatures. Energy, industry, transportation, buildings, agriculture, and land use are among the major sectors causing greenhouse gas emissions. (Climate Action (UN), 2025).

2.2. The economic effects of greenhouse gas emissions:

The main economic effects of greenhouse gases emiddions are: (Zhang, 2023, pp. 8-9)

— **Gross domestic product**: the Swiss Re Institute indicates that failure to achieve net-zero emissions targets and a 3.2°C temperature rise could result in a loss of up to 18% of global GDP by 2050. The International Monetary Fund also warns that climate change poses a significant global economic threat, as it is an externality that affects all countries. According to Bloomberg Economics models, rising temperatures, as in the "Hothouse Planet" scenario, will have long-term impacts on major economies.

— **The energy industry**: since energy is the primary sector that produces emissions from the burning of coal and oil, it is among the industries most affected by global warming. Governments are attempting to transition to renewable energy sources, such as solar and wind.

— **Agriculture**: due to rising temperatures and unpredictable rainfall, climate change harms crop yields and livestock. Also, the accelerated spread of pests and diseases affects food security and prices. Global warming may also lead to the displacement of farmers, and trade patterns may shift due to the decline in agricultural land areas resulting from extreme climate conditions.

— **Production and tourism outputs**: many industries that heavily rely on the climate and natural resources are exposed to lower production due to severe weather events that damage infrastructure and disrupt supply chains. Due to higher ocean temperatures, the tourism industry may be impacted by the destruction of coral reefs, and fisheries production may decline as a result. The cost of healthcare is also increasing, and unsafe populations are disproportionately affected by the lack of essential services, including food, water, and healthcare.

2. 3. Sources of greenhouse gas emissions:

The main sources of greenhouse gas emissions are: (Climate Action (UN), 2025)

— **Power generation**: since it relies heavily on the combustion of fossil fuels, resulting in substantial greenhouse gas emissions, and renewable energy sources, which still account for a small portion of total production.

— **Manufacturing**: it generates significant emissions, both from the burning of fossil fuels for energy generation and from industrial processes such as cement and steel production, as well as mining and plastics manufacturing.

— **Deforestation**: cutting down trees releases stored carbon, reducing the forests' ability to absorb carbon dioxide. Deforestation, along with agricultural activities, accounts for approximately a quarter of global emissions.

— **Transportation**: most transportation relies on fossil fuels, making it a significant source of carbon dioxide emissions, particularly from road vehicles, while emissions from aircraft and ships continue to rise.

— **Food production**: contributes to emissions through deforestation, fertilizer use, agricultural and livestock operations, and the energy consumed in operating equipment and transporting food products.

— **Buildings:** due to the increased use of electrical appliances and the fact that residential and commercial buildings use more than half of the world's electricity and rely on fossil fuels for heating and cooling, greenhouse gas emissions are rising.

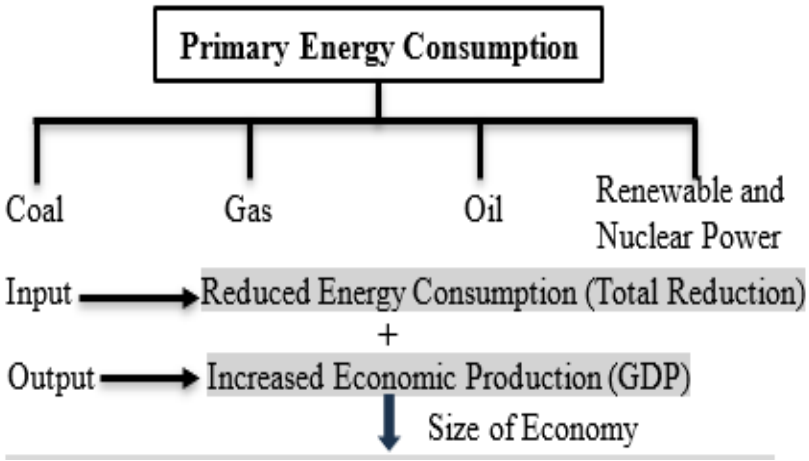
— **Excessive consumption**: lifestyle impacts emissions, from energy use in homes and transportation to the consumption of products such as clothing and electronics. The wealthy bear the brunt of these emissions, with the richest 1% of the population producing more greenhouse gases than the poorest 50%.

