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From Fossil to Future: Trade, Technology and Clean Energy Transitions in High-Impact Developing Economies

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Received: 29 June 2025; Accepted: 25 August 2025; Available online: 3 September 2025

JEL Codes: Q53; Q56; F18; O44; C33

ABSTRACT: This study examines the impact of economic growth, renewable energy equipment imports, and energy use on CO_2 emissions in seven developing countries over the period 2000–2021, employing second-generation panel estimators (Augmented Mean Group AMG, The Common Correlated Effects Mean Group CCEMG) that account for cross-sectional dependence and slope heterogeneity. Results show that economic growth and energy use significantly increase emissions, while renewable energy equipment imports display no direct or robust mitigating effect. This limited impact likely reflects adoption and integration challenges and the absence of complementary policies, underscoring the need for strategies that link imports to technology transfer and domestic manufacturing capacity. Granger causality tests indicate that growth and renewable energy imports drive emissions, highlighting the necessity for integrated green industrial policies, carbon pricing mechanisms, and sustainable finance instruments. These findings suggest that, for developing economies, achieving low-carbon growth requires a coordinated policy mix that aligns environmental objectives with economic development goals.

Keywords: Carbon emissions; Economic growth; Renewable energy equipment; Energy use; Panel data analysis

1. Introduction

In today's world, the environmental costs of economic development are being scrutinized more carefully than ever before within the framework of the sustainable development paradigm. Developing countries face a critical dilemma: while striving to achieve their growth objectives, they must also contend with environmental degradation, depletion of natural resources, and rising carbon emissions. In this context, the growth–environment trade-off has been theoretically and empirically examined through the lens of the Environmental Kuznets Curve (EKC). However, the need to revisit this relationship by considering national contexts and policy instruments has become increasingly evident.

This study addresses the fundamental challenge faced by developing economies in aligning rapid economic growth with environmental sustainability, focusing specifically on the role of renewable energy technology imports within complex multi-country dynamics. While these imports represent a crucial pathway for technology transfer, their actual effectiveness in mitigating carbon emissions remains poorly understood. This gap is particularly critical in the context of accelerating climate change, where policy decisions must be informed by an accurate understanding of the structural and cross-country variations that shape environmental outcomes.

Recent studies further highlight the importance of this inquiry. For instance, [1] compare developed and developing economies and find that renewable energy adoption alone may have limited short-term effects on emissions unless complemented by broader policy frameworks. Similarly, [2] emphasize that the effectiveness of environmental provisions in trade agreements depends heavily on enforcement mechanisms and the integration of social sustainability elements. In the context of emerging economies, [3] demonstrate that renewable energy consumption reduces CO_2 emissions more effectively when supported by technological innovation and structural transformation.

Carbon emissions, as a primary driver of climate change, threaten not only environmental integrity but also economic and social sustainability. Importantly, emissions are not solely a byproduct of production processes. Consumption patterns, import composition, and energy use play significant roles, especially in a world where global value chains transcend national boundaries. Therefore, analyzing how changes in trade structures and energy consumption preferences influence environmental outcomes is crucial for formulating environmentally sound development policies.

In recent years, developing countries have significantly increased their imports of renewable energy equipment, presenting an important opportunity for technological transformation and the construction of sustainable energy infrastructures. However, the impacts of this transition remain underexplored. The direct or indirect effects of energy equipment imports on total emissions depend not only on technical efficiency but also on how such equipment is utilized domestically. Thus, incorporating specific variables like renewable energy equipment imports offers a more refined approach to understanding the trade–environment nexus.

At this point, a growing body of literature emphasizes that the environmental effects of trade should not be viewed solely through the lens of exports; the structure of imports also plays a decisive role. In developing economies, the quality of imports is closely linked to their technological capacity and energy transition trajectory. In particular, the importation of clean energy technologies, while not generating immediate environmental costs, may reduce emissions in the long term by enhancing energy efficiency. However, empirical studies supported by robust data are necessary to test this hypothesis.

