THE IMPACT OF ECONOMIC GROWTH AND ENERGY CONSUMPTION ON ENVIRONMENTAL QUALITY

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Abstract
In recent years, research interest in anthropogenic impacts on the environment has been particularly intense, as evidenced by the range of empirical research related to climate change. Climate change and especially its negative effects is a field of continuous research and study. This research examines how economic growth, consumption of energy resources and population affect the quality of the environment in the case of Greece employing appropriate econometric techniques. Specifically, using an ARDL model, the long- and short-term effects of these variables on environmental quality, measured by carbon dioxide emissions, are examined. Carbon dioxide (CO2) is the most important anthropogenic greenhouse gas. The findings reveal that economic growth and energy consumption have a positive and significant impact on environmental degradation. These results underline the urgent need for sustainable development policies that promote economic growth while mitigating environmental damage. These policies should aim to reduce CO2 emissions and focus on increasing energy efficiency.

Key words: *climate change, energy consumption, environmental quality, ARDL*

1. Introduction

The relationship among economic growth, energy consumption and environmental quality has become increasingly significant in the context of global climate change and sustainable development goals. In recent years climate change poses a significant threat to the ability to maintain economic prosperity. In this context many researchers are seeking evidence on how economic growth impacts environmental quality across different stages of development and what the relationship is between energy consumption patterns and environmental degradation. There is not always a clear path between seemingly opposite directions. Energy consumption is a crucial factor, as it drives economic growth and is a major source of environmental pollution, especially through fossil fuel combustion like coal and oil. Non-renewable energy sources are primarily associated with high greenhouse gas emissions.

The Greek economy is highly dependent on fossil fuels and therefore highly vulnerable to the risks stemming from it (IEA, 2023). However, we should not lose sight of the fact that significant efforts have been made in recent years to move to more environmentally friendly energy sources. Greece has adopted a national climate law that sets ambitious targets for reducing greenhouse gas emissions. This law aims for climate neutrality by 2050 in accordance with European Green Deal.

The case of Greece is extremely interesting because the Greek economy suffered an unprecedented economic debt crisis for a country in the developed world that set it back several years with very significant repercussions on the productive and social fabric. However, the restoration of normality did not last long, since the Covid 19 pandemic broke out very soon. In this light, the new data allows us to study the correlation between economic growth and environmental quality in abnormal conditions.

2. Literature Review

The cornerstone of any new study is the Environmental Kuznets Curve (EKC). The Environmental Kuznets Curve (EKC) hypothesis suggests an inverted U-shaped relationship between economic development and environmental degradation. The main idea is that as economies expand, they typically consume more energy, often leading to increased pollution and resource depletion, especially in early stages and this pattern reverses as income rises, due to adoption of cleaner technologies and stricter regulations, potentially leading to improvements in environmental quality. Initial studies by Grossman and Krueger (1991) found that economic growth initially leads to environmental deterioration, but beyond a certain income threshold, environmental quality begins to improve. Although subsequent research has supported these findings, other results are challenging this hypothesis. Stern (2004) argues that while some pollutants follow the EKC pattern, others, particularly global pollutants like CO_2 emissions, may not demonstrate the same relationship.

Early studies primarily focused on total energy consumption and soon after research interest expanded to include different types of energy, such as electricity, nuclear, and renewable energy, recognizing that not all forms of energy have the same impact on growth (Payne, 2010). Energy consumption plays a very important role in environmental degradation. Evidence from developing countries indicated that rapid economic growth leads to higher energy consumption due to high participation of carbon and oil in the energy mix exacerbating environmental degradation (Kais et al., 2016). Apart from EKC analysis, many research studies have been conducted in related areas, including various aspects forming the energy consumption, CO_2 emissions – growth nexus. Studies employ various methods, including panel data, time series analysis, and econometric techniques like OLS, fixed effects, and ARDL. Acaravsci and Ozturk (2010) by applying an ARDL model on data from 19 European countries, found in many cases significant long-run relationship between real GDP, CO_2 emissions and energy consumption. Similar conclusions were reported by Menyah et al (2010) for Saudi Arabia. Manu et al (2017) using simple OLS analyzed the impact of energy consumption and economic growth on CO_2 emissions. Energy consumption patterns significantly influence environmental quality through various channels like direct emissions from fossil fuel consumption and land use changes for energy infrastructure. Studies by Zhang and Cheng (2009) demonstrate strong causal relationships between energy consumption and carbon emissions in developing economies.