2.4. Energy efficiency:

2.4.1. Definition of energy efficiency: It refers to the ratio of the output of goods, services, performance, or energy to the energy input. (Erbach, 2015, p.2)

2.4.2. Distinction between energy efficiency and energy intensity: Energy efficiency refers to producing more economic output (GDP) with the same or less energy input. It reflects improvements in technology, management, and energy use. Energy intensity, by contrast, measures total primary energy consumption per unit of GDP and serves as a macro-level indicator of an economy's energy dependency. Improving energy efficiency helps reduce energy intensity, but intensity can also fall due to structural changes or a cleaner energy mix. The figure below illustrates this relationship: reducing fossil energy use and increasing GDP leads to better energy efficiency and lower energy intensity, supporting sustainable growth and emissions reduction. (Sueyoshi & Goto, 2023, p 9).

Figure 01: The energy efficiency and Energy Intensity



Source: Sueyoshi, T., & Goto, M. (2023). Energy intensity, energy efficiency and economic growth among OECD nations. Energies, 16(4), 1927. p.9

2.4.3. Energy Efficiency Indicators:

Energy efficiency indicators are tools used to assess energy savings and monitor efficiency improvements. These indicators vary depending on the areas and levels at which energy efficiency is measured, relying on the available statistics for each level. At the macroeconomic level, energy intensity indicators link energy consumption to economic metrics like GDP or value added (ODYSSEE-MURE Project Team, 2020, p.1-2). In other words, they express the amount of energy input required to create a unit of output. At the national level, energy intensity is commonly measured as the ratio of total annual energy used to GDP, where a lower energy intensity indicates higher energy efficiency. (Pillai & Narayanan, 2019, p.6)

3. Data and methodology

3.1 The econometric model:

3.1.1. Data Source and Variable Description: Data were obtained from World Bank Open Data- World Development Indicators for the period 1990-2022. The variables employed in the empirical analyses include:

- Carbon Emissions (CEM): refers to the quantity of CO2 emissions (Mt CO2e).
- Electricity Intensity (INT): reflects the consumption of electricity per unit of GDP
- GDP per Capita (CAP): represents the economic output per person.
- Labour (LAB): refers to the total labour input (% of male population ages 15-64).

In addition to the main independent variable, electricity intensity, other independent variables were included based on previous empirical studies that recognize them as key determinants of carbon emissions, particularly those by Liu et al. (2022) and Li et al. (2022).

3.1.2. Definition of the econometric model:

To conduct the empirical study, the Autoregressive Distributed Lag model (ARDL) is employed. This modelling approach is particularly advantageous because it accommodates variables that are integrated of different orders - specifically, I(0) or I(1)-but excludes variables integrated of order two (I(2)). The cointegration testing within the ARDL model is valid regardless of whether variables are I(0) or I(1). The ARDL bounds testing approach enables robust inference in the presence of mixed orders of integration and is particularly appropriate for small sample sizes. In contrast to classical cointegration methods, the Autoregressive Distributed Lag (ARDL) model enables the estimation of both short-run and long-run dynamics within a single-equation framework. Additionally, ARDL modelling allows for the assessment of the direction and strength of each independent variable's influence in both the short and long term since it captures the integrating relationship between dependent and independent variables across different periods. A notable advantage of the ARDL model is its capacity to incorporate an optimal

number of lagged terms, which enhances model specification and improves the reliability of estimates. The selection of appropriate lag lengths is typically guided by information criteria such as the Akaike Information Criterion (AIC) and the Schwarz Criterion (SC), with the optimal lag structure corresponding to the minimum values of these criteria. (Nkoro & Uko, 2016, p.76-79).

