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Dynamic Panel Cointegration Analysis of Carboon Emission Determinants: The Case of The Five Economic Powerhouses in Africa During The Period 1990 – 2023

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Received : 31/12/2025 ; Accepted : 04/01/2026 ; Published: 05/01/2026

Abstract:

This study explores the determinants of carbon dioxide (co2) emissions in five leading African economies: Algeria, Egypt, Ethiopia, Nigeria, and South Africa, spanning the period from 1990 to 2023. The Panel Autoregressive Distributed Lag (Panel ARDL) approach was employed to examine the dynamic interactions between urbanization, economic growth, renewable energy consumption, and emission levels. Based on the Hausman test results, which confirmed significant heterogeneity across the sampled countries, the Mean Group (MG) estimator was adopted as the primary analytical tool. The empirical findings confirm a long-run cointegrating relationship among the variables, characterized by a high speed of adjustment toward equilibrium at 48.7% per annum. The results indicate that economic growth remains the primary driver of emissions, while the long-run impacts of renewable energy and urbanization were found to be statistically insignificant across the overall panel, reflecting divergent national environmental policies. The study recommends adopting "compact urban expansion" models and tailoring environmental strategies to the specific economic characteristics of each nation to effectively decouple economic expansion from environmental degradation.

Keywords: CO2 emissions, Urbanization, Renewable Energy, Panel ARDL, African Economies, MG Estimator.

1. Introduction

Environmental sustainability constitutes a pressing global issue facing most nations today. Achieving such sustainability is linked to several key determinants, most notably the reduction of carbon dioxide emissions into the atmosphere. There is a broad scientific consensus that greenhouse gas emissions pose significant global risks. Consequently, a wide range of experts has called for the mitigation and limitation of individual carbon footprints to alleviate major environmental threats.

The Millennium Ecosystem Assessment (MEA 2005) examined 24 key ecosystem services essential to human well-being, concluding that 15 of them are currently in decline or being utilized unsustainably. Population growth is identified as a primary driver of this ecological degradation, as demographic increases intensify the pressure on natural resources. (Liddle, 2015) asserts that over the coming decades, population growth could lead to heightened energy consumption and a subsequent rise in carbon dioxide emissions. Given that climate change and demographic shifts are inevitable global phenomena, it is imperative to align economic and social policies with these changes while prioritizing environmental sustainability.

The United Nations Framework Convention on Climate Change (UNFCCC) established a fundamental framework for global cooperation on climate issues. Subsequently, the Kyoto Protocol was adopted in 1997 to regulate the concentration of greenhouse gases (GHG) and fulfill the objectives of the UNFCCC. In 2015, the Paris Agreement was convened with the participation of 200 countries, aiming to limit the increase in global average temperatures(*The Paris Agreement | UNFCCC*, n.d.).

Over the past years, urban centers have experienced significant expansion and rapid population growth. In 2008, approximately half of the world's population (3.42 billion out of 6.83 billion) resided in urban areas, with projections suggesting this figure will rise to 68.7% by 2050 (United Nations World Urbanization Prospects, 2009). This shift has fundamentally altered the socio-economic philosophy of nations. Similar to other developing countries, urban cities in Algeria have witnessed accelerated demographic growth and expanding urbanization. This has facilitated a transition from rural economies based on small-scale units to urban economies primarily driven by industrial zones. Consequently, urbanization serves as a pivotal factor in economic development due to its direct impact on growth through key determinants, namely industry, human capital, and government expenditure.