Population growth rate is another factor to be considered. The empirical analysis at the aggregate level demonstrates the country-specific impact of population density on CO_2 emissions, emphasizing the need for policies that address the environmental impacts of population growth (Ohlan, 2015). Sulaiman et al (2018) added population growth rate to the equation, but there was no evidence of long-term relationship between population growth and CO_2 emissions. Population density also plays a crucial role in environmental quality. Higher population density can lead to increased demand for resources and energy, resulting in higher emissions and greater environmental degradation. The combined approach to investigate the dynamic relationships among economic growth, environmental degradation, and energy consumption has provided valuable insights. Studies using time series analysis and panel data analysis have explored the relationship between environmental pollutants, renewable and fossil energy consumption, and economic growth (Bölük & Mert, 2015). These analyses are crucial for formulating policies that balance economic development with environmental sustainability.

3. Methodology

3.1 Data analysis

Greece's annual data employed by this study cover the period from 1990 to 2018 and the main source is Energy Institute (2024), Statistical Review of World Energy 2024 and the World Bank. This time period covers a period with extremely interesting features, like the fiscal crisis that the country has experienced since 2010 and the period of Covid 19 lockdown. CO_2 emissions are modeled as a dependent variable, while economic growth, energy consumption and population growth rate as independent. More details on those variables exist in Table 1.

Table 1. Data variables details

INDICATOR_NAME	SOURCE_NOTE	SOURCE_ORGANIZATION	Unit
GDP (constant 2015 US$)	GDP at purchaser's prices is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Data are in constant 2015 prices, expressed in U.S. dollars.	World Bank national accounts data, and OECD National Accounts data files.	US $
Population Growth	Population Growth rate derived from total population	Energy Institute (2024), Statistical Review of World Energy 2024	
Consumption per capita	In this review, primary energy comprises commercially-traded fuels, including modern renewables used to generate electricity. Energy from all sources of non-fossil power generation is accounted for on an input-equivalent basis.	Energy Institute (2024), Statistical Review of World Energy 2024	Gigajoule per capita
Carbon Dioxide Emissions from Energy	Notes: The carbon emissions above reflect only those through consumption of oil, gas and coal for combustion related activities, and are based on 'Default CO_2 Emissions Factors for Combustion' listed by the IPCC in its Guidelines for National Greenhouse Gas Inventories (2006). This does not allow for any carbon that is sequestered, for other sources of carbon emissions, or for emissions of other greenhouse gases. Our data is therefore not comparable to official national emissions data.	Energy Institute (2024), Statistical Review of World Energy 2024	Million tonnes of carbon dioxide

3.2. Empirical model

This study employs an ARDL model. In recent years, ARDL models have gained increasing popularity in econometrics and environmental research due to their flexibility and ability to handle small sample sizes effectively. These models are particularly useful for examining the dynamic relationships between variables over time, allowing for both short-term and long-term analysis. By incorporating lagged variables, ARDL models can disentangle the complex interactions between economic growth, energy consumption, and environmental quality, providing more robust and insightful results. One very important advantage of this model is that the order of integration of the variables is not so important. Variables can be of any order. They can be I(0), I(1) or mixed. The only restriction is that they cannot be greater than I(1). The ARDL(p,q) model is represented by the following general equation:

$$\mathrm{lnCO2_t} = \alpha_0 + \sum_{i=1}^{p} \alpha_i \mathrm{lnCO2_{t-i}} + \sum_{j=0}^{q} \beta_1 \mathrm{lnGDP_{t-j}} + \sum_{j=0}^{q} \beta_2 \mathrm{lnENC_{t-j}} + \sum_{j=0}^{q} \beta_3 \mathrm{lnPOP_{t-j}} + \epsilon_t \quad (1)$$