3.1.3. Functional form of the model: The general specification of the ARDL model is given as follows:

$$d(\gamma_t) = c + \lambda\gamma_{t-1} + \beta X_{t-1} + \sum_{i=1}^{m} \alpha_{1,i} * d(\gamma_{t-i}) + \sum_{i=0}^{k} \alpha_{2,i} * d(X_{t-i}) + \varepsilon_t$$

Where :

- The first section of the equation represents the long-term relationship information.
- The second part represents the lags of the dependent variable.
- The third section represents the first-differenced lags of the independent variables. The second and third sections represent short-term relationships.
- The last section represents the residual term (white noise error term).

3.1.4. Econometric modeling steps: The main steps of ARDL modelling are as follows: (Bachouche &Tahraoui, 2024)

– Use unit root tests to ensure that variables are not integrated of order two.

– Create an unrestricted error correction model.

– Select the appropriate lag length for the model.

– Ensure that there is no autocorrelation among the errors in the model.

– Be sure that the model is dynamically stable.

– Conduct a "bounds test" to examine the presence of a long-run relationship.

– If the previous step yields a positive outcome, estimate the long-term and short-term relationships, as well as the unrestricted error correction model.

– Measure the dynamic effects of the short and long-term relationships between the variables using the estimated model results from the previous step.

3.2 Model Estimation:

3.2.1. Time series stationary: To examine unit roots in time series data, several methods can be applied, including the Augmented Dickey-Fuller (ADF) test. This test assesses the stationarity properties, integration order, and behavior of each variable included in the study model.

Table 01: ADF Test Results for Time Series Stationarity

Type Series \ Model		Model 3			Model 2		Model 1	Result
		B	C	Φ	C	Φ	Φ	
cem	p.value	0.0865			0.9114		1.0000	DS
int	p.value	0.1976			0.5894		0.0002	Stationary at level
cap	p.value	0.1680			0.6589		0.9710	DS
lab	p.value	0.0096		0.2265				DS
After the 1st difference								
			Series	**p.value**				
			D(cem)	0.0007				
			D(cap)	0.0272				
			D(lab)	0.0131				

Source: Prepared by the researcher based on the Eviews 13 outputs

According to the above table, the INT time series is stationary at the level, and the others are differenced stationary (DS). Therefore, the first difference was applied to them to become stationary.

3.2.2. Optimal lag selection and ARDL estimation: The selection of optimal lag structure based on the Akaike Information Criterion (AIC) (appendix 01). Accordingly, the ARDL model with the lag order (3, 4, 4, 4) was chosen as the most appropriate specification.

Table 02: Estimation of the ARDL Model with Lag Order (3, 4, 4, 4)

Dependent Variable: CEM
Method: ARDL
Date: 07/07/25 Time: 15:57
Sample: 1994 2022
Included observations: 29
Dependent lags: 4 (Automatic)
Automatic-lag linear regressors (4 max. lags): INT CAP LAB
Deterministics: Restricted constant and no trend (Case 2)
Model selection method: Akaike info criterion (AIC)
Number of models evaluated: 500
Selected model: ARDL(3,4,4,4)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
CEM(-1)	0.085362	0.212682	0.401360	0.6966
CEM(-2)	-0.281193	0.209657	-1.341206	0.2095
CEM(-3)	0.375836	0.157669	2.383702	0.0384
INT	5.065440	1.550042	3.267937	0.0085
INT(-1)	5.169382	2.179778	2.371518	0.0392
INT(-2)	3.364115	2.350825	1.431036	0.1829
INT(-3)	-2.086968	2.218635	-0.940654	0.3690
INT(-4)	-3.221817	1.978650	-1.628291	0.1345
CAP	0.771878	0.374786	2.059516	0.0664
CAP(-1)	0.267941	0.487521	0.549600	0.5947
CAP(-2)	0.373756	0.456277	0.819142	0.4318
CAP(-3)	0.016046	0.415675	0.038603	0.9700
CAP(-4)	0.916093	0.358412	2.555981	0.0286
LAB	0.126112	0.060709	2.077326	0.0645
LAB(-1)	0.021419	0.101065	0.211931	0.8364
LAB(-2)	0.156669	0.103181	1.518390	0.1599
LAB(-3)	-0.116828	0.232450	-0.502592	0.6261
LAB(-4)	0.554427	0.217560	2.548386	0.0289
C	-24.65857	7.550275	-3.265917	0.0085

Source: from Eviews 13 outputs

As shown in the table above, the F-value of (414.682), along with a p-value of (0.0000), indicates that the model is globally significant.

