Science, Education and Innovations in the Context of Modern Problems
Issue 8, Vol. 8, 2025

Title of research article

Energy Management and Structural Transformation in Emerging Economies: Empirical Evidence on the Role of Renewable Electricity Generation in Reducing Carbon Intensity through CS-ARDL and Method of Moments Quantile Regression Approaches

Bilal Toumi	Doctor
	University of Blida 2
	Algeria
	E-mail: bilaltoumitoumi@gmail.com │ ORCID: 0009-0000-2889-9845
Mohamed Toumi	Doctor
	University of Blida 1
	Algeria
	Email: toumi_mohamed@univ-blida.dz │ ORCID: 0009-0002-7552-6969
Fatima Zahra Derbal	Doctor
	University of Ain Temouchent, Laboratory of Strategies for Developing the Agricultural and Tourism Sectors
	Algeria
	Email: fatima.derbal@univ-temouchent.edu.dz │ ORCID: 0009-0002-5686-221X
Samira Talbi	Doctor
	University of Ain Temouchent, Laboratory of Economic Studies and Local Development in the Southwest
	Algeria
	Email: talbi.samira@univ-bechar.dz │ ORCID: 0000-0002-3110-385X

Issue web link	https://imcra-az.org/archive/375-science-education-and-innovations-in-the-context-of-modern-problems-issue-8-vol-8-2025.html
Keywords	Renewable electricity; carbon intensity; fossil fuels; emerging economies; CS-ARDL; Method of Moments Quantile Regression (MM-QR); Environmental Kuznets Curve (EKC); energy transition; structural transformation; sustainable development.

Abstract

This paper investigates the critical nexus between renewable electricity generation, fossil fuel–based power, and carbon intensity in emerging economies, focusing on the period 2000–2024. The study addresses the dual challenge of sustaining economic growth while reducing greenhouse gas emissions, a dilemma that has intensified with rising energy demand and dependence on fossil fuels. To overcome methodological limitations of previous research, the study employs two complementary advanced econometric approaches: the Cross-Sectionally Augmented Autoregressive Distributed Lag (CS-ARDL) model, which accounts for cross-sectional dependence and slope heterogeneity, and the Method of Moments Quantile Regression (MM-QR), which captures heterogeneous effects across different levels of carbon intensity.

The empirical findings demonstrate three major outcomes. First, renewable electricity generation significantly reduces carbon intensity across the full sample and distributional quantiles, underscoring its role as a cornerstone of sustainable energy transitions. Second, fossil fuel–based electricity generation remains the primary driver of rising emissions, amplifying the carbon intensity of the electricity sector. Third, evidence supports the Environmental Kuznets Curve (EKC) hypothesis: economic growth initially exacerbates carbon intensity but eventually reduces it once a threshold income level is surpassed. Furthermore, electricity demand

has a moderating effect, intensifying carbon intensity where reliance on fossil fuels persists.
These results provide robust evidence that renewable electricity can serve as an effective decarbonization pathway in emerging economies. Policy recommendations include targeted incentives for renewable deployment, demand-side management, promotion of energy efficiency, and reduction of fossil fuel dependence through fiscal and regulatory reforms. By addressing methodological shortcomings and providing nuanced empirical insights, this study contributes to advancing theoretical and policy debates on energy management, climate change mitigation, and structural transformation in developing contexts.

Citation. Bilal T.; Mohamed T.; Fatima Z. D; Samira T. (2025). Energy Management and Structural Transformation in Emerging Economies: Empirical Evidence on the Role of Renewable Electricity Generation in Reducing Carbon Intensity through CS-ARDL and Method of Moments Quantile Regression Approaches. *Science, Education and Innovations in the Context of Modern Problems*, 8(8), 918–931. https://doi.org/10.56334/sei/8.8.81

Received: 01.12.2024 | Accepted: 22.04.2025 | Published: 28.08.2025 (available online)

1- Introduction

Global greenhouse gas emissions from fossil fuel combustion continue to escalate, positioning climate change as one of the most urgent threats to sustainable development worldwide (IPCC, 2023). For emerging economies, this challenge is particularly acute because they must sustain rapid economic expansion, industrialization, and rising living standards while simultaneously reducing dependence on carbon-intensive fossil fuels. This dual pressure creates a policy dilemma: how can these economies achieve growth without locking themselves into high-emission trajectories that jeopardize long-term sustainability? Within this context, the structural transformation of energy systems has become central to both academic debates and policy discussions.

Renewable electricity generation is widely recognized as a critical strategy for decarbonizing the power sector, given its potential to substitute fossil-based generation and curb emissions. However, in emerging economies, its effectiveness is still uncertain. On the one hand, renewables offer opportunities to diversify the energy mix and foster sustainable development; on the other hand, these countries face significant barriers, including rapidly growing electricity demand, limited financial and technological capacity, and continued reliance on fossil fuel–dominated infrastructures. Understanding the dynamic interplay between renewable energy, fossil fuels, electricity demand, and economic development is therefore essential for crafting effective and context-specific decarbonization pathways.

Despite growing scholarly attention, the literature reveals three persistent gaps. First, most studies primarily examine advanced economies, leaving the unique structural challenges of emerging economies underexplored. Second, methodological shortcomings remain: traditional econometric models often neglect cross-sectional dependence, slope heterogeneity, and variations across carbon intensity levels, which can bias empirical outcomes. Third, long-term empirical evidence that integrates both average effects and heterogeneous distributional impacts of renewable and fossil-based electricity generation is scarce, limiting our understanding of how these dynamics evolve over time.

Against this background, the present study seeks to answer several fundamental questions: What is the impact of renewable electricity generation on the carbon intensity of electricity in emerging economies? How does fossil fuel–based electricity influence carbon intensity? Does rising electricity demand amplify or mitigate these effects? And does GDP per capita exhibit a nonlinear relationship with carbon intensity consistent with the Environmental Kuznets Curve (EKC)? Based on these questions, the study hypothesizes that renewable electricity generation exerts a negative and statistically significant impact on carbon intensity, while fossil fuel–based generation increases it. Furthermore, it is assumed that higher electricity demand exacerbates carbon intensity due to greater reliance on fossil fuels, whereas GDP per capita follows an EKC trajectory—initially increasing carbon intensity but reducing it after a certain income threshold. The study also posits the existence of cross-sectional dependence and slope heterogeneity across emerging economies, underscoring the necessity of advanced econometric approaches.