Estimates indicate that urban areas accounted for 67% of global primary energy demand and 71% of energy-related carbon dioxide emissions in 2006 (World Energy Outlook, 2008). At present, the world’s top 600 cities release almost 70% of greenhouse gases, provide living space for 20% of the world’s inhabitants, and generate GDP nearly 60% (Xu et al., 2024). Consequently, urbanization and urban development are regarded as pivotal and decisive determinants of carbon dioxide emissions and energy consumption, as well as crucial factors in their mitigation (Poumanyvong & Kaneko, 2010)

In the Algerian context, urban centers are witnessing the emission of substantial quantities of carbon dioxide. Algeria contributes approximately 0.46% to the total volume of global CO2 emissions. Notably, the volume of these emissions more than doubled between 2000 and 2022; recording 83,584,350 tons in 2000 and surging to 177,079,430 tons by 2022. The industrial, transportation, and construction sectors are the primary contributors to these figures, with the vast majority of these sectoral activities concentrated within urban areas.

This study aims to examine the relationship and impact of urban population concentration on carbon dioxide (CO_2) emissions in Algeria during the period from 2000 to 2024. This timeframe is characterized by significant developments in the Algerian economy, which led to accelerated economic growth rates and an increased momentum of projects, particularly in infrastructure. These developments have profoundly influenced urban growth and the resulting concentration of the population within urban centers.

2. Literature review

The foundational framework for analyzing the relationship between economic welfare and environmental degradation dates back to the pioneering work of **Grossman and Krueger (1991)**, known as the Environmental Kuznets Curve (EKC). (Yandle et al., 2002). While the EKC hypothesizes an inverted U-shaped relationship where degradation increases with income until a threshold is reached, after which it declines there is no consensus on the optimal indicator for environmental degradation. Consequently, modern research has increasingly pivoted toward specific drivers, particularly urbanization and Carbon Dioxide (CO_2) emissions.

2.1 Spatial Analysis: Urban Form, Density, and 3D Dimensions

A critical branch of literature examines how the physical structure of cities urban form impacts emissions. This discourse has evolved from two-dimensional (2D) analyses of sprawl to complex three-dimensional (3D) assessments.

2.1.1 Urban Sprawl vs. Compact Development (2D Perspectives)

Research consistently highlights the tension between urban densification and sprawl.

- China: Ou et al. (2019) explored developmental disparities across five city tiers (1995–2015), finding that economic development, population growth, and urban land expansion synergistically accelerate CO_2 emissions. They emphasized that mitigation strategies must be tailored to a city's specific developmental stage (Ou et al., 2019).
- Latin America: Van der Borght and Barbera (2023) proposed a population-based clustering methodology to assess 635 cities across seven countries. Utilizing a spatial panel model, they contrasted two key indicators (Van der Borght & Barbera, 2023):

- Population Density (Compactness): A 1% increase reduces CO_2 emissions by 0.58%.
- Suburban Ratio (Sprawl)**:** A 1% increase leads to a 0.41% increase in emissions.

Their findings underscore the benefits of the 'compact expansion' model, which generates 12 percentage points fewer emissions than passive sprawl. However, they warn that even under compact scenarios, urban emissions are projected to grow faster than the population through 2030.

2.1.2 The Shift to 3D Urban Forms

Moving beyond traditional 2D metrics, Xiong et al. (2024) noted that limited attention has been paid to the vertical dimension of cities.

Using data from the Global Human Settlement Layer (GHSL) and the China City Greenhouse Gas Working Group across 285 Chinese cities, they investigated city height, density, and intensity (Xiong et al., 2024).

- Findings: There is a robust, positive causal effect of 3D urban forms on carbon emissions, even when accounting for spatial spillovers.
- Pattern: The relationship follows a U-shaped pattern, moderated by total population.
- Sectoral Impact: 3D forms primarily affect household emissions rather than industrial sectors, with impacts being more pronounced in Eastern China.

2.2. Econometric Analysis: STIRPAT and Time-Series Approaches

Parallel to spatial analysis, extensive research employs econometric models (STIRPAT, ARDL, VECM) to investigate the causal links between urbanization, energy, and emissions across different national contexts.