To investigate the long run relationship among the variables we will apply the ARDL bounds test approach to cointegration (Pesaran et el., 2001) and use critical values for small samples (Narayan, 2005). By reparameterization of the ARDL equation into an unrestricted error correction model we have the following equation which enables the analysis of long and short run relationship:

$$\Delta CO2_t = \alpha_0 + \pi_{CO2} CO2_{t-1} + \pi_{GDP} GDP_{t-1} + \pi_{ENC} ENC_{t-1} + \pi_{POP} POP_{t-1} + \sum_{i=1}^{p-1} \phi_i \Delta CO2_{t-i} + \sum_{j=0}^{q_1-1} \beta_j \Delta GDP_{t-j} + \sum_{j=0}^{q_2-1} \gamma_j \Delta ENC_{t-j} + \sum_{j=0}^{q_3-1} \delta_j \Delta POP_{t-j} + \epsilon_t \quad (2)$$

Where, Δ is the first difference operator, α_0 is the intercept term, $\pi_{CO2}, \pi_{GDP}, \pi_{ENC}, \pi_{POP}$ are the long-run multipliers, $\phi_i, \beta_j, \gamma_j, \delta_j$ are the short-run dynamic coefficients, p is the lag length for the dependent variable and q_1, q_2, q_3 the lag lengths for the independent variables. The bounds test is based on F-Statistics. The null hypothesis $Ho : \pi_{CO2} = \pi_{GDP} = \pi_{ENC} = \pi_{POP} = 0$ is tested against the alternative. The calculated F-statistic is compared to two sets of critical values, the Lower bound, which assumes all variables are I(0) and the Upper bound, which assumes all variables are I(1).Critical values are provided in tables by Pesaran, Shin, and Smith (2001). There are three possible outcomes, first if F is greater than the upper bound, we reject the null hypothesis, which eventually means that there is evidence of cointegration. If F is lower than the lower bound, we fail to reject the null hypothesis. There is no evidence of cointegration. In case F falls between the two bounds the test is inconclusive.

4. Empirical Results

Investigating statistical data through Exploratory Data Analysis (EDA) is a critical preliminary step in econometric analysis that involves summarizing, visualizing, and interpreting the main characteristics of a dataset. The primary objective of EDA is to uncover patterns, detect anomalies, test assumptions, and generate hypotheses about the relationships between variables. In Table 2 we present a descriptive statistics summary for all variables employed in this study. There are no missing values in our dataset.

Figure 1 presents the trends in CO2 emissions, energy consumption, GDP, and population in Greece from 1990 to 2022. It visually illustrates the relationships and changes among these variables over time, highlighting significant economic and environmental events and their impact on each parameter. From the graphic illustration we observe that in 2010, a year that coincides with the beginning of the fiscal crisis in the country, there was a significant decline in carbon dioxide emissions and energy consumption. Greece's GDP follows the same path. The economic turmoil led to reduced industrial activities and energy use, contributing to lower carbon emissions. Greece's GDP mirrors the trend of CO2 emissions and energy consumption. Figure 1 demonstrates the interconnected nature of environmental and economic factors in Greece, highlighting how economic crises can lead to significant reductions in pollution and energy usage.

In Figure 2 a correlation analysis presents the correlation coefficients between variables employed. These figures show the relationship among CO2 emissions, energy consumption, GDP, and population. The correlation coefficients provide insight into the strength and direction of these relationships. There is strong positive correlation between GDP and energy consumption, and as excepted energy consumption and CO2 emissions, suggesting that higher economic activity is associated with higher carbon emissions. The first step is to test our data for stationarity using the augment Dickey Fuller test (Dickey & Fuller, 1981).