Accordingly, the objectives of this research are fourfold: first, to quantify the management effects and dynamics of renewable and fossil fuel electricity generation on carbon intensity in eight emerging economies over the period 2000–2024; second, to examine the moderating role of electricity demand and GDP per capita within the EKC framework; third, to capture both average and heterogeneous effects across carbon intensity levels using the CS-ARDL and MM-QR approaches; and fourth, to provide policy-relevant insights into the effectiveness of renewable electricity generation as a decarbonization pathway in the context of structural transformation. Ultimately, the study contributes to the literature on sustainable energy transitions while offering practical guidance for policymakers in balancing economic growth with environmental sustainability.

2- Literature Review

The shift toward renewable electricity generation is extensively recognized as a vital strategy for reducing carbon intensity in the power sector; however, the existing literature highlights significant gaps, particularly within the context of emerging economies. Several studies confirm that renewable electricity contributes to emissions reduction by substituting fossil-based generation, though its effectiveness remains constrained by financial, technological, and infrastructural barriers (Voumik, 2022) . Conversely, fossil fuel–based generation continues to dominate electricity production, reinforcing carbon lock-in and driving emissions upward, as evidenced in recent research linking fossil dependency to rising global CO_2 emissions and climate-related damages (Behera, 2023). Moreover, the relationship between economic growth and environmental outcomes remains contested. While some empirical findings validate the Environmental Kuznets Curve (EKC) hypothesis, suggesting that emissions initially rise with income but decline beyond a threshold (Sharif, 2023) , others argue that growth exacerbates environmental degradation in the absence of strong regulatory frameworks and technological innovation (Bekun, 2019) .From a methodologically, traditional panel econometric models often fail to account for cross-sectional dependence and slope heterogeneity, which may bias empirical results. Recent advances, including the Cross-Sectionally Augmented Autoregressive Distributed Lag (CS-ARDL) model and the Method of Moments Quantile Regression (MM-QR), offer more robust approaches by capturing long-run dynamics and distributional heterogeneity, thereby providing deeper insights into the energy–emissions nexus in structurally transforming economies (Chudik, 2015).Despite these contributions, substantial gaps remain. In particular, limited attention has been paid to how renewable electricity generation interacts with fossil-based generation, electricity demand, and structural economic changes in shaping carbon intensity in emerging economies. This study addresses these gaps by integrating CS-ARDL and MM-QR frameworks to provide novel theoretical insights and robust empirical evidence on the role of renewable electricity generation in reducing carbon intensity during structural transformation.

3- Data and methodology

3-1 Data

This study utilizes panel data covering eight major emerging economies—Turkey, China, South Africa, India, Mexico, Brazil, Argentina, and Indonesia—over the period 2000–2024. The sample is selected for three main reasons: (1) these countries represent the largest emerging economies with substantial energy demand and growing influence in global climate policy; (2) they are undergoing rapid structural transformations in their energy sectors, with diverse reliance on both renewable and fossil-based electricity; and (3) they provide consistent and comparable long-term data availability. The time frame 2000–2024 is chosen to capture the most recent phase of energy transition, characterized by the accelerated deployment of renewable technologies, major policy reforms, and heightened international commitments to carbon reduction. Data are obtained from internationally recognized repositories such as *Our World in Data* and the *World Bank Development Indicators*, ensuring reliability and comprehensiveness.

The dependent variable is the carbon intensity of electricity generation (car_int_elec), measured as grams of CO_2 equivalents per kilowatt-hour of electricity produced, reflecting the environmental efficiency of power generation. The main explanatory variables are renewable electricity generation (ren_elec) and fossil fuel electricity generation (fos_elec), both expressed in terawatt-hours. Renewable electricity is hypothesized to mitigate carbon intensity, whereas fossil-based generation is expected to exacerbate emissions.

To capture the demand side of the energy system, electricity demand (elec_dem), measured in terawatt-hours, is included. Additionally, GDP per capita (gdp_pc) and its squared term (gdp_pc2), measured in constant 2015 US$, are incorporated to test the Environmental Kuznets Curve (EKC) hypothesis, which posits a nonlinear relationship between economic growth and environmental degradation. Table 1 summarizes the study variables, including their units, symbols, and data sources.

3-2 Econometric specification

The core analytical framework of this study assumes that the carbon intensity of electricity generation is determined by renewable electricity generation, fossil fuel electricity generation, and a set of socio-economic variables. To empirically assess the effects of the structural transformation of the energy sector on carbon intensity, the study specifies and estimates the following econometric model:

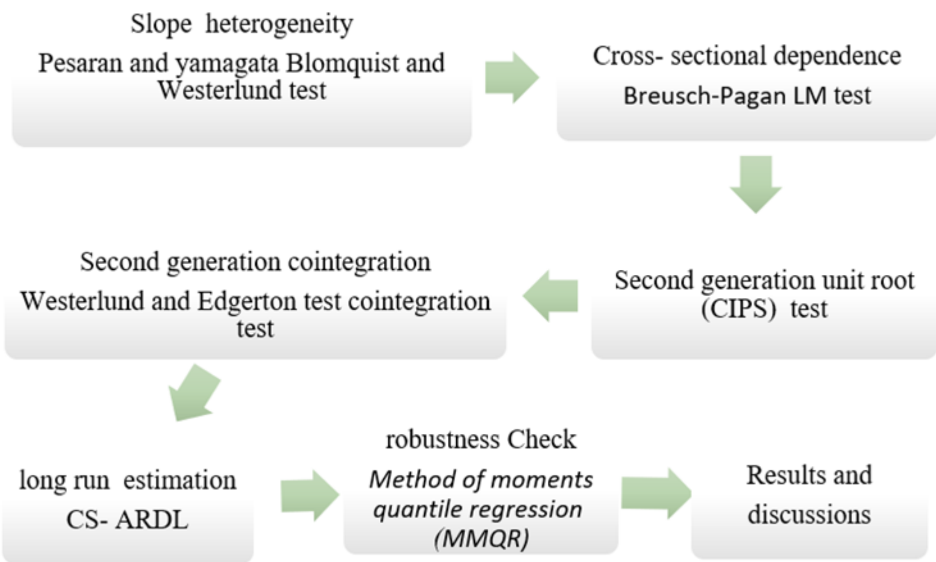
$$\boldsymbol{lncar\_int\_elec_{i,t} = f(ren_{elec_{i,t}} + fos_{elec_{i,t}} + elec_{dem_{i,t}} + gdp_{pc_{i,t}} + gdp_{pc2_{i,t}}) \ldots\ldots (1)}$$