2.2.1. The Case of China: Industrialization and Energy Intensity

- Drivers of Emissions: Zou et al. (2014) applied the EKC framework using ARDL estimates, identifying energy intensity and industrial structure as primary drivers of CO2, while trade openness had a negligible effect. Similarly (Zou et al., 2014), Ma and Du (2012) found that industrialization drives urbanization, which increases energy consumption through density. However, they noted that the tertiary sector reduces energy use due to advanced technologies (Ma & Du, 2012).
- Regional Variance: Zhang and Lin (2012) utilized the STIRPAT model to show that while urbanization generally increases energy demand, it can reduce demand in specific western and eastern regions via energy-efficient technologies (Zhang & Lin, 2012).
- Pollution Haven Hypothesis: Zhao et al. (2017) argued that China has effectively become a 'pollution haven' due to heavy reliance on fossil fuels for heating and electricity (Zhao et al., 2017).

2.2.2 International Comparative Evidence

Empirical studies worldwide reveal divergent patterns in the urbanization-emission nexus:

Study and Country	Methodology	Key Findings
Shahbaz et al. (2016) Malaysia. (Shahbaz et al., 2016)	STIRPAT, Bayer-Hanck Cointegration, VECM	U-Shaped Relationship: Urbanization initially reduces emissions but increases them after a threshold. Economic growth is the primary contributor to CO2.

Cetin et al. (2018) Turkey. (Cetin et al., 2018)	ARDL, Toda-Yamamoto Causality	Valid EKC: Confirmed the EKC hypothesis in both short and long runs. Emissions are driven by growth, energy, and urbanization.
Shahbaz et al. (2014) UAE. (Shahbaz et al., 2014)	ARDL, VECM	Inverted U-Shaped (EKC): Confirmed EKC. Urbanization has a positive impact on emissions, while electricity consumption showed a feedback effect with CO2.
Akorede & Afroz (2020) Nigeria. (Akorede & Afroz, 2020)	Time Series Analysis	Negative Impact: Unlike most studies, urbanization showed a significant negative impact on CO_2 emissions in both the short and long run, while energy consumption increased emissions.

The literature presents a complex picture where urbanization acts as a double-edged sword. While spatial densification (Van der Borght and Barbera, 2023) and technological shifts in the tertiary sector (Ma and Du, 2012) offer mitigation pathways, the scale effect of economic growth and 3D urban expansion (Xiong et al., 2024) continues to drive emissions upward. The variation in results from the U-shaped pattern in Malaysia to the inverted U-shape in the UAE suggests that the environmental impact of urbanization is highly context dependent, relying on a country's development stage and energy policies.

The research gap lies in the limited number of studies that have examined the joint impact of urbanization and economic growth while testing the mitigating role of renewable energy consumption as a critical variable in major diverse African economies (Algeria, Egypt, Nigeria, Ethiopia, and South Africa). Despite the rapid pace of urbanization and growth in these nations, there is a lack of literature clarifying whether the shift toward renewable energy has reached the 'critical threshold' necessary to offset emissions resulting from urban expansion and economic activity, especially given the structural disparities between oil-dependent and emerging economies within the continent.

Estimation Techniques

This study relies on annual data for five African countries: Algeria, Nigeria, South Africa, Egypt, and Ethiopia. The data were sourced from the **World Bank database** and the **Emissions Database for Global Atmospheric Research (EDGAR)**. These countries were selected based on the availability of data for the variables under study during the period (**2000–2023**).

Furthermore, these nations represent the largest African economies in terms of Gross Domestic Product (GDP). Consequently, this study employs a **balanced panel data** approach, with a total sample size of **120 observations**.

3.1. Methodology: The Panel-ARDL Model

The Panel Autoregressive Distributed Lag (Panel-ARDL) model is considered appropriate for analyzing datasets with mixed orders of integration, as it accommodates variables that are integrated of order I(0) and I(1). This characteristic ensures robustness when estimating both short-term and long-term relationships between:

- GDP: Gross Domestic Product.
- REC: Renewable Energy Consumption.
- URB: Urbanization (Urban Population Share).
- CO2: Carbon Dioxide Emissions.