Although ARDL does not require checking the integration order of variables, the unit root test was conducted to ensure no variable exceeded 1 and to verify the methodology's appropriateness. The presence of stationarity of I(2) would force us to ender the methodology. Pesaran et al. (2001) developed the ARDL method assuming all variables are I(0), I(1), or mixed; I(2) variables would invalidate it. Therefore, these tests were performed, and the results are in Table 3. Results reveal that only population growth (PG) is stationary at level, that is I(0) and all the other variables, energy consumption (lnEC), economic growth (lnGDP) and CO2 emissions (lnCO2) are stationary at first difference, that is, I(1). Therefore, considering the mix order of integration of the variables, the ARDL approach is the most fitted methodology rather than the standard or conventional cointegration approaches.

Optimal lag selection is a critical step in time series analysis, particularly when building models like ARDL (Autoregressive Distributed Lag) or VAR (Vector Autoregression). The goal is to determine the appropriate number of lags for the dependent and independent variables to ensure the model is well-specified, avoids overfitting, and captures the true dynamics of the data. Including too many lags can lead to overfitting, where the model captures noise instead of the underlying relationship on the other side, including too few lags can lead to underfitting, where the model fails to capture important dynamics in the data.

The optimal lag length for the dependent and independent variables was selected using the Akaike Information Criterion (AIC), which balances model fit and complexity. A maximum lag order of 3 was chosen based on the frequency of the data and prior studies. The AIC was computed for all possible lag combinations, and the model with the lowest AIC value was selected as the optimal specification, as shown in Table 2. The lag selection process identified an optimal lag of 2 for the dependent variable (lnCO2). For the independent variables, the optimal lags were 3 for lnGDP, 2 lags for POP and 0 for lnENC.

Having identified the optimum lag length in the previous section, we will estimate now long-run relationship among the variables by applying OLS. The null hypothesis of no cointegration was tested against the alternative. Pesaran et al., (2001) provide two sets of critical values, which form two bounds. The lower bound assumes that all variables are I(0) and the upper bound that all variables are I(1). If the computed F-statistics are greater than the upper bound, we reject the null hypothesis of no cointegration and if it is below the lower bound, we fail to reject the null hypothesis. Between the bounds, the test is inconclusive. The result of this test is presented in Table 5. As the F-statistics (12,9542) lie above the upper bound at 5% and 10%, these indicate that the null hypothesis could not be accepted. As such, a long-term cointegration relationship exists at all levels. Results for the ARDL model and diagnostic checks are represented in Table 6.

ARDL model's diagnostic tests indicate that all assumptions are statistically significant at level 5%. Favorable results indicate a robust and reliable model. This means that the residuals are free from autocorrelation and heteroscedasticity, are normally distributed, and the model passes stability tests. Consequently, the estimated coefficients, representing both short-run and long-run relationships, can be interpreted with a high degree of confidence, suggesting that the model accurately captures the dynamic interactions between the variables under analysis. The validation of these diagnostic tests is crucial for ensuring the validity of any subsequent inferences or policy recommendations derived from the model.

CUSUM and CUSUMSQ charts are presented in Figures 3 & 4. It is important that the blue line does not cross the 5% critical bounds (red and the green line) in any chart. From the charts we can infer that there is not issue of recursive residuals in terms of mean (CUSUM chart) and in terms of variance (CUSUMSQ chart).

After establishing a cointegration relationship among the variables, the long-run model in Equation 2 is estimated to obtain the long-run coefficients as reported in Table 7. The results reveal that economic growth is positive and significant at 5% level in determining CO2 emissions. A 1% increase in economic growth will cause a 0.65% increase in CO2 emissions. Population growth and energy consumption have a positive sign and are statistically significant at 5% level.