where the subscripts i = 1,...,8 and t = 2000,...,2024 denote the cross-sectional units (countries) and time periods (years), respectively. Based on the general functional form in Equation (1), the primary model of this research is specified as follows:

$$\boldsymbol{lncar\_int_{elec_{i,t}} = B_0 + B_1 lnren_{elec_{i,t}} + B_2\, lnfos_{elec_{i,t}} + B_3\, lnelec_{dem_{i,t}} + B_4\, lnelec_{dem_{i,t}} + B_5\, lngdp_{pc_{i,t}} + B_6\, lngdp_{pc2_{i,t}} .. + U_{i,t} \ldots\ldots (2)}$$

where $lncar\_int_{elec_{i,t}}$ denotes the natural logarithm of carbon intensity of electricity generation. $lnren_{elec_{i,t}}$ represents the natural logarithm of electricity generation from renewables, and $lnfos_{elec_{i,t}}$ represents the natural logarithm of electricity generation from fossil fuels. The natural logarithm of electricity demand is denoted by $ln\mathrm{elec}_{\mathrm{dem}_{i,t}}$. Additionally, $lngdp_{pc_{i,t}}$ and its squared term $lngdp_{pc2_{i,t}}$ represent the natural logarithmic form of per capita GDP and its quadratic term, respectively. The parameters β_1 through β_6 denote their respective coefficients, with β_0 representing the intercept and $U_{i,t}$ serving as the error term.

Figure *1* : Steps of empirical methods



Source: Adopted from Sohail and Abbasi (Sohail et al., 2023) and modified by authors

The empirical analysis starts by assessing slope homogeneity as proposed by (M.H. Pesaran, 2008) . This test, a standardized dispersion test statistic called ($\tilde{\Delta}$), which estimates slope homogeneity based on the work of Swamy (P.A.V.B. Swamy, 1970) . This statistic can be illustrated as:

$$\boldsymbol{\tilde{\Delta} = \sqrt{N}\left(\frac{N^{-1}\quad \bar{s} - k}{\sqrt{2k}}\right) \sim \frac{x^2}{k} \ldots\ldots (3)}$$

The Swamy (P.A.V.B. Swamy, 1970), inquiry is indicated by $\bar{s}$. For a small sample with T > N, the adjusted $\tilde{\Delta}$ is adjusted to $\boldsymbol{\tilde{\Delta}}_{adj}$ as follows:

$$\boldsymbol{\tilde{\Delta}\mathrm{adj} = \sqrt{N}\left(\frac{N^{-1}\quad \bar{s} - k}{\sqrt{v}(T, k)}\right) \sim N(0,1) \ldots\ldots (4)}$$

Here, N denotes the number of cross-sectional entities, S represents the estimates derived from the Swamy (P.A.V.B. Swamy , 1970) , inquiry, and k signifies the number of predictors. The null hypothesis is rejected at a 5 % significance level if the p-value is below 5%, which indicates heterogeneity in the co-integrating coefficient of the inquiry statistics. The transformation of the $\tilde{\Delta}$ form into $\tilde{\Delta}_{adj}$ incorporates a "mean variance bias adjusted" mechanism with the adjusting variance parameter v.

To address autocorrelation concerns, the standard $\tilde{\Delta}$ inquiry must be free of such issues. To mitigate problems from homoscedasticity and serial correlation, (M.H. Pesaran A. U., 2008) and Blomquist and Westerlund (J. Blomquist, 2013) developed dynamic heteroscedasticity and autocorrelation consistent (HAC) techniques for the slope homogeneity examination, denoted as Δ_{HAC} and Δ_{HAC} adj Respectively.

$$\Delta_{HAC} = \sqrt{N}\left(\frac{N^{-1}\ \ s_{HAC} - k}{\sqrt{2k}}\right) \sim \frac{x^2}{k} \ldots\ldots (5)$$

$$\Delta_{HAC\ adj} = \sqrt{N}\left(\frac{N^{-1}\ \ s_{HAC} - k}{\sqrt{v}(T,k)}\right) \sim N(0,1) \ldots\ldots (6)$$

The null hypothesis of slope homogeneity is rejected when the p-value is <0.05 for all panel units. Furthermore, if heterogeneity is present among the panel squads, using a heterogeneous panel technique is appropriate.

Secondly, to determine the most appropriate generation of unit root tests, cross-sectional dependence (CSD) tests were conducted on the variables. For this purpose, a wide range of CSD tests were employed, including the Breusch-Pagan Lagrangian Multiplier (LM) test (Breusch TS, 1980). The null hypothesis of this test is cross-sectional independence, with its rejection indicating the presence of CSD. Additionally, more recent tests such as the CD test by (pesaran, 2015) , the CDW test by Joudis and Reese (juodis, 2021) the CDW+ test by (fan, 2015), and the *CDW test by* (pesaran m. &., 2021) were also applied. These more advanced tests have a null hypothesis of weak cross-sectional dependence, and their rejection suggests the presence of strong CSD among the variables. However, primary reliance was placed on the Breusch-Pagan LM test, as it is particularly suitable for panel data where the time period (T) is greater than the number of cross-sections (N) (De Hoyos RE, 2006). The test is formulated as follows:

$$LM = \sum_{i-1}^{N-1} \sum_{j=i+1}^{N} T_{ij}\hat{\rho}_{ij}^2 \rightarrow X^2 \frac{N(N-1)}{2} \ldots\ldots (7)$$

whereX^2 represents the asymptotic circulation for N fixed as T_{ij}, and $\hat{\rho}_{ij}^2$ $\rightarrow\infty$ indicates the correlation coefficients.