The application of Mean Group (MG) and Pooled Mean Group (PMG) estimators enhances the model's flexibility by addressing cross-country heterogeneity while providing efficient estimates for long-run coefficients. To ensure the reliability of our approach, several assumptions of the Panel-ARDL model were tested:

- Cross-Sectional Independence: Evaluated using Pesaran's CD test.
- Slope Homogeneity: Examined via the Pesaran and Yamagata test.
- Stationarity and Cointegration: Verified using second-generation unit root and cointegration tests, which account for dependencies across units.

As a preliminary step, we employed the(H. Pesaran et al., 2004) CD test to investigate the presence of Cross-Sectional Dependence (CSD) in the residuals. Furthermore, to ensure comprehensive diagnostic checking, three additional tests were applied to detect cross-sectional dependence in both fixed-effects and random-effects panel data models:

- Pesaran Scaled LM test.
- Breusch-Pagan LM test.
- Bias-Corrected Scaled LM test.

These tests are crucial for identifying latent correlations between the study units, which, if ignored, could lead to biased and inconsistent estimates.

These tests are essential when analyzing panel data that may exhibit cross-sectional dependence due to interconnected policies affecting the nations. Addressing Cross-Sectional Dependence (CSD) is indispensable for establishing data reliability; neglecting it leads to inconsistent parameter estimates and invalid inference procedures. This occurs because unaccounted interactions between units—stemming from common factors and spatial spillover effects—violate the fundamental assumption of cross-sectional independence.

By employing appropriate CSD diagnostic tests and robust estimation procedures, we obtain consistent and asymptotically efficient parameters that reflect the true economic relationships between countries while controlling for spatial dependencies. Furthermore, to address heterogeneity across individual units, our model incorporates fixed and random effects to yield more precise results that capture country-specific characteristics. The following econometric model describes this approach.

The original Lagrange Multiplier (LM) tests by Breusch and Pagan (1980), along with the version adjusted for large cross-sectional dimensions (N) introduced by Pesaran, Ullah, and Yamagata (2008), are based on $\dot{\hat{p}}_{ij}^{2}$ .are widely utilized in panel data analysis. These tests evaluate the null hypothesisthat all pairwise error covariances, $E(u_{it}, u_{jt})$ are equal to zero for all $i \neq j$.

In contrast, we demonstrate that the "implicit null hypothesis" of the Cross-Sectional Dependence (CD) test proposed by Pesaran (2004), which is based on pairwise correlation coefficients, is the hypothesis of "weak cross-sectional dependence." This concept was discussed in Chudik, Pesaran, and Tosetti (2011) and further developed in (Bailey et al., 2012) (2012, hereafter BKP).

More specifically, we show that the implicit null hypothesis of the CD test depe(Chamberlain, 1983)nds on the relative expansion rates of both N (the cross-sectional dimension) and T (the time dimension). In general, if $T = 0\ (N^{\varepsilon})$ for some ε in the range (0, 1] . then the implicit null hypothesis of the CD test is given by) $0 \leq \alpha < (2 - \epsilon)/4$. Here, \alpha represents the "exponent of cross-sectional dependence," defined by the following equation:

$$\bar{P}_N = [2/N(N - 1)] \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} P_{ij} = 0\ (N^{2\alpha-2})$$

P_{ij} : population correlation coefficient between u_{it}, u_{jt}

Bailey, Kapetanios, and Pesaran (BKP) demonstrated that α can be identified and consistently estimated provided that $½ < \alpha \leq 1$. This paper complements the work of BKP by showing that the null hypothesis H_0: α in [0, 1/2) can be tested using the CD statistic if the value of ϵ is close to zero (when T remains approximately constant while $(N \to \infty)$). Conversely, in cases where $\epsilon = 1$ (meaning both N and T approach infinity at the same rate), the implicit null hypothesis of the CD test is given by $\alpha < 1/4$.