The relevance of this topic lies in the pressing need to evaluate whether renewable energy technology imports can effectively contribute to decarbonization in emerging economies. Existing research has largely concentrated on aggregate trade–environment relationships, often neglecting the structural composition of imports and their integration into domestic energy systems. This study addresses this gap by introducing renewable energy equipment imports as a distinct explanatory variable and applying second-generation heterogeneous panel estimators (AMG and CCEMG) that account for slope heterogeneity and cross-sectional dependence—methodological aspects often overlooked in prior empirical works. The findings are intended to advance understanding of the conditions under which such imports can meaningfully reduce emissions, offering theoretical contributions to the trade–environment literature and actionable insights for policymakers in high-impact developing economies.

The countries examined in this study—Türkiye, Brazil, Indonesia, Mexico, India, Vietnam, and South Africa—hold critical positions in sustainable development due to their rapid growth trajectories and increasing carbon emissions. As leading representatives of the developing world, these countries play pivotal roles in the global energy transition and account for a substantial share of global emissions. Yet, they exhibit significant variation in growth strategies, energy compositions, and trade structures. This diversity underscores the importance of panel data analysis in understanding complex relationships that cannot be captured by one-size-fits-all models.

While existing literature has largely focused on macro-level relationships between trade, growth, and emissions, it has paid insufficient attention to structural aspects of imports and the technological transition to renewable energy. Moreover, many empirical studies fail to account for cross-sectional dependence and slope heterogeneity in developing countries. The originality of this study lies in its use of a specific variable—renewable energy equipment imports—and in its application of heterogeneous panel data models (AMG and CCEMG) to explore their effects on carbon emissions in detail.

Accordingly, the primary objective of this study is to analyze the impact of per capita GDP, renewable energy equipment imports, and energy consumption on carbon emissions using panel data techniques. By applying Pesaran's AMG and CCEMG estimators, both overall trends and group-specific interactions are identified, while accounting for inter-country differences. This methodological approach not only enhances statistical robustness but also offers policymakers more targeted insights.

In conclusion, this study argues that sustainable growth in developing countries should be assessed not merely in terms of GDP growth, but also through changes in energy composition and the qualitative nature of foreign trade. In doing so, it provides meaningful contributions at both academic and policy levels.

Anticipating the empirical results, the analysis reveals that renewable energy equipment imports currently exhibit a limited or statistically insignificant direct mitigating effect on CO_2 emissions. This outcome underscores the complexity of translating technology imports into tangible environmental benefits, pointing to potential challenges in adoption, integration, and the absence of complementary policy frameworks. By framing the research question with this nuance from the outset, the study not only investigates a statistical relationship but also seeks to uncover the structural and policy conditions necessary for such imports to become effective instruments in clean energy transitions.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature on the relationship between economic growth, renewable energy technology imports, energy use, and carbon emissions. Section 3 describes the data and methodology used in the analysis. Section 4 presents empirical results, while Section 5 discusses the findings in light of existing research and outlines the study's conclusions. The final section offers policy implications and suggestions for future research.