Thirdly, we employ panel unit root tests proposed by (Pesaran, 2007) (2007). The objective is to identify the stationarity features of the variables. Pesaran (2007) extended the Dickey-Fuller (DF) regression model to account for potential cross-sectional dependence in the panel data series. The CSD Augmented DF statistic (CADF) is calculated as:

$$\Delta y_{i,t} = \alpha_i + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_i \Delta\bar{y}_t + u_{it} \ldots\ldots (8)$$

Where Δ is the difference operator, yt is the average of the target variable for N observations. Based on Equation (8), a cross-sectional augmented Im-Pesaran-Shin (CIPS) test with the following statistics is calculated:

$$CIPS = \frac{1}{N}\sum_{i=1}^{N} CADF_i \ldots\ldots (9)$$

For a more robust CIPS statistic, Pesaran (2007) recommends additional tests to determine the truncated version of the CIPS statistic as follows:

$$CIPS - TR = \frac{1}{N}\sum_{i=1}^{N} CADF_i^* \ldots\ldots (10)$$

Where $CADF_i^*$. suggests that the derived CIPS statistic has been truncated to limit the effect of extreme values that could result from the size of T not being sufficiently large.

In our study of cointegration relation (an important stage of empirical analysis), we preferred Westerlund and Edgerton's (2007) bootstrap panel LM cointegration technique (Westerlund, 2007), which considers the horizontal cross-sectional dependence of second generation techniques. Important advantages of the technique include the determination of reliable results with Monte Carlo simulations in small sample groups and the allowance of changing variance with autocorrelation. The statistics used in this test are as follows (Westerlund, 2007)

$$\boldsymbol{LM_N^+} = \frac{\mathbf{1}}{\boldsymbol{NT^2}}\sum_{i=1}^{N}\sum_{t=0}^{T}\widehat{\boldsymbol{w}}_i^{-2}\boldsymbol{S}_{it}^2 \ldots\ldots(\mathbf{11})$$

where S_{it}^2 represents the fractional sum of error terms in the equation and $\widehat{w}_i^{-2}$ represents the error terms' variance in the long run. Here, we assessed the hypothesis of the test against the null hypothesis and the alternative hypothesis. The null hypothesis means there is cointegration, and the alternative hypothesis means there is no cointegration. The test's hypotheses are as follows: H_{0i} : θ_i^2 = 0 for all i's
H_{1i} : θ_i^2 > 0 for some i's

Next-to-lastly, we employ the CS-ARDL model developed by Chudik and Pesaran (Chudik A, 2015) to investigate the short-run and the long-run dynamics among the study variables. This method is particularly well-suited for panel data where the variables exhibit a mix of stationarity levels, specifically I(0) or I(1), significant CSD, and slope heterogeneity. The model accounts for CSD and slope heterogeneity by employing a dynamic common correlated effect (DCCE) approach. The CS-ARDL model extends the traditional panel ARDL model by incorporating cross-sectional averages of the dependent variable and all regressors to account for CSD and slope heterogeneity as represented in Eq.12

$$\boldsymbol{lncar\_int_{elec_{it}}} = \sum_{j=1}^{p}\boldsymbol{\varphi_{ij}lncar\_int_{elec_{i,t-j}}} + \sum_{j=0}^{q}\boldsymbol{B'_{ij}X_{i,t-j}} + \sum_{j=1}^{p}\boldsymbol{\gamma_j\Delta\overline{lncar\_int_{elec_{i,t-j}}}} + \sum_{j=1}^{q}\boldsymbol{\delta'_{ij}\Delta\overline{X_{i,t-j}}} + \boldsymbol{u_{it}} \ldots\ldots(\mathbf{12})$$

Where $X_{i,t}$ is a k × 1 vector of regressors for cross-section i at time t. $\overline{lncar\_int_{elec_{i,t-j}}}$ and $\overline{X_{i,t-j}}$ represent the cross-sectional average of $lncar\_int_{elec_i}$ and X_i at time t - j, respectively, where j represents the lag order. The scalars φ_{ij} represent the coefficients of the lagged dependent variable. B_{ij} is a k × 1vector of coefficients for the explanatory variables. The scalars γ_j represents the coefficients for the cross-sectional averages of the lagged dependent variable, δ_{ij} is a k × 1vector of coefficients for the cross-sectional averages of the explanatory variables, and u_{it} denotes the error term, assumed to be independently and identically distributed across *i* and *t* .To address the effects of the error correction mechanism (ECM) within the panel CS-ARDL model, Eq. (3) can be reformulated as follows:

$$\boldsymbol{\Delta lncar\_int_{elec_{i,t}}} = \boldsymbol{\phi_i lncar\_int_{elec_{i,t-j}}} + \boldsymbol{\lambda'_i X_{i,t}} + \sum_{j=1}^{p-1}\boldsymbol{\varphi_{ij}^*\Delta lncar\_int_{elec_{i,t-j}}} + \sum_{j=0}^{q-1}\boldsymbol{\beta^*_{ij}\Delta X_{i,t-j}} + \sum_{j=1}^{p}\boldsymbol{\gamma_j\Delta\overline{lncar\_int_{elec_{i,t-j}}}} + \sum_{j=1}^{q}\boldsymbol{\delta'_{ij}\Delta\overline{X_{i,t-j}}} + \boldsymbol{u_{it}} \ldots\ldots(\mathbf{13})$$

Where $\Delta lncar\_int_{elec_{i,t}}$ is the change in $lncar\_int_{elec_{i,t}}$. ϕ_i = -(1-$\sum_{j=1}^{p}\varphi_{ij}$) denotes the error correction term (ECT) for each crosssection i , and $\lambda_i = \sum_{j=0}^{q} B_{ij}$ denotes long-run coefficients for each cross-section i.
φ_{ij}^* = - $\sum_{m=j+1}^{p}\varphi_{im}$ for j = 1.2 ....p-1 , and $\beta^*_{ij} = \sum_{m=j+1}^{q} B_{im}$, for j = 1.2 ....q-1 are the short-run parameters for each i.