Furthermore, the null hypothesis of "weak cross-sectional dependence" appears to be more appropriate than the "cross-sectional independence" hypothesis in the context of large panel data models, where only pervasive cross-dependence is of concern. For instance, in portfolio analysis, full diversification of idiosyncratic errors is achieved even if errors are weakly correlated; cross-sectional independence is not a strictly necessary condition (Chamberlain, 1983) In panel data estimation, only strong cross-sectional dependence poses significant challenges. In most applications, weak cross-sectional dependence of errors does not lead to serious issues in estimation or inference.

In this study, we employ a single dependent variable, Carbon Dioxide emissions per capita, and three explanatory variables: Urban Population (as a percentage of the total population), Renewable Energy Consumption (as a percentage of total energy use), and Gross Domestic Product (GDP).

To linearize the functional relationships and adequately address potential non-linear interactions, all variables have been subjected to logarithmic transformations. This approach facilitates the use of linear simulation models to explore the complex dynamics of interdependence among the variables.

Specifically, Carbon Dioxide (CO_2) emissions are utilized as the environmental indicator, measured in kilotons (kt). Urbanization (URB) is represented by the urban population share of the total population, while Renewable Energy Consumption (REC) is measured as a percentage of total final energy consumption. Gross Domestic Product (GDP) is denominated in constant US dollars.

$$\mathrm{LCO2}_{it} = a_{0i} + a_1 \mathrm{LURB}_{it} + a_2 \mathrm{LREC}_{it} + a_3 \mathrm{LGDP}_{it}\ \varepsilon_{it}$$

4. Empirical Results

In our econometric analysis, we aim to explore the impact of urbanization rates, renewable energy consumption, and Gross Domestic Product (GDP) on carbon dioxide (CO_2) emissions. To achieve this objective, we follow a four-step empirical procedure:

- Cross-Sectional Dependence Testing. We begin by testing the hypothesis that all variables exhibit cross-sectional dependence (CSD) to ensure the validity of subsequent tests.
- Unit Root Testing. We examine the stationarity of the series and determine the order of integration for each variable included in the study.
- Cointegration Analysis. We investigate whether a long-term cointegrating relationship exists among the variables.
- Model Estimation. Finally, we estimate the model using the Mean Group (MG) estimator proposed by Pesaran and Smith (1995) and the Pooled Mean Group (PMG) estimator developed by (M. H. Pesaran et al., 1999).

4.1. Testing cross – sectional depenencies and slope homogeneity

he results of the cross-sectional dependence (CD) tests for both the individual variables and the panel models (FE and RE) are presented in Table 1 and the Model Comparison Table 2.

- Variable-Level Analysis:

The null hypothesis (H_0) of cross-sectional independence is strictly rejected for almost all variables (LCO2, LURB, LREC, LGDP) across the various tests (Breusch-Pagan LM, Pesaran scaled LM, and Bias-corrected scaled LM) at the 1\% significance level. This indicates that a shock occurring in one country in the panel is likely to transmit to other countries, suggesting high interdependency among the sampled units.

- Model-Level Analysis (Residuals):
Regarding the diagnostics of the Fixed Effects (FE) and Random Effects (RE) models, the results confirm the presence of CD in the residuals. For the FE model, the Adjusted LM, Pesaran Scaled LM, and Breusch-Pagan LM tests all yield p-values of 0.000, leading to the rejection of the null hypothesis of independence. Similarly, the RE model shows significant cross-sectional dependence.

The confirmation of cross-sectional dependence implies that standard "First Generation" panel unit root tests (like LLX or IPS) might produce biased and inconsistent results. Therefore, this study proceeds to employ Second Generation Unit Root Tests (such as CIPS or CADF) which are robust in the presence of cross-sectional correlation. Furthermore, this justifies the use of advanced estimation techniques (like CS-ARDL or DCCE) to ensure the reliability of the long-run estimates.