Short run results are reported to table 6. Most coefficients are statistically significant at level 5% except dLNGDP and dPG. GDP exhibits a positive sign but is not statistically significant, energy consumption is positive and statistically significant, population growth and its lag are negative. The error correction term (ECT) which measures the deviation from a long-run equilibrium between variables is negative and significant, which is expected to satisfy econometric requirements.

Table 2. Descriptive Statistics Summary

	CO2	GDP	ENC	POP	lnCO2	lnGDP	lnENC
count	33	33	33	33	33	33	33
mean	88,83	204,25	114,05	10,82	4,47	26,03	4,73
std	15,69	31,05	11,66	0,26	0,19	0,15	0,10
min	56,27	158,31	94,85	10,30	4,03	25,79	4,55
25%	76,14	184,91	103,84	10,63	4,33	25,94	4,64
50%	89,08	200,14	109,72	10,88	4,49	26,02	4,70
75%	103,38	218,00	122,26	11,06	4,64	26,11	4,81
max	112,75	265,97	136,11	11,12	4,73	26,31	4,91
median	89,08	200,14	109,72	10,88	4,49	26,02	4,70
kurtosis	-0,85	-0,57	-1,11	-1,05	-0,32	-0,72	-1,16
skewness	-0,34	0,50	0,40	-0,53	-0,65	0,23	0,28

Figure 1 - CO2 emissions, Energy Consumption, GDP and Population, Greece (1990-2022)