2. Literature Review

The relationship between international trade and environmental performance has been extensively addressed in recent years through theoretical and empirical studies at various levels. [4] emphasize that trade exerts significant micro- and macro-level effects on environmental performance, which can be analyzed through indicators such as energy consumption and emission levels. Within this framework, firm heterogeneity and the Pollution Haven and Halo hypotheses are among the most used theoretical foundations. Similarly, [5] examine the differentiated effects of trade on consumption-based emissions, showing that trade liberalization may increase pollution in capital-abundant countries. While [6] support the argument that trade can weaken environmental regulations, they also note that the relocation of polluting industries to low-income countries remains limited. The model developed by [7] links the rise in CO_2 emissions to short-term temperature changes and the associated costs, thereby illustrating the connection between trade and climate change. [2] evaluate the impact of environmental regulations integrated into trade agreements on business practices, noting that their effectiveness depends on implementation mechanisms and elements of social sustainability. [8] draw attention to the endogeneity of abatement costs in the context of trade's environmental effects, highlighting the decisive role of structural differences in markets. [9] discusses the effectiveness of environmental taxes and emission standards in a theoretical context, showing how trade policy interacts with environmental policy. [10] explore more complex dimensions of this interaction, such as value chains and carbon leakage, and argue for the development of next-generation environment–trade models. [11], focusing on Pakistan, find that trade increases CO_2 emissions, though technological advances may mitigate this effect. [12] confirms the EKC hypothesis, revealing that the impact of trade openness on environmental quality varies with income levels. These studies highlight that the environmental consequences of international trade are complex and context-dependent, shaped by scale, composition, and technique effects.

The relationship between renewable energy consumption and CO_2 emissions has a multi-dimensional character in the literature, particularly for developing countries. [13] argue that when renewable energy usage exceeds capacity thresholds, per capita CO_2 emissions may rise, drawing attention to the nonlinear nature of this relationship. Similarly, [1] state that energy dependency increases energy and carbon intensity, particularly complicating the transition from fossil fuels in developing economies. [3] using OECD country data, find a clear negative relationship between renewable energy consumption and CO_2 emissions, further strengthened by technological innovation. Employing innovative methodologies, [14] provide panel data evidence that renewable energy and green technologies reduce CO_2 emissions and that this interaction is reinforced by structural transformation and ICT. [15] stress the positive contributions of renewable energy consumption not only to environmental protection but also to economic growth, while [16] find that only two countries have successfully achieved this balance. In the African context, [17] report that renewable energy consumption has a strong emission-reducing effect, although high energy intensity hinders this process. [18], focusing on solar energy, highlight the significant potential of PV systems in developing countries points also point out barriers such as infrastructure, cost, and lack of knowledge. In the EU context, [19] emphasize the need to create conditions that promote both the production and consumption of renewable energy to ensure sustainable growth. These studies collectively underscore the necessity for holistic policy designs that consider not only the environmental benefits but also the economic impact of renewable energy in both developed and developing countries.

The link between economic growth and carbon emissions lies at the heart of environmental sustainability debates. Numerous empirical studies have examined it in the Environmental Kuznets Curve (EKC) framework. [20], in a study of 50 developing countries, report a long-run relationship between per capita income and CO_2 emissions, with evidence of an inverted-U shaped EKC pattern in some countries. Similarly, [21], using panel data from 58 countries, find that energy consumption and economic growth increase CO_2 emissions, confirming the EKC hypothesis in most cases. [22] argue that income levels influence consumption patterns and production structures, leading to a reduction in both direct and indirect emissions as income per capita rises. In contrast, [23] show that in BRI and OECD countries, economic growth and CO_2 emissions drive increased energy consumption, highlighting the need for energy structure reforms. [24], using data from 132 countries, show that CO_2 emissions increase up to a certain income threshold, beyond which the growth rate slows. [25], examining China and India, identify a bidirectional causality among energy consumption, growth, and CO_2 emissions in developing countries, whereas G7 countries exhibit partial decoupling of growth from environmental degradation. [26] find that in 19 G20 countries, energy efficiency and the structure of energy use shape emission intensity depending on development level, while [27] argue that the pollution effects of growth may vary through indirect channels such as financial development and trade openness. [21] also note a bidirectional causality between energy consumption and growth and CO_2 emissions, underlining the strategic role of energy use in the economy. Finally, [28] assert that while growth and financial development reduce emissions in high-income groups, these effects are negative in low- and middle-income groups, indicating that the EKC hypothesis varies with income level.