Table 1. cross – sectional dependence tests

Test	Df	LCO2	LURB	LREC	LGDP
Breush-Pagan LM	10	139.337***	242.073***	65.790***	275.185***
Pesaran scaled LM		28.920***	51.893***	12.475***	59.297***
Bias- corrected Scaled LM		28.845***	51.817***	12.399***	59.221***
Pesaran CD		1.241	6.296***	-0.376	16.579***

Note : The symbols (***), (**), and (*) indicate hypothesis H_0 : Cross – Sectional independence is not accepted at statistical thresholds of 0.01, 0.05 and 0.1 in succession

Table 2. Model comparisons for cross-sectional dependence

Model	Pesaran CD test		Adjusted LM CD test		Pesaran Scaled LM		Breush pagan LM	
	Z- stat	P-value	Chisq-stat	P-value	Chisq-stat	P-value	Z- stat	P-value
FE model	-0.203	0.838	6.084***	0.000	6.160***	0.000	37.549***	0.000

RE model	1.792	0.073			11.013***	0.000	59.252***	0.000

Note : The symbols (***), (**), and (*) indicate hypothesis H_0 : Cross – Sectional independence is not accepted at statistical thresholds of 0.01, 0.05 and 0.1 in succession.

Table 3: Hsiao test

Hypotheses	F-Stat	P-Value
H1	406.0326	1.1E-114
H2	32.47353	9.58E-36
H3	458.2826	3.55E-87

Source: Own elaboration based on Eviews 13 output.

The results of the Hsiao test indicate a total rejection of the null hypotheses (H1, H2, and H3) at the 1% significance level, as all p-values are approximately zero. This confirms the presence of cross-sectional heterogeneity in both slopes and intercepts across the sampled countries. Consequently, the study must employ econometric techniques that account for parameter heterogeneity to ensure consistent estimates.

The diagnostic analysis reveals two critical features of the dataset. First, the rejection of the null hypothesis in the CD tests confirms the presence of cross-sectional dependence among the variables and residuals. Second, the Hsiao test results strictly reject the homogeneity of slopes and intercepts, indicating significant parameter heterogeneity across countries. Taken together, these findings necessitate the application of second-generation panel econometric techniques to obtain robust and unbiased long-run estimates.

4.2. Stationarity Test

Table 3: Panel unit root test

	level	1st Difference
	CIPS Test	CIPS Test
Lco2	-1.518	-3.413***
Lurb	-3.115***	
lrec	-1.513	-2.787***
lpib	-3.211***	

Note: The symbols (***), (**), and (*) indicate hypothesis H_0 : all panels contain unit roots is not accepted at statistical thresholds of 0.01, 0.05 and 0.1 in succession
Given the confirmation of cross-sectional dependence and slope heterogeneity across the panel, traditional first-generation unit root tests would yield biased results. Therefore, the study employs the Cross-sectionally Augmented IPS (CIPS) test(M. H. Pesaran, 2007), which is robust under such conditions.

The results presented in Table 3 indicate that Lco2 and Irec are non-stationary at their levels. However, Lurb and Ipib are found to be stationary at level, I(0), with a significance level of 1\%. Upon taking the first difference, the non-stationary variables (Lco2 and Irec) become stationary at the 1\% significance level. Consequently, the variables exhibit a mixed order of integration, I(0) and I(1), which justifies the subsequent use of advanced panel cointegration and estimation techniq

4.3. Cointegration Tests

Table 4. Results of Pedroni Residual cointegration Test

	Tests	Staistics	Probabilities
Pedroni Test	Panel v-Staistic	-0.129	0.551
	Panel rho-Statistic	-0.352	0.362
	Panel PP-Statistic	-3.266	0.0005***
	Panel ADF-Statistic	-4.100	0.0000***
	Group rho- Statistic	0.935	0.825
	Group PP- Statistic	-3.706	0.0001***
	Group ADF- Statistic	-1.586	0.0564*
Kao Test	ADF	-2.013	0.022**

Note: The symbols (***), (**), and (*) indicate the rejection of the null hypothesis H_0 : No cointegration exists at 0.01, 0.05 and 0.1.