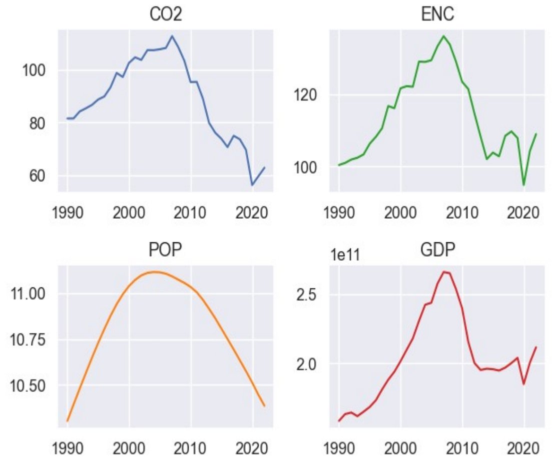

Figure 2 - Correlation analysis

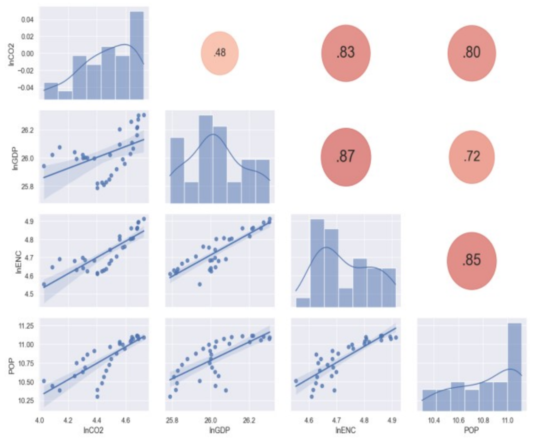

Figure 3 - Plot of Cumulative Sum of Squares of Recursive Residuals

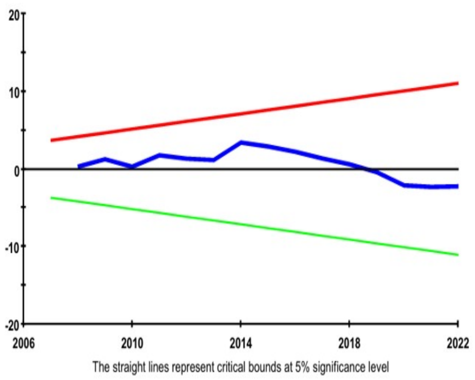

Figure 4 - Plot of Cumulative Sum of Squares of Recursive Residuals

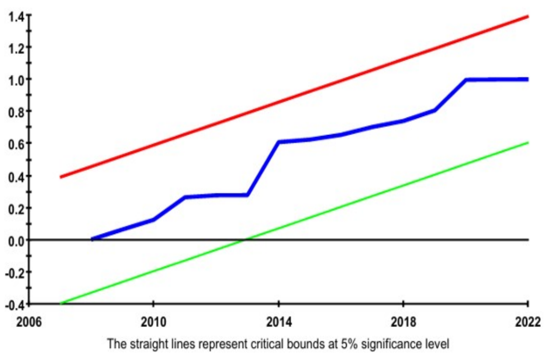

Table 3 - Unit Root Test Using Augmented Dickey Fuller (ADF)

Var	Specification	Test Statistic	P-value	Stationary at 1%	Stationary at 5%	Stationary at 10%
POP I(0)	Level - Constant	-5,5740	0,0000	TRUE	TRUE	TRUE
	Level - Constant & Trend	-5,6897	0,0000	TRUE	TRUE	TRUE
	First Diff. - Constant	-4,4961	0,0002	TRUE	TRUE	TRUE
	First Diff. - Constant & Trend	-4,4256	0,0020	TRUE	TRUE	TRUE
lnCO2 I(1)	Level - Constant	-2,0572	0,2621	FALSE	FALSE	FALSE
	Level - Constant & Trend	-2,4139	0,3722	FALSE	FALSE	FALSE
	First Diff. - Constant	-6,3997	0,0000	TRUE	TRUE	TRUE
	First Diff. - Constant & Trend	-6,2892	0,0000	TRUE	TRUE	TRUE
lnGDP I(1)	Level - Constant	-0,6320	0,8636	FALSE	FALSE	FALSE
	Level - Constant & Trend	0,0295	0,9945	FALSE	FALSE	FALSE
	First Diff. - Constant	-5,1253	0,0000	TRUE	TRUE	TRUE
	First Diff. - Constant & Trend	-5,6890	0,0000	TRUE	TRUE	TRUE
lnENC I(1)	Level – Constant	-2,0228	0,2767	FALSE	FALSE	FALSE
	Level - Constant & Trend	-2,5090	0,3235	FALSE	FALSE	FALSE
	First Diff. – Constant	-5,6013	0,0000	TRUE	TRUE	TRUE
	First Diff. - Constant & Trend	-5,6600	0,0000	TRUE	TRUE	TRUE

Table 4 - Optimal Lag Length Selection Based on AIC

AIC	AIC
-156,094	(2, {'lnGDP': 3, 'lnENC': 0, 'POP': 2})
-155,109	(2, {'lnGDP': 2, 'lnENC': 3, 'POP': 1})
-154,1	(2, {'lnGDP': 1, 'lnENC': 3, 'POP': 2})
-153,69	(2, {'lnGDP': 2, 'lnENC': 3, 'POP': 2})
-153,674	(2, {'lnGDP': 1, 'lnENC': 3, 'POP': 3})
-153,42	(2, {'lnGDP': 0, 'lnENC': 3, 'POP': 3})
-153,113	(2, {'lnGDP': 3, 'lnENC': 3, 'POP': 1})
-153,033	(2, {'lnGDP': 0, 'lnENC': 3, 'POP': 1})
-152,734	(2, {'lnGDP': 0, 'lnENC': 3, 'POP': 2})
-152,721	(2, {'lnGDP': 3, 'lnENC': 0, 'POP': 1})
-152,103	(2, {'lnGDP': 2, 'lnENC': 3, 'POP': 3})
-152,079	(2, {'lnGDP': 2, 'lnENC': 0, 'POP': 2})
-152,03	(2, {'lnGDP': 3, 'lnENC': 3, 'POP': 2})