The above-reviewed literature reveals that the impacts of renewable energy use and economic growth on carbon emissions differ across countries, and that in developing economies, this relationship is influenced by factors such as dependence on energy imports, technological capacity, and trade structure. These studies highlight the importance of accounting for direct and indirect effects in panel data analyses. Considering these multi-dimensional findings, the primary aim of this study is to examine the effects of per capita GDP, renewable energy equipment imports, and energy consumption on carbon emissions using panel data methods, thereby offering policy-relevant insights from a sustainable development perspective.

Although the reviewed literature provides valuable insights into the relationship between trade, renewable energy use, and carbon emissions, many empirical works treat countries as homogeneous units, overlooking the role of context-specific structural and policy variables. For instance, differences in energy policy frameworks, levels of technological maturity, and the existence or absence of carbon pricing mechanisms can significantly alter the environmental impact of renewable energy imports. Yet, such factors are rarely integrated into empirical models, resulting in a limited understanding of why similar trade and energy patterns may yield divergent environmental outcomes. This omission restricts the applicability of findings to diverse national contexts and underscores the need for analytical approaches—such as heterogeneous panel estimations—that explicitly account for cross-country variations. By adopting this lens, the present study positions itself to contribute more directly to policy-relevant knowledge tailored to the specificities of developing economies.

A second critical gap in the existing literature concerns the conditions under which renewable energy technology imports translate into measurable environmental benefits. Several studies note that the effectiveness of such imports depends on complementary domestic capacities, including local manufacturing capabilities, grid infrastructure readiness, and the integration of clean energy imports into broader green industrial strategies. [29] emphasizes that in countries such as Albania, Brazil, India, and Kenya, fiscal restrictions, institutional barriers, and limited technological capacity constrain the successful deployment of renewable energy policies, suggesting targeted solutions for policymakers. Similarly, [30] show that in Sub-Saharan Africa, structural barriers and the limited effectiveness of public–private partnerships in rural contexts necessitate a paradigm shift to achieve universal access to clean energy. Challenges in technology transfer—ranging from high initial costs to a lack of technical expertise—are also highlighted by [31], who stress the need for enabling policies that strengthen local actor capacity and institutional engagement. Without supportive mechanisms such as carbon pricing, targeted subsidies, and sustainable finance instruments, the deployment of renewable energy technologies may remain suboptimal. By synthesizing these perspectives, the present study contextualizes its empirical finding that renewable energy equipment imports currently have a limited or statistically insignificant direct impact on CO_2 emissions, highlighting the necessity of integrated policy frameworks that extend beyond macroeconomic indicators to include social inclusion and institutional capacity.

3. Dataset and Methodology

This study aims to analyze the impact of clean energy technology imports on carbon emission intensity in developing countries. To this end, annual panel data covering the period from 2001 to 2021 are utilized. The countries included in the analysis are Türkiye, Brazil, Indonesia, Mexico, India, Vietnam, and South Africa. These countries were selected based on their geographical diversity, economic growth dynamics, and energy transition processes. They not only account for a growing share of global carbon emissions but also exhibit a high level of dependence on foreign trade in renewable energy technologies. Moreover, they stand out among developing economies for actively implementing clean energy transition policies and for their ability to provide consistent data on renewable energy equipment imports. The selected countries offer a rich basis for multi-dimensional comparisons regarding regional representation (Asia, Africa, Latin America, and Eurasia) and their structural differences regarding carbon intensity.

The dependent variable used in this study is the "CO_2 intensity of GDP," measured as carbon emissions per unit of gross domestic product in constant 2015 US dollars. This variable indicates the environmental cost of economic output and is widely used in the environmental economics literature as a proxy for carbon efficiency.

The primary independent variable—renewable energy technology import-comprises the total value of imports of solar panels, wind turbines, batteries, and inverters. The corresponding customs tariff codes are as follows: 8541.40 for photovoltaic cells and modules, 8502.31 for wind-powered generating sets, 8507.80 for batteries and accumulators (including lithium-ion types), and 8504.40 for static converters (inverters). These items represent the core components used in installing and producing renewable energy systems and are treated as proxies for technology transfer via trade. This variable reflects the extent to which countries rely on imported technologies to build their clean energy infrastructures, thereby allowing an analysis of the potential environmental implications of technology transfer through trade.