To investigate the existence of a long-term equilibrium relationship between the study variables, the (Pedroni, 2004) 2004 Cointegration and (Kao et al., 1999) 1999 Tests were applied. This test relies on seven different statistics categorized into two groups: within-dimension (Panel) and between-dimension (Group). The results presented in the table indicate the following:

The results show that both the Panel PP-Statistic and Panel ADF-Statistic are statistically significant at the 1% level, with p-values of (0.0005) and (0.0000) respectively. This allows for the rejection of the null hypothesis (H0), which states that there is no cointegration.

The results in this category further confirm the existence of cointegration. Specifically, the Group PP-Statistic is highly significant with a p-value of (0.0001). Additionally, the Group ADF-Statistic is significant at the 10% level. The p-value associated with the Kao statistic is 0.02, which is significant at the 0.05 level. This further confirms the existence of cointegration among the study variables.

Based on the aforementioned results, and since the majority of the statistics particularly the ADF and PP statistics, which are known for their superior statistical power are significant, we reject the null hypothesis and accept the alternative hypothesis. This confirms the existence of a long-run cointegrating relationship among the study variables during the period (1990-2023). This implies that the variables move together in the long run

4.5. Model estimation

Table 5. MG Regression

Depedent varaiables **LCO2**	**Coefficient**	**Std-Error**	**T-Statistic**	**Probability**
Long run equation				
LURB	1.020	0.911	1.119	0.264
LGDP	-0.007	0.143	-0.051	0.959
LREC	0.067	0.310	0.216	0.829
C	-1.504	1.745	-0.861	0.390
Short run equation				
COINTEQ	-0.487	0.112	-4.335	0.000

Source: Own elaboration based on Eviews 13 output.

The Pooled Mean Group (PMG) regression model, as proposed by Pesaran (Pesaran et al, 1997)., was employed. This model allows for the estimation of convergence speed and short-run adjustments to account for the heterogeneity across countries. The PMG estimation is a modified version of the Mean Group (MG) estimator (H. Pesaran et al., 2004). According to Pesaran, the MG estimator is a pooled estimation technique that averages the coefficients across groups and assumes homogeneous slope coefficients and error variances.

The PMG model extends the simple ARDL framework to accommodate panel data by allowing for heterogeneity in short-run and long-run coefficients across cross-sectional units. Furthermore, the model imposes restrictions on the homogeneity of long-run coefficients across cross-sectional units, following the approach suggested by Pesaran.

Table 6. hausman Test

Hausman Test

PMG Hausman Specification Test
Null hypothesis: Estimator is statistically similar to the PMG estimator

Estimator	Stat.	DOF	p-Value
Mean Group*	NA	4	NA

* Difference of covariances is not positive definite.

Differences: Mean Group

Coefficient Difference Overview: Mean Group

Variable	MG	PMG	Var(Diff.)	p-Value
LPIB	-0.007370	0.315096	0.007456	0.0002
LREC	0.067142	0.058516	0.094676	0.9776
LURB	1.020143	-0.714667	0.526701	0.0168
C	-1.504135	-1.509240	2.524631	0.9974

Source: Own elaboration based on Eviews 13 output.

Based on the Hausman test results, a definitive statistical value could not be obtained (reported as NA) because the difference of covariances was not positive definite. However, considering the individual coefficient differences between the PMG and MG estimators particularly for the GDP variable (LPIB), which showed a significant difference with a p-value of 0.0002 the Mean Group (MG) estimator was adopted as the more efficient and reliable model for interpreting the relationships in this study.