3.2.3. Error correction model estimation:

Table 03: Error Correction Model Estimation Results

Error Correction

Dependent Variable: D(CEM)
Method: ARDL
Date: 07/07/25 Time: 15:57
Sample: 1994 2022
Included observations: 29
Dependent lags: 4 (Automatic)
Automatic-lag linear regressors (4 max. lags): INT CAP LAB
Deterministics: Restricted constant and no trend (Case 2)
Model selection method: Akaike info criterion (AIC)
Number of models evaluated: 500
Selected model: ARDL(3,4,4,4)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
COINTEQ*	-0.819994	0.128297	-6.391359	0.0000
D(CEM(-1))	-0.094644	0.120328	-0.786550	0.4447
D(CEM(-2))	-0.375836	0.110820	-3.391398	0.0044
D(INT)	5.065440	1.064458	4.758703	0.0003
D(INT(-1))	1.944670	1.262318	1.540555	0.1457
D(INT(-2))	5.308785	1.378742	3.850456	0.0018
D(INT(-3))	3.221817	1.501590	2.145603	0.0499
D(CAP)	0.771878	0.216311	3.568373	0.0031
D(CAP(-1))	-1.305895	0.314398	-4.153641	0.0010

As shown in the above table, the error correction term (COINTEQ*), has a coefficient of (–0.819994), which is both negative and highly significant (p=0.0000), confirming the presence of a strong short-run equilibrium relationship among carbon emissions (CEM) as a dependent variable, and energy intensity (INT), GDP per capita (CAP), and labor (LAB) as independent variables. Additionally, the magnitude of the error correction term coefficient indicates that nearly 82% of deviations from the long-run equilibrium are corrected within one year, suggesting a rapid and robust adjustment mechanism.

3.2.4. Bounds Test for Long-Run Relationship Determination:

Table 04: Bounds test results

Bounds Test

Null hypothesis: No levels relationship
Number of cointegrating variables: 3
Trend type: Rest. constant (Case 2)
Sample size: 29

Test Statistic	Value
F-statistic	5.835638

Bounds Critical Values

	10%		5%		1%	
Sample Size	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
30	2.676	3.586	3.272	4.306	4.614	5.966
Asymptotic	2.370	3.200	2.790	3.670	3.650	4.660

According to bounds test results (table 04), the calculated F-statistic (5.836) lies above the upper bound (I(1)) critical value at the 5% level (4.306), showing that there is strong evidence of cointegration at the 5% significance level, confirming the presence of an equilibrium relationship in the long run between variables. This justifies the estimation and interpretation of the long-run coefficients within the ARDL framework.

3.2.5. Estimation of the long-term model: This process allows for the identification of the long-term dynamics among the variables by capturing the cointegrating relationship within a single reduced-form equation. Accordingly, the estimation yielded the following long-run coefficients:

Table 05: Results of the Long-term Model Estimation

Cointegrating Specification

Deterministics: Rest. constant (Case 2)

CE = CEM(-1) - (10.110012*INT(-1) + 2.860647*CAP(-1) + 0.904640*LAB(-1) - 30.071635)

Cointegrating Coefficients

Variable *	Coefficient	Std. Error	t-Statistic	Prob.
INT(-1)	10.11001	1.456230	6.942591	0.0000
CAP(-1)	2.860647	0.780832	3.663590	0.0012
LAB(-1)	0.904640	0.394189	2.294942	0.0304
C	-30.07164	10.48547	-2.867935	0.0083