Table 5 - Bound Test Results

```
Testing for existence of a level relationship among the variables in the ARDL model
*****************************************************************************
 F-statistic  95% Lower Bound  95% Upper Bound  90% Lower Bound  90% Upper Bound
   12.9542         3.8177          5.1388          3.0558           4.2425

 W-statistic  95% Lower Bound  95% Upper Bound  90% Lower Bound  90% Upper Bound
   51.8167        15.2709         20.5552         12.2231          16.9699
*****************************************************************************
 If the statistic lies between the bounds, the test is inconclusive. If it is
 above the upper bound, the null hypothesis of no level effect is rejected. If
 it is below the lower bound, the null hypothesis of no level effect can't be
 rejected. The critical value bounds are computed by stochastic simulations
 using 20000 replications.
```

Table 6 – ARDL estimation

```
                   Autoregressive Distributed Lag Estimates
         ARDL(2,3,0,3) selected based on Akaike Information Criterion
*****************************************************************************
 Dependent variable is LNCO2
 25 observations used for estimation from 1994 to 2018
*****************************************************************************
 Regressor              Coefficient       Standard Error        T-Ratio[Prob]
 LNCO2(-1)                 -.31995            .14406            -2.2209[.045]
 LNCO2(-2)                 -.44680            .15557            -2.8720[.013]
 LNGDP                     .048835            .17415             .28042[.784]
 LNGDP(-1)                  .74738            .21023             3.5551[.004]
 LNGDP(-2)                 -.14609            .18778            -.77797[.451]
 LNGDP(-3)                  .50494            .13872             3.6400[.003]
 LNENC                      .75517            .16890             4.4711[.001]
 PG                        -1.5070            1.2544            -1.2014[.251]
 PG(-1)                    -.68055            2.0606            -.33027[.746]
 PG(-2)                    -1.5017            2.1132            -.71062[.490]
 PG(-3)                     7.4129            1.5702             4.7209[.000]
 C                        -25.7948            6.6535            -3.8769[.002]
*****************************************************************************
 R-Squared                    .99761   R-Bar-Squared                   .99560
 S.E. of Regression         .0096234   F-Stat.    F(11,13)   494.2483[.000]
 Mean of Dependent Variable   4.5337   S.D. of Dependent Variable      .14501
 Residual Sum of Squares    .0012039   Equation Log-likelihood        88.7896
 Akaike Info. Criterion      76.7896   Schwarz Bayesian Criterion     69.4764
 DW-statistic                 2.1645
*****************************************************************************
```

```
                          Diagnostic Tests
*******************************************************************************
*    Test Statistics  *        LM Version        *          F Version          *
*******************************************************************************
*                     *                          *                             *
* A:Serial Correlation*CHSQ(1)  =   .31049[.577]*F(1,12)       =   .15091[.704]*
*                     *                          *                             *
* B:Functional Form   *CHSQ(1)  = .0079419[.929]*F(1,12)       = .0038133[.952]*
*                     *                          *                             *
* C:Normality         *CHSQ(2)  =   .71000[.701]*       Not applicable         *
*                     *                          *                             *
* D:Heteroscedasticity*CHSQ(1)  =   .24425[.621]*F(1,23)       =   .22693[.638]*
*******************************************************************************
   A:Lagrange multiplier test of residual serial correlation
   B:Ramsey's RESET test using the square of the fitted values
   C:Based on a test of skewness and kurtosis of residuals
   D:Based on the regression of squared residuals on squared fitted values
```