Gross domestic product per capita (GDP per capita) is included in the model to control the level of economic development. This variable is crucial for understanding how income levels relate to emission patterns within the framework of the environmental demand hypothesis and the Environmental Kuznets Curve (EKC). Additionally, energy use per capita is included in capturing the relationship between total energy demand and the socio-economic structure, and to control for the effect of energy consumption levels on carbon intensity.

Logarithmic transformation has been applied to renewable energy imports and GDP per capita variables to mitigate the influence of extreme values and to enable the modeling of nonlinear relationships. Descriptive information on the variables is presented in Table 1. All econometric analyses were conducted using Stata version 19.5.

Table 1. Variables Used in the Study.

Variable Name	**Definition**	**Unit**	**Source**
CO_2 intensity of GDP	Carbon emissions per unit of GDP in constant 2015 USD	kg CO_2e per constant 2015 US$ of GDP	World Bank
Renewable energy imports (total)	Total imports of solar panels, wind turbines, batteries, and inverters (HS 8541.40, 8502.31, 8507.80, 8504.40)	USD	TradeMap
GDP per capita	Gross domestic product per capita at constant 2015 prices	constant 2015 USD	World Bank
Energy use per capita	Annual total energy consumption per capita	kg of oil equivalent	World Bank

Note: Table constructed by the author.

Panel data analysis was employed to examine the impact of renewable energy technology imports on carbon emission intensity. In line with the structure of the panel, a cross-sectional dependence (CD) test was first conducted, revealing statistically significant relationships among the variables stemming from common shocks. Additionally, a slope homogeneity test was applied to determine whether the slope coefficients were uniform across countries; the results indicated the presence of cross-country heterogeneity. Based on these findings, it was concluded that the panel data set exhibits both cross-sectional dependence and heterogeneity.

Given these features, first-generation panel unit root tests were deemed inadequate. Therefore, to determine the stationarity properties of the variables, the second-generation unit root test—namely, the Cross-Section Augmented Dickey-Fuller (CADF) test—was applied. The test results indicated that the variables are stationary at different levels. Accordingly, to analyze the long-run relationship between the dependent and independent variables, the Augmented Mean Group (AMG) estimator was employed. The AMG method is a second-generation panel cointegration technique that accounts for both slope heterogeneity and common factor structures, making it effective in estimating dynamic long-run relationships among variables. This estimator has been widely adopted in recent environmental economics and trade studies that involve heterogeneous panels with cross-sectional dependence (e.g., [32,33].

The Common Correlated Effects Mean Group (CCEMG) estimator was also employed as an alternative method to evaluate the robustness of the model and test the consistency of the estimated relationships. Furthermore, a two-way panel Granger causality test was performed at the end of the empirical analysis to uncover causality patterns among the variables. All applied tests and chosen methods were selected based on the data set's intrinsic characteristics and the model's economic interpretability. Structural robustness and consistency checks were also incorporated to enhance the model's reliability. The regression model has been formulated as follows:

$$CO2it = \alpha + \beta 1 log\ (RE\_Importit) + \beta 2 log\ (GDPit) + \beta 3\ (EnergyUseit) + \mu i + \lambda t + \varepsilon it$$

In this model, the dependent variable $CO2it$ represents per capita carbon dioxide emissions for country i in year t. The key explanatory variable is $log(RE\_Importit)$, which denotes the logarithm of renewable energy technology imports, including solar panels, wind turbines, batteries, and inverters. This variable captures the extent of international technology transfer through clean energy trade. The model also includes $log(GDPit)$, the logarithm of per capita gross domestic product measured in constant 2015 US dollars, to account for the influence of economic development on emissions. Additionally, $EnergyUseit$ reflects primary energy consumption per capita, measured in kilograms of oil equivalent, serving as an indicator of energy intensity. Country-specific fixed effects μi are included to control for unobserved heterogeneity across countries, while time-specific effects λt capture common global shocks or trends over time. Finally, the idiosyncratic error term εit accounts for random disturbances not explained by the model. This specification allows for robust estimation of the long-run relationship between renewable energy imports and carbon intensity, while controlling for structural and temporal dynamics.