The long-run relationship equation is:

$$CEM_{-1} = -30.07164 + 10.11001 * INT_{-1} + 2.860647 * CAP_{-1} + 0.904640 * LAB_{-1} \quad .....(1)$$

3.3. ARDL Model Diagnostic Tests: To ensure the validity of the estimated model and verify that it is free from common issues such as autocorrelation of errors, heteroskedasticity, and non-normality of residuals, the following diagnostic test results were obtained (appendices 02, 03, and 04):

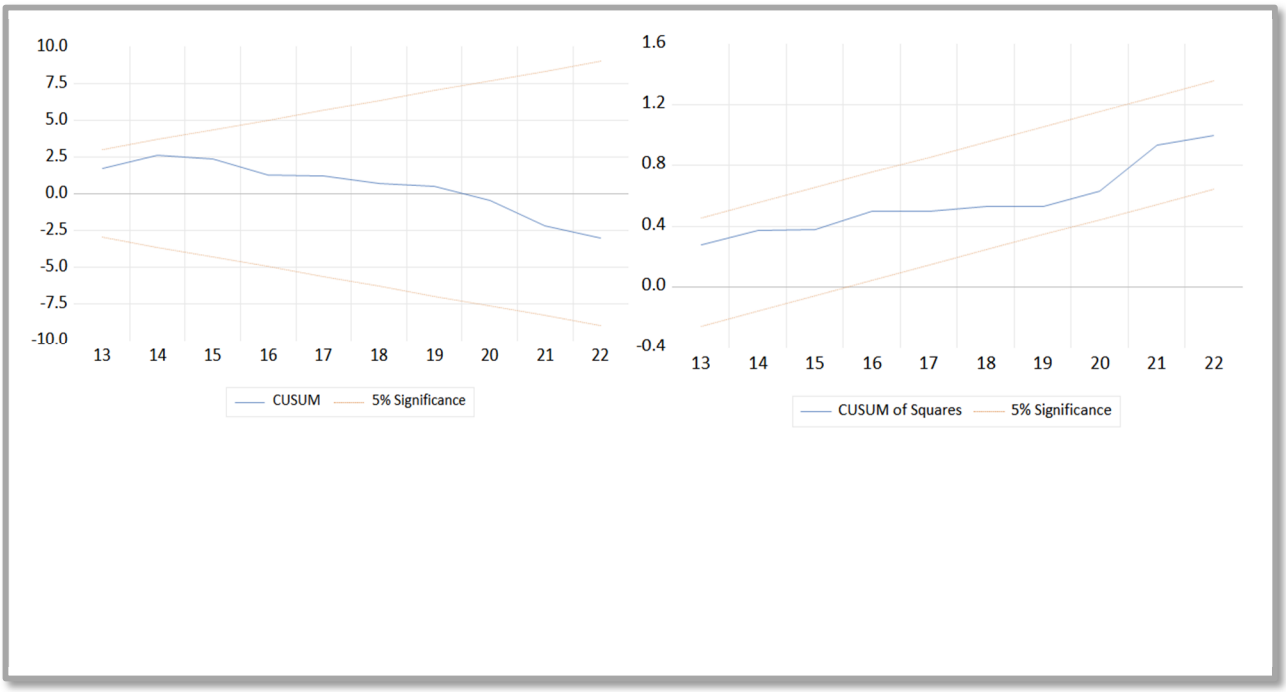
Table 06: ARDL Model Diagnostic Test Results

Test / Diagnostic	Test Statistic / Result	p-Value	Interpretation
Breusch-Godfrey Serial Correlation LM	F-statistic = 0.0316 Obs*R^2 = 0.1015	0.8628 0.7500	No evidence of autocorrelation. Residuals are independently distributed.
Breusch–Pagan–Godfrey Heteroskedasticity	F-statistic = 1.2031 Obs*R^2 = 19.1839 Scaled Explained SS = 2.4121	0.3941 0.3420 1.0000	Residuals are homoskedastic. Variance of the errors is stable.
Jarque–Bera Normality Test	JB = 0.0153	0.9924	Strong evidence of normality. Residuals are symmetric and distributed normally.