3-3 Method of moments quantile regression (MM-QR)

The Quantile Regression via Moments (MM-QR) technique, developed by (J.A.F. Machado, 2019) represents an advanced methodological framework for panel data analysis, surpassing traditional regression methods that are limited to measuring only conditional means. This methodology measures the impact of independent variables across the entire distribution of the dependent variable ,allowing for a deeper understanding of relationships at different response levels. This method is distinguished by its effectiveness in handling non-normal distributions of variables and its ability to accommodate outliers in the dependent variable, making it a robust and suitable tool for data that does not conform to the assumptions of classical linear regression. Furthermore, it effectively addresses individual fixed effects and potential endogeneity ,and ensures consistent and non-crossing quantile estimates, which provides a precise and reliable statistical analysis.The MMQREG equation for our basic model is presented as follows:

$$Q_{lncar\_int_{elec_{it}}}(\tau_k|\alpha_i, X_{it}) = B_0 + B_1\, lnren_{elec_{i,t}} + B_2\, lnfos_{elec_{i,t}} + B_3\, lnelec_{dem_{i,t}} + B_4\, lngdp_{pc_{i,t}} + B_5 lngdp_{pc2_{i,t}} + u_{it} \ldots\ldots (14)$$

τ indicates the conditional distribution's number of quantiles, and X_{it}represents the independent variables. The parameters β_1 through β_6 denote their respective coefficients, with β_0 representing the intercept and $U_{i,t}$ serving as the error term.

4- Results and Discussion

4-1 Descriptive Statistics

The descriptive analysis of the dataset encompassing eight emerging economies from 2000 to 2024 provides critical insights into the underlying patterns and relationships among the studied variables. Summary statistics (Table 2) indicate substantial heterogeneity across countries, as evidenced by consistently larger “between-country” standard deviations compared to the “within-country” values, suggesting that structural differences dominate temporal variations within each economy. Distributional analyses further reveal that the carbon intensity of electricity generation exhibits a left-skewed pattern with several extreme outliers, confirmed by skewness and kurtosis tests ($p < 0.01$) for lncar_int_elec, lngdp_pc, lngdp_pc², and lnfos_elec. These observations highlight the necessity of employing robust econometric techniques capable of capturing heterogeneous effects across the full distribution, rather than focusing solely on average trends. Correlation analysis (Figure 4) demonstrates a strong positive relationship ($r = 0.77$) between renewable electricity generation (lnren_elec) and total electricity demand (lnelec_dem), indicating that the expansion of renewable capacity is closely tied to rising energy requirements. The dependent variable lncar_int_elec shows moderate negative correlations with lngdp_pc ($r = -0.41$) and lnren_elec ($r = -0.36$), supporting the hypothesis that economic growth and renewable energy deployment play a significant role in reducing carbon intensity. Taken together, these findings suggest that while emerging economies face structural and demand-driven challenges, renewable electricity generation represents a critical lever for decarbonizing the power sector, highlighting the importance of policy interventions aimed at enhancing renewable energy adoption and managing electricity demand efficiently.

4-2 Slope homogeneity test results

Table 3 reports the results of Pesaran and Yamagata’s and Blomquist and Westerlund’s slope homogeneity tests. Both tests reject the null hypothesis of slope homogeneity, confirming the existence of slope heterogeneity in the panel. This finding indicates that conventional homogeneous panel estimators may be inappropriate, thereby justifying the use of advanced techniques such as CS-ARDL and MM-QR to account for heterogeneity and cross-sectional dependence.

4-3 Cross-section dependence and Rank Condition results

The results in Table 4 reveal significant cross-sectional dependence ($p < 0.01$) across all variables, requiring the use of second-generation unit root tests. Table 5 further confirms the validity of the classifier rank condition (RC = 1; g = 3 > m = 1), indicating that cross-sectional averages capture latent common factors. Together, these findings justify the application of advanced panel techniques that account for both dependence and unobserved heterogeneity.

4-4 Stationarity and Cointegration

The CIPS unit root test results (Table 6) indicate that most variables—including lncar_int_elec, lnfos_elec, lnelec_dem, lngdp_pc, and lngdp_pc2—are non-stationary and integrated of order one, I(1), whereas lnren_elec is stationary at level, I(0). Furthermore, the Westerlund and Edgerton cointegration tests (Table 7) reject the null hypothesis of no long-run equilibrium relationship ($p < 0.01$ for G□, G_a, and P_a), suggesting the existence of a potential long-run equilibrium relationship among the variables.

4-5 CS-ARDL and MMQR results

The CS-ARDL results confirm the long-run equilibrium between carbon intensity and its key determinants but highlight contrasting effects. Fossil-fuel electricity generation (lnfos_elec) exerts a positive and highly significant impact, reaffirming its role as the dominant driver of emissions in the power sector. By contrast, electricity demand (lnelec_dem) shows a negative and statistically significant coefficient, suggesting that expanding electricity consumption may reduce relative carbon intensity, possibly through efficiency improvements or cleaner energy integration. Renewable electricity generation (lnren_elec), however, displays an unexpected positive but insignificant effect, which likely reflects its limited penetration within the energy mix of emerging economies during the study period. With respect to income, GDP per capita (lngdp_pc) is positive and significant, while its squared term (lngdp_pc2) is negative but insignificant, tentatively indicating an Environmental Kuznets Curve (EKC) pattern, though not conclusive at this stage.

The short-run results align with these findings, showing that immediate changes in fossil-fuel generation increase carbon intensity, while changes in electricity demand reduce it. Renewable energy remains insignificant in the short term, while the highly significant error correction term (ECM = −0.9466, $p<0.01$) demonstrates a strong adjustment mechanism, with nearly 95% of disequilibrium corrected annually.

Given the limitations of CS-ARDL, particularly the insignificant renewable effect and inconclusive EKC evidence, MM-QR estimations provide a more nuanced perspective. They reveal a robust negative and significant effect of renewables across all quantiles, with stronger impacts at higher levels of carbon intensity, confirming the critical role of renewables in highly fossil-dependent contexts. Fossil-fuel electricity consistently shows a positive and significant effect, which intensifies in higher quantiles, while electricity demand continues to exert a mitigating influence. Importantly, MM-QR provides strong support for the EKC hypothesis: GDP per capita has a positive coefficient, while its squared term is negative across quantiles. The estimated turning point at the median quantile (Q=0.50) is approximately USD 1,436 per capita. This implies that carbon intensity rises with economic growth up to this threshold, after which further growth contributes to a decline in carbon intensity. In other words, economies initially experience “growth-driven environmental pressure,” but upon reaching the turning point, structural changes, technological adoption, and energy diversification lead to a decoupling of growth and emissions.