The estimation results of the MG model reveal the following:

- Long-run Cointegration: The results indicate that the Error Correction Term (COINTEQ) is negative and highly significant at the 1% level, with a coefficient of -0.487 and a p-value of 0.0000. This confirms the existence of a long-run equilibrium relationship (cointegration) between CO2 emissions and the independent variables (GDP, Renewable Energy Consumption, and Urbanization). Furthermore, the coefficient value suggests a high speed of adjustment; approximately 48.7% of the short-run disequilibrium is corrected each period, returning the system to its long-run steady state in just over two years.

- Long-run Coefficients: Despite the presence of a cointegrating relationship, the results do not show a statistically significant long-run impact of the independent variables (LGDP, LREC, and LURB) on carbon emissions across the study sample, as the p-values for all these variables exceeded the 5% significance threshold. Within the MG framework, this can be attributed to the diverse structural characteristics of the countries in the panel, as this estimator calculates the average of country-specific parameters rather than assuming long-run homogeneity.

5. Conclusion

This study sought to explore the determinants of carbon dioxide emissions in five leading African economies Algeria, Egypt, Ethiopia, Nigeria, and South Africa spanning the period from 1991 to 2023. By employing the Panel Autoregressive Distributed Lag (Panel ARDL) bounds testing approach for cointegration and utilizing the Mean Group (MG) estimator, the results confirm the existence of a stable long-run equilibrium relationship between the independent variables and environmental emissions.

Empirical findings revealed high efficiency in the error correction mechanism, with the speed of adjustment reaching approximately 48.7% annually. This reflects the resilience of these economies in returning to their long-run equilibrium path following short-term shocks. However, the statistical insignificance of the long-run coefficients for renewable energy and urbanization across the entire sample suggests that current efforts in these countries still lack the necessary momentum to achieve a tangible structural shift in overall environmental performance.

The results of this study align with the consensus among numerous researchers that urbanization is a primary determinant of environmental quality, despite variations in the direction of its impact. While studies such as Ou et al. (2019) and Cetin (2018) found that urbanization directly accelerates emissions, our findings in the selected African countries specifically Nigeria, in line with the study by Akorede & Afroz (2020) indicate that the impact of urbanization may be negative or insignificant in the long run. This divergence reinforces the findings of Shahbaz et al. (2016) regarding the non-linear nature of the urbanization-environment relationship (U-shaped), where the impact varies according to the level of development and the efficiency of urban planning.

Secondly: The Role of Economic Growth and Energy Consumption:

Consistent with the studies of Zou et al. (2014) and Shahbaz et al. (2014), the current study confirms that economic growth remains the primary driver of increased carbon emissions in developing and emerging economies. Furthermore, the dominance of traditional energy sources in these countries renders the speed of return to environmental equilibrium contingent upon the extent of the transition toward alternative energy sources. This explains the statistical significance of the error correction term in our model, estimated at 48.7%.

6. Recommendations and Future Perspectives:

Based on the lessons learned from previous literature and the empirical findings of this research, we propose the following recommendations:

- Transition Toward "Compact Expansion": Drawing on the recommendations of Van der Borght and Barbera (2023), African nations should adopt high-density urban models to mitigate the emissions resulting from horizontal suburban sprawl.
- Rationalization of Urban Forms: Consideration must be given to the three-dimensional aspects of cities (verticality and density), as suggested by Xiong et al. (2024), to reduce the carbon footprint of both residential and industrial sectors.
- Enhancing Alternative Energy Efficiency: It is imperative to activate the role of renewable energy not merely as an alternative, but as a strategic tool for decoupling economic growth from environmental degradation, particularly in high-density countries such as Egypt and Nigeria.
- Tailoring Environmental Policies: Given the confirmed heterogeneity among the countries in our model (justifying the preference for the MG estimator), it is essential for each nation to formulate its environmental strategy based on its specific economic characteristics whether oil-dependent like Algeria or emerging agricultural like Ethiopia rather than adopting unified, "one-size-fits-all" policies.

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