Source: Prepared by the researcher based on the Eviews 13 outputs

3.4. Structural stability diagnostics: For assessing the structural stability of the estimated coefficients in the ARDL model, we apply the (CUSUM) and the (CUSUM of Squares) tests. These diagnostic tests evaluate whether the regression coefficients remain stable over time. Stability is confirmed when the plots of the CUSUM and CUSUM of Squares statistics lie within the 5% significance bounds. As shown in the figure, both test statistics remain entirely within their respective critical bounds throughout the sample period, indicating that the model does not suffer from structural breaks and that the estimated coefficients are stable and reliable for inference.

Figure 02: "CUSUM" and "CUSUM of Squares" Test Results



4. Results and discussion:

4.1. The short-run relationship:

The short-run relationship of the ARDL model (table 03) reveals that electricity intensity has a positive, statistically significant, and persistent effect on carbon emissions. Specifically, a one-kilowatt-hour per dollar (kWh/$) increase in electricity intensity leads to an immediate rise of approximately 5.06 million metric tons of CO_2 equivalent (Mt CO_2e) in carbon emissions. This means that inefficient electricity consumption has a direct impact on environmental degradation, and these effects persist over time.

Regarding the impact of GDP per capita, a one-dollar increase results in a 0.77 Mt CO_2e increase in carbon emissions, suggesting that early-stage growth tends to be pollution-intensive. Finally, the labor force also demonstrates a statistically significant positive effect on emissions in the short run. As a one-percentage-point increase in labour force participation leads to a 0.126 Mt CO_2e increase in emissions (p=0.0100).

4.2. The long-run relationship:

The results of the bounds testing (Table 04) confirm the existence of a long-run cointegrating relationship among carbon emissions (CEM), electricity intensity (INT), GDP per capita (CAP), and labor force participation (LAB) at the 5% significance level. The results of the Long-term model estimation (Table 05) and the cointegrating equation (equation (1)) highlight that electricity intensity, measured in kilowatt-hours per dollar (kWh/$), has the strongest long-run influence on emissions. Specifically, a one kWh/$ increase in electricity intensity leads to an increase of 10.11 (Mt CO_2e) in emissions ($p = 0.01$), more than double the most considerable short-run effect. This finding highlights the significant impact of energy inefficiency in contributing to Algeria's long-term environmental degradation, likely due to its heavy reliance on fossil-fuel-based power generation. GDP per capita has a statistically significant and positive long-run effect on carbon emissions. As a one-dollar increase in GDP per capita results in a long-term rise in 2.861 Mt CO_2e ($p = 0.0012$), indicating that Algeria's current economic growth trajectory is environmentally unsustainable. This result reflects sustained reliance on carbon-intensive production sectors and incomplete integration of renewable energy sources. The labour force also demonstrates a positive, statistically significant long-run effect on carbon emissions. As a one-percentage-point increase in labour force participation leads to a 0.905 Mt CO_2e increase in emissions ($p=0.0304$). This is likely due to the dominance of high-emission sectors in overall employment.

These findings confirm that electricity intensity is a significant determinant of long-term carbon emissions, reflecting that Algeria's environmental problem is primarily linked to poor energy efficiency rather than the amount of economic activity itself. High electricity intensity means that producing one unit of added value requires more electricity, indicating lower energy productivity. Given that electricity generation relies mainly on fossil fuels, this inefficiency translates directly into a structural increase in carbon emissions.

To mitigate the effect of electricity intensity on carbon emissions, energy efficiency should be improved by modernizing outdated equipment and technologies that consume large amounts of electricity, particularly in the industrial sector. Adopting clear energy efficiency standards for production also reduces the amount of electricity required to produce one unit of output.

Furthermore, expanding the use of renewable energy, especially solar energy, helps reduce the carbon footprint of electricity consumption. Rationalizing energy subsidies and encouraging efficient production practices also help reduce electricity waste, leading to lower consumption intensity and emissions without negatively impacting economic growth.