Table 7 - Estimated Long Run Coefficients

```
          Estimated Long Run Coefficients using the ARDL Approach
        ARDL(2,3,0,3) selected based on Akaike Information Criterion
******************************************************************************
 Dependent variable is LNCO2
 25 observations used for estimation from 1994 to 2018
******************************************************************************
 Regressor              Coefficient       Standard Error         T-Ratio[Prob]
 LNGDP                       .65378            .097031             6.7379[.000]
 LNENC                       .42744             .13770             3.1041[.008]
 PG                          2.1077            .094342            22.3405[.000]
 C                         -14.6001             1.8855            -7.7433[.000]
******************************************************************************

Testing for existence of a level relationship among the variables in the ARDL model
******************************************************************************
 F-statistic  95% Lower Bound  95% Upper Bound  90% Lower Bound  90% Upper Bound
   12.9542         3.8177           5.1388           3.0558          4.2425

 W-statistic  95% Lower Bound  95% Upper Bound  90% Lower Bound  90% Upper Bound
   51.8167        15.2709          20.5552          12.2231         16.9699
******************************************************************************
 If the statistic lies between the bounds, the test is inconclusive. If it is
 above the upper bound, the null hypothesis of no level effect is rejected. If
 it is below the lower bound, the null hypothesis of no level effect can't be
 rejected. The critical value bounds are computed by stochastic simulations
 using 20000 replications.
```

Table 8 - Estimated Short Run Coefficients

```
        Error Correction Representation for the Selected ARDL Model
        ARDL(2,3,0,3) selected based on Akaike Information Criterion
*******************************************************************************
 Dependent variable is dLNCO2
 25 observations used for estimation from 1994 to 2018
*******************************************************************************
 Regressor              Coefficient       Standard Error         T-Ratio[Prob]
 dLNCO21                    .44680             .15557              2.8720[.012]
 dLNGDP                   .048835              .17415              .28042[.783]
 dLNGDP1                  -.35886              .17232             -2.0825[.055]
 dLNGDP2                  -.50494              .13872             -3.6400[.002]
 dLNENC                    .75517              .16890              4.4711[.000]
 dPG                      -1.5070              1.2544             -1.2014[.248]
 dPG1                     -5.9113              1.8514             -3.1928[.006]
 dPG2                     -7.4129              1.5702             -4.7209[.000]
 ecm(-1)                  -1.7668              .25149             -7.0252[.000]
*******************************************************************************
 List of additional temporary variables created:
 dLNCO2 = LNCO2-LNCO2(-1)
 dLNCO21 = LNCO2(-1)-LNCO2(-2)
 dLNGDP = LNGDP-LNGDP(-1)
 dLNGDP1 = LNGDP(-1)-LNGDP(-2)
 dLNGDP2 = LNGDP(-2)-LNGDP(-3)
 dLNENC = LNENC-LNENC(-1)
 dPG = PG-PG(-1)
 dPG1 = PG(-1)-PG(-2)
 dPG2 = PG(-2)-PG(-3)
 ecm = LNCO2   -.65378*LNGDP   -.42744*LNENC   -2.1077*PG +  14.6001*C
*******************************************************************************
 R-Squared                     .97445   R-Bar-Squared                   .95283
 S.E. of Regression          .0096234   F-Stat.    F(9,15)      55.0919[.000]
 Mean of Dependent Variable -.0059236   S.D. of Dependent Variable     .044310
 Residual Sum of Squares     .0012039   Equation Log-likelihood        88.7896
 Akaike Info. Criterion       76.7896   Schwarz Bayesian Criterion     69.4764
 DW-statistic                  2.1645
*******************************************************************************
 R-Squared and R-Bar-Squared measures refer to the dependent variable
 dLNCO2 and in cases where the error correction model is highly
 restricted, these measures could become negative.
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5. Conclusions

This study investigates the impact of economic growth, energy resource consumption, and population on environmental quality in Greece using appropriate econometric methods. Specifically, an ARDL model is employed to analyze the long- and short-term effects of these variables on environmental quality, as indicated by carbon dioxide emissions. Carbon dioxide (CO2) is the most significant anthropogenic greenhouse gas. The results demonstrate that all variables under consideration economic growth, energy consumption and population growth have a positive and substantial effect on environmental degradation in the long run. In the short run only energy consumption seems to explain CO2 emissions. These findings highlight the imperative need for sustainable development policies that foster economic growth while mitigating environmental damage. Such policies should aim to reduce CO2 emissions and prioritize enhancing energy efficiency.

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