In summary, the CS-ARDL model emphasizes the existence of long-run equilibrium relationships, but underestimates the role of renewables and fails to confirm the EKC, while MM-QR provides robust evidence that renewable energy effectively reduces carbon intensity and validates the EKC turning point. This underscores that sustained economic growth, once it surpasses the threshold level, can act as a catalyst for environmental improvements in emerging economies, provided that it is accompanied by accelerated renewable deployment and reduced fossil fuel dependence.

5- Policy implications

This study examined the role of renewable electricity generation in reducing carbon intensity in eight emerging economies (2000–2024), considering fossil fuel–based electricity, electricity demand, and economic growth. The findings confirm that renewable electricity significantly reduces carbon intensity (H1 supported), while fossil-based generation drives emissions upward (H2 confirmed). Electricity demand exhibits a mitigating role that varies across carbon intensity levels (H3 partially supported), and GDP per capita follows an Environmental Kuznets Curve pattern, initially increasing and later reducing carbon intensity (H4 validated). Cross-sectional dependence and slope heterogeneity are evident, justifying the use of CS-ARDL and MM-QR (H5 supported). These results highlight the importance of accelerating renewable integration, diversifying energy sources, and implementing demand-side management policies. Overall, the study provides a pathway for emerging economies to achieve sustainable energy transition, balancing economic growth with environmental protection.

6- Conclusions

Although this study employing CS-ARDL and MM-QR provides robust evidence on the role of renewable electricity in reducing carbon intensity in emerging economies, several limitations remain. The analysis does not fully capture potential nonlinear interactions among renewable and fossil-based electricity, electricity demand, and economic growth over time. Additionally, the study does not account for sectoral differences or regional heterogeneity within countries, which may influence the effectiveness of decarbonization policies. Future research could address these limitations by exploring nonlinear and threshold effects using advanced panel techniques, integrating sector-specific data, or employing simulation models to evaluate policy interventions. Such extensions would enhance our understanding of the complex dynamics of energy transitions and provide more precise, actionable guidance for policymakers aiming to achieve sustainable and low-carbon electricity systems.

Table 1 Data Sources and Variable Definitions

Symbol	Variable Name	unit	Source

car_int_elec	Carbon intensity of electricity generation - Greenhouse gases emitted per unit of generated electricity,	grams of CO_2 equivalents per kilowatt-hour	https://ourworldindata.org
ren_elec	Electricity generation from renewables	terawatt-hours	https://ourworldindata.org
fos_elec	Electricity generation from fossil fuels	terawatt-hours	https://ourworldindata.org
elec_dem	Electricity demand	in terawatt-hours	https://ourworldindata.org
gdp_pc	GDP per capita	constant 2015 US$	https://data.worldbank.org
gdp_pc2	squared term GDP per capita	constant 2015 US$	https://data.worldbank.org

Table 2 Descriptive Statistics

Variable		**Mean**	**Std. dev.**	**Min**	**Max**	**Observations**
lncar_int_elec	overall	6.19	0.59	4.47	6.70	N = 200
	between		0.62	4.77	6.66	n = 8
	within		0.10	5.89	6.68	T = 25
lnren_elec	overall	4.32	1.65	0.23	8.12	N = 200
	between		1.65	1.53	6.82	n = 8
	within		0.57	2.92	6.26	T = 25
lnfos_elec	overall	5.54	1.26	3.42	8.73	N = 200
	between		1.29	4.17	8.09	n = 8
	within		0.34	4.46	6.33	T = 25
lnelec_dem	overall	6.04	1.12	4.50	9.21	N = 200
	between		1.14	4.87	8.37	n = 8
	within		0.33	4.87	6.88	T = 25
lngdp_pc	overall	8.66	0.74	6.62	9.62	N = 200
	between		0.74	7.19	9.41	n = 8
	within		0.27	7.66	9.43	T = 25
lngdp_pc2	overall	75.59	12.44	43.94	92.65	N = 200
	between		12.31	51.92	88.60	n = 8
	within		4.64	58.87	89.29	T = 25

Skewness/Kurtosis tests for Normality			———joint———	
	Pr(Skewness)	**Pr(Kurtosis)**	**chi2(2)**	**Prob > chi2**
lncar_int_elec	0.0000	0.0003	51.93***	0.0000
lnren_elec	0.3960	0.5912	1.02	0.6006
lnfos_elec	0.0000	0.4082	19.41***	0.0001
lnelec_dem	0.0000	0.0904	27.45***	0.0000
lngdp_pc	0.0000	0.7842	20.67***	0.0000
lngdp_pc2	0.0000	0.4224	17.17***	0.0002

Table 3 Slope Heterogeneity Test Results

Statistic	**Value**	**p-value**
Delta (Δ)	11.246***	0.000
Delta adjusted (Δ_{adj})	13.253***	0.000
Delta $_{HAC}$ (Δ_{HAC})	3.470***	0.001
Delta $_{HAC}$ adjusted ((Δ_{HAC}) adj)	4.089***	0.000

Table 4 Cross-Sectional Dependence Tests Result

Variable	**Breusch-Pagan LM**	**CD**	**CD_w**	**CD_{w+}**	**CD^***	**alpha**
lncar_int_elec	201.53***	4.47***	0.12	66.26***	-2.12**	0.38

lnren_elec	481.43***	21.49***	2.22***	115.95***	-4.54***	1.00
lnfos_elec	430.21***	18.85***	2.29***	102.32***	1.11	0.94
lnelec_dem	525.95***	21.97***	2.29***	118.53***	3.68***	1.00
lngdp_pc	451.94***	20.93***	2.03**	112.77***	-2.10**	1.00
lngdp_pc2	447.70***	20.82***	2.00**	112.16***	-1.99**	1.00

Table 5 Rank Condition

Classifier for Rank Condition (De Vos, Everaert and Sarafidis, 2024)		
RC (1-I(g < m))	Estimated Rank (g)	**Number of Factors (m)**
1	3	**1**

Table 6 CIPS Unit Root Test Result

Variables	**I(0)**	**I(1)**
lncar_int_elec		-5.150***
lnren_elec	-2.299***	
lnfos_elec		-3.816***
lnelec_dem		-3.236***
lngdp_pc		-3.063***
lngdp_pc2		-3.011***

Note: ***p-value<0.01.