5. Conclusion:

This study examines the role of electricity efficiency in mitigating climate change by reducing carbon dioxide (CO_2) emissions in Algeria from 1990 to 2022. To achieve this objective, an econometric analysis was conducted using the ARDL model. The dependent variable was CO_2 emissions, while the independent variables included electricity intensity, GDP per capita, and labour force.

Hypothesis testing: The key hypothesis that electricity consumption efficiency contributes to emissions reduction in Algeria is empirically validated.

The main study results are as follows:

- Electricity intensity has a statistically significant and positive effect on carbon emissions in both the short and long run in Algeria. This implies that inefficient electricity consumption contributes directly to environmental degradation, and these effects persist over time. This is consistent with the results of: Li et al (2022), Mirza et al. (2022), Hakan Altın (2024), Liu et Al (2022), and Mecu et al. (2023).
- GDP per capita has a statistically significant and positive impact on carbon emissions in both the short and long run, indicating that sustained economic growth may eventually lead to increased environmental pressure unless mitigated by structural changes.
- Labour force participation demonstrates a statistically significant positive effect on emissions in the short and long-run.

➢ **Recommendations:** For Algeria's Climate Policy:

- The findings underscore that improvements in electricity efficiency should accompany structural reforms in energy production, particularly a shift from coal.
- Policies should not just aim at reducing electricity per unit of output but also at greening the electricity itself.
- Emphasizing technological upgrading, smart grid systems, and demand-side management becomes essential.

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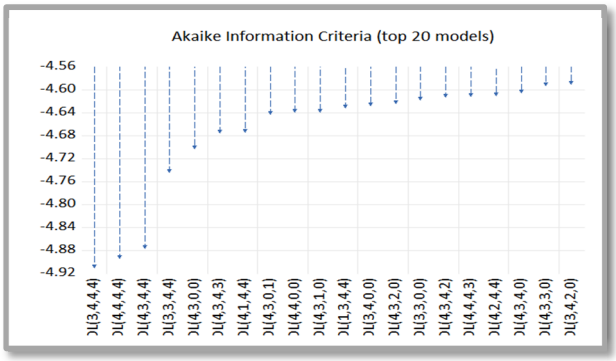
6. Appendices:

Appendix 01

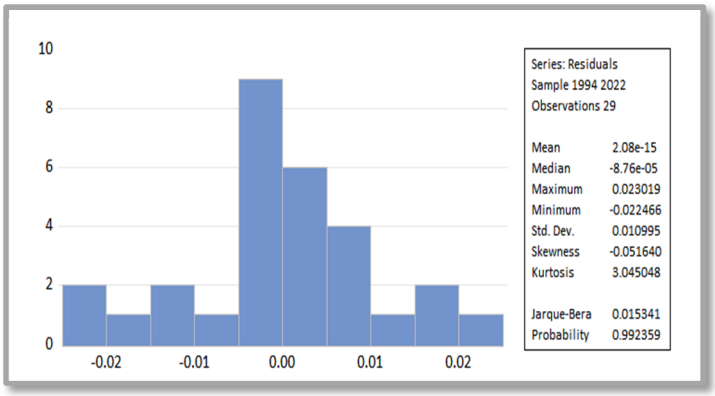


Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 1 lag

F-statistic	0.031620	Prob. F(1,9)	0.8628
Obs*R-squared	0.101529	Prob. Chi-Square(1)	0.7500

Test Equation:
Dependent Variable: RESID
Method: ARDL
Date: 07/07/25 Time: 19:08
Sample (adjusted): 1994 2022
Included observations: 29 after adjustments
Presample missing value lagged residuals set to zero.

Appendix 02



Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	2.075746	Prob. F(18,10)	0.1194
Obs*R-squared	22.87713	Prob. Chi-Square(18)	0.1954
Scaled explained SS	2.889248	Prob. Chi-Square(18)	1.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 07/03/25 Time: 17:37
Sample (adjusted): 1994 2022
Included observations: 29 after adjustments