The research question guiding this study is whether renewable energy technology imports, economic growth, and energy consumption exert a significant and measurable influence on carbon emission intensity in developing economies. Per capita GDP is included as a key explanatory variable because economic growth shapes production structures, consumption patterns, and energy demand, which in turn affect emissions, as discussed in the literature review. Renewable energy equipment imports are incorporated to capture the potential for technology transfer and the diffusion of low-carbon production capacity, which may contribute to emission reduction if supported by complementary domestic policies and infrastructure, as highlighted in previous studies reviewed earlier. Energy consumption is included to reflect the direct link between energy use and CO_2 emissions, addressed in the literature review, and to account for the composition of energy sources, especially relevant in countries where fossil fuels remain dominant.

This choice of variables and empirical design is consistent with previous panel data studies that examine the nexus between renewable energy trade, economic growth, and carbon emissions across developing economies, using approaches that account for heterogeneity and cross-sectional dependence (e.g.,[34–36]. These studies have demonstrated that integrating trade-related indicators with macroeconomic and energy variables provides a more comprehensive understanding of the structural and policy factors influencing environmental outcomes.

Together, these variables enable a comprehensive assessment of both macroeconomic and structural determinants of carbon emissions, thereby providing a nuanced understanding of how trade in renewable energy technologies interacts with growth and energy use in shaping environmental outcomes. Based on these considerations, the following empirical strategy is designed to investigate the hypothesized relationships, using panel econometric methods that account for both cross-sectional dependence and slope heterogeneity.

4. Analysis and Findings

The analyses and their corresponding results, as outlined in the methodology section above, are presented below. While the primary statistical findings are reported in this section, their broader economic implications and theoretical underpinnings are discussed in detail in the Discussion and Conclusion section to avoid redundancy and ensure a more focused presentation of results.

4.1. Cross-Sectional Dependence Test (CD Test)

To assess the presence of potential cross-sectional dependence in panel data analysis, the CD test developed by [37] is employed. This test is designed to detect the existence of dependence among cross-sectional units—such as countries in a panel—due to common shocks or shared dynamics. It is particularly useful in datasets with a large time dimension and is widely applied to examine whether observations are correlated across units. The CD test, proposed by [37,38] aims to identify cross-sectional dependence that may arise from common shocks or spillover effects across units. The hypotheses for the test are defined as follows:

H0 (Null Hypothesis): There is weak cross-sectional dependence among the variables; for example, a country's import levels are independent of those in other countries.

H1 (Alternative Hypothesis): There is strong cross-sectional dependence; import behavior across countries is mutually influenced.

The statistical formulation of the test is based on the average pairwise correlation coefficients among panel units and is calculated as follows:

$$CD = \frac{\sqrt{N}}{\sqrt{2T}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{P}_{i_j}$$

In the equation, N represents the number of countries in the panel, and T denotes the time dimension. The term $\hat{P}_{ij}$ refers to the correlation coefficient between the variables of country i and country j. The p-value obtained from the *CD* test determines whether the null hypothesis (H0) can be rejected at conventional significance levels (e.g., 1%, 5%, or 10%). If the p-value is below 0.10, H0 is rejected, indicating the presence of strong cross-sectional dependence among the variables (Pesaran, 2004). The results of the CD test are presented in Table 2.

Table 2. Results of the Cross-Sectional Dependence Test.