Table 7 Cointegration Tests

Statistics	Value	Robust P-value
Gt	-2.428***	0.000
Ga	-5.682***	0.000
Pt	-4.787	0100
Pa	-4644***	0.000

Table 8 CS-ARDL Long and Short Run Analysis

Variable	**Coef .**	**Std. Err.**
Long-run analysis		
lnren_elec	0.02298	0.0211
lnfos_elec	0.6855***	0.1468
lnelec_dem	-0.4822***	0.1849
lngdp_pc	12.0026*	7.2025
lngdp_pc2	-0.6494	0.4020
Short Run analysis		
LD. lncar_int_elec	0.05335	0.0968
lnren_elec	-0.1330	0.1026
D. lnfos_elec	0.7437***	0.1241
D. lnelec_dem	-0.5623***	0.2151
D. lngdp_pc	5.9392	6.1669
D.lngdp_pc2	-0.3364	0.3522
L. lnren_elec	0.1529	0.1175
LD. lnfos_elec	-0.0724	0.1313
LD. lnelec_dem	0.1373	0.1210
LD. lngdp_pc	6.7918	10.2606
LD. lngdp_pc2	-0.3625	0.5671
ECM (-1)	-0.9466***	0.0968
Residuals		
CD-test value	-0.344	
p.value	0.731	

Table 9 Moment quantile regression result

variable	location	scale	Q_{10}	Q_{20}	Q_{30}	Q_{40}	Q_{50}	Q_{60}	Q_{70}	Q_{80}	Q_{90}
lnren_elec	-0.046***	0.009***	-0.060***	-0.056***	-0.052***	-0.048***	-0.047***	-0.045***	-0.042***	-0.037***	-0.030***
lnfos_elec	0.821***	-0.017***	0.795***	0.803***	0.810***	0.817***	0.821***	0.825***	0.830***	0.839***	0.851***
lnelec_dem	-0.701***	-0.034***	-0.648***	-0.664***	-0.679***	-0.693***	-0.700***	-0.708***	-0.719***	-0.737***	-0.762***
lngdp_pc	0.719***	-0.189*	1.016***	0.925***	0.844***	0.764***	0.727***	0.683***	0.624***	0.521***	0.383
lngdp_pc2	-0.049***	0.013*	-0.069***	-0.063***	-0.058***	-0.052***	-0.050***	-0.047***	-0.043***	-0.036***	-0.027***
cons	3.566***	0.795*	2.313**	2.699***	3.037***	3.376***	3.533***	3.719***	3.967***	4.399***	4.980***

Table 10 List of Selected Emerging Economies

China	Turkiye
India	South Africa
Brazil	Mexico
Indonesia	Argentina

Figure 2 Histogram of lncar_int_elec

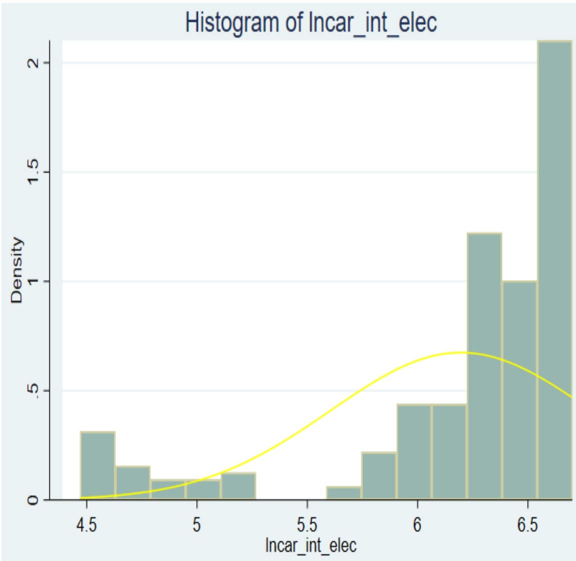


Figure 3 Box Plot of lncar_int_elec

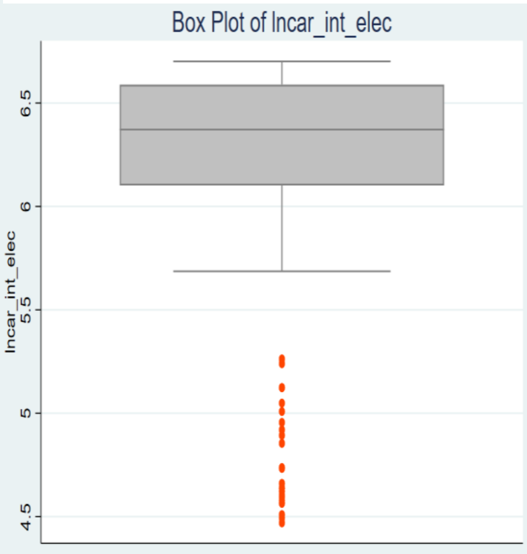
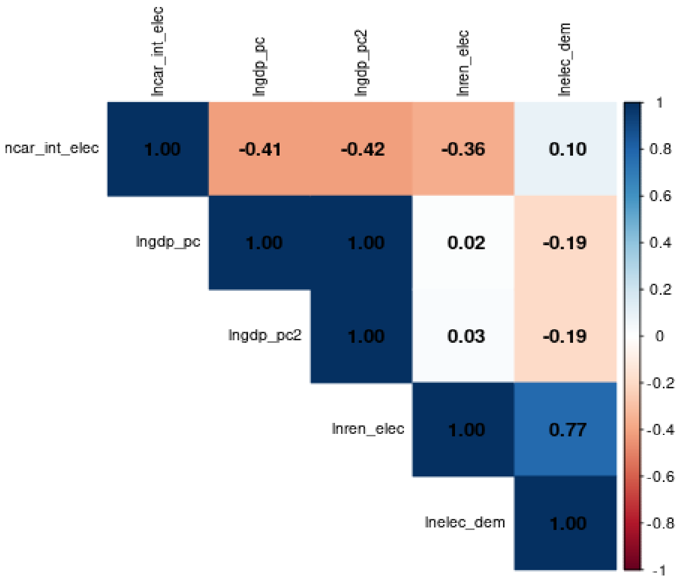


Figure 4 Results of correlation matrix.



Findings

- Renewable electricity generation exerts a statistically significant negative impact on carbon intensity, confirming its role as a decarbonization instrument across emerging economies.
- Fossil fuel–based power generation continues to drive emissions upward, offsetting gains from renewables where fossil dependence remains dominant.
- GDP per capita follows an EKC trajectory—carbon intensity rises at early stages of development but declines once a critical income threshold is achieved.
- Rising demand amplifies carbon intensity in fossil-dependent systems, but in renewable-intensive contexts, demand growth becomes less carbon-intensive.
- Results vary across countries and quantiles, highlighting the importance of tailored policies that account for structural differences in energy systems.
- Strengthening renewable energy support schemes, adopting regional technology transfer programs, and integrating carbon reduction into national growth strategies are vital for sustainable transitions.

Actuality of the Study

This research provides one of the most comprehensive empirical analyses of renewable electricity and carbon intensity in emerging economies, a context often overlooked in existing studies that focus on developed countries. By applying advanced econometric models (CS-ARDL and MM-QR), the study not only addresses cross-sectional dependence and slope heterogeneity but also captures heterogeneous effects across different levels of carbon intensity. This dual methodological innovation ensures greater robustness and policy relevance of the findings. The study's originality lies in bridging the gap between structural energy transformation theory and empirical evidence from emerging economies, thereby offering fresh insights into the dynamics of low-carbon development under conditions of rapid growth and energy demand pressures.

Ethical Considerations

This research complies with international standards of academic integrity. The study relies exclusively on secondary data from recognized statistical databases and does not involve human participants or sensitive personal information. No manipulation, falsification, or misrepresentation of results was undertaken. Proper credit has been given to all data sources and referenced works.

Acknowledgments

The authors extend their gratitude to the University of Blida 1, University of Blida 2, and University of Ain Temouchent for institutional support, and to colleagues from the Laboratory of Economic Studies and Local Development for their valuable feedback during the research process.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. The study was self-funded by the authors.

Conflict of Interest

The authors declare no conflict of interest with respect to the research, authorship, and publication of this article.

References

1. Altın, H. (2024). The impact of energy efficiency and renewable energy consumption on carbon emissions in G7 countries. *International Journal of Sustainable Engineering, 17*(1), 134-142.
2. Behera, P. (2023). Fossil fuels and the persistence of emissions: Evidence from emerging markets. *Renewable and Sustainable Energy Reviews, 176,*, 113170.
3. Bekun, F. V. (2019). Economic growth and environmental degradation in sub-Saharan Africa: Revisiting the EKC hypothesis. *Environmental Science and Pollution Research, 26(1),* , 651–667.
4. Breusch TS, P. A. (1980). The lagrange multiplier test and its applications to model specification in econometrics. . *Rev Econ Stud. https://doi.org/10.2307/2297111.*, 239–53. .
5. Chudik A, P. M. (2015). Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenousregressors. . *J Econometrics. : https://doi.org/10.1016/j.jeconom.2015.03.007.*, 393–420.
6. Chudik, A. &. (2015). Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. . *Journal of Econometrics, 188(2),* , 393–420.
7. De Hoyos RE, S. V. (2006). Testing for cross-sectional dependence in panel-data models. Stata J. *6(4):. https://doi.org/10.1177/1536867X0600600403*, 482–96.
8. fan, J. l. (2015). POWER ENHANCEMENT IN HIGH-DIMENSIONAL CROSSSECTIONAL TESTS. *The Econometric Society, 83,* , 1497-1541.
9. J. Blomquist, J. W. (2013). Testing slope homogeneity in large panels with serial correlation . *, Econ. Lett. 121 (https://doi.org/10.1016/j. econlet.2013.09.012*, 374–378,.
10. J.A.F. Machado, J. S. (2019). Quantiles via moments,. *Econom. 213 (2019) https://doi.org/10.1016/j.jeconom.2019.04.009*, 145–173,.
11. juodis, A. &. (2021). The Incidental Parameters Problem in Testing for Remaining CrossSection Correlation. *Journal of Business & Economic Statistics, 40, doi: https://doi.org/10.1080/07350015.2021.1906687*, 1191-1203. .
12. M.H. Pesaran, A. U. (2008). , Econom. J. 11 https://doi.org/10.1111/j.1368- 423X.2007.00. *Yamagata, A bias-adjusted LM test of error cross-section independenc*, 105–127,.
13. M.H. Pesaran, A. U. (2008). A bias-adjusted LM test of error cross-section independence. *Econom. J. 11 https://doi.org/10.1111/j.1368- 423X.20*, 105-127.
14. P.A.V.B. Swamy . (1970). Efficient inference in a random coefficient regression model,. *Econometrica 38 https://doi.org/10.2307/1913012*, 311–323,.
15. P.A.V.B. Swamy. (1970). Efficient inference in a random coefficient regression model, . *Econometrica 38 (1970) , https://doi.org/10.2307/1913012*, 311–323.
16. P.A.V.B. Swamy, E. (1970). fficient inference in a random coefficient regression model, . *Econometrica 38, https://doi.org/10.2307/1913012.*, 311–323.
17. pesaran, m. &. (2021). A Bias-Corrected CD Test for Error Cross-Sectional Dependence in Panel Data Models with Latent Factors. . *Cambridge Working Papers in Economics. Faculty of Economics, University of Cambridge.*
18. Pesaran, M. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics, 22,* , 265–312.

19. pesaran, m. (2015). Testing Weak Cross-Sectional Dependence in Large Panels. . *Econometric Reviews, 34, https://doi.org/10.1080/07474938.2014.956623*, 1089-1117. .
20. Sharif, A. e. (2023). Economic growth, urbanization, and environmental quality in emerging economies: Testing the EKC hypothesis. *Environmental Research, .*, 216, 114564.
21. Sohail, A., Du, J., & Abbasi, B. A. (2023). Exploring the interrelationship among health status, CO2 emissions, and energy use in the top 20 highest emitting economies: based on the CS-DL and CS-ARDL approaches. *Air Quality, Atmosphere & Health, 16*(7), 1419-1442.
22. Voumik, L. C. (2022). Renewable electricity deployment in developing economies: Challenges and prospects. *Energy Reports,* , 899–912.
23. Westerlund, J. &. (2007). A panel bootstrap cointegration test. Economics Letters, 97(3), . *doi:10.1016/j.econlet.2007.03.003*, 185–190.