Variable	CD	CDw	CDw⁺	CD*
renewabletotalIM	11.74 (0.000) ***	5.35 (0.000) ***	59.00 (0.000) ***	7.37 (0.000) ***
GDP	19.64 (0.000) ***	8.44 (0.000) ***	98.46 (0.000) ***	1.93 (0.053) *
CO_2	3.71 (0.000) ***	−1.22 (0.222)	56.25 (0.000) ***	0.83 (0.406)
ENERGYUSE	4.86 (0.000) ***	6.11 (0.000) ***	70.85 (0.000) ***	0.62 (0.534)

Note: p-values are reported in parentheses. * and *** indicate statistical significance at the 10% and 1% levels, respectively. CDw^+ and CD* denote the enhanced and factor-structure-based versions of the cross-sectional dependence test.

According to the cross-sectional dependence test results based on [38,39], all core variables in the panel dataset exhibit cross-sectional dependence. In particular, the variables renewabletotalIM, GDP, and ENERGYUSE are statistically significant in both the conventional CD test and the enhanced CDw^+ test ($p < 0.01$). Although the CO_2 variable appears significant in the standard CD test, it demonstrates weaker dependence in factor-structure-based tests such as CD*. Overall, these results indicate the presence of common shocks across countries—such as global economic cycles, fluctuations in energy markets, and differences in trade regimes—and suggest that the assumption of cross-sectional independence is violated.

4.2. Slope Homogeneity (Heterogeneity) Test

The slope homogeneity test developed by [40], also known as the delta test, is used to determine whether the regression coefficients across panel units are similar. This method tests the validity of a common coefficient across the entire panel. The core idea is to statistically assess how much each unit's individual coefficient deviates from the overall average. In doing so, it helps determine whether parameter heterogeneity should be considered in panel data modeling.

The delta test is expressed through the following formulas:

1. Standard Delta Test: $\Delta = \sqrt{\frac{N}{2}}\left(\frac{1}{N}\sum_{i=1}^{N}\hat{\beta}_i - \beta\right)$
2. Augmented Delta Test (Delta Tilde): $\tilde{\Delta} = \sqrt{N}\left(\frac{1}{N}\sum_{i=1}^{N}\frac{\hat{\beta}_i-\beta}{\sigma_i}\right)$.

In these formulas, N represents the number of panel units, $\hat{\beta}i$, is the estimated slope coefficient for unit i, β is the average slope coefficient across all units, and σi denotes the standard error of the estimated coefficient for unit i.

The results of the slope homogeneity test are presented in Table 3.

Table 3. Results of the Slope Homogeneity Test.

Test Statistic	Value	*p*-Value
Δ (Delta)	6.811	0.000 ***
Δ_adj (Adjusted Delta)	7.803	0.000 ***

Note: Under the null hypothesis of slope homogeneity, both the Delta and Adjusted Delta tests are asymptotically normally distributed. The p-values indicate significance at the 1% level ($p < 0.01$). p-values are reported in parentheses *** indicate statistical significance at the 1% level.

According to the slope homogeneity test developed by [40], both the Δ and adjusted Δ test statistics are statistically significant ($p < 0.01$). This result indicates that the regression coefficients across countries are not homogeneous, implying the presence of structural differences among the countries in the panel. In other words, the effects of the independent variables on the dependent variable vary from one country to another.

The findings from the cross-sectional dependence and slope homogeneity tests collectively reveal that the panel data set is characterized by sensitivity to common shocks across countries as well as structural heterogeneity. Specifically, the null hypotheses of cross-sectional independence and slope homogeneity are rejected based on the [38] CD test and the [40] slope homogeneity test, respectively. These results suggest that first-generation panel data tests would be methodologically inadequate for this study, thereby necessitating the use of second-generation panel estimation techniques in the subsequent analysis.

4.3. Unit Root Test

The Augmented Dickey-Fuller test developed by [41] offers a unit root testing approach that accounts for cross-sectional dependence in panel data settings. Known as the Cross-sectionally Augmented Dickey-Fuller (CADF) test, this method improves the reliability and realism of unit root testing by incorporating interdependencies among countries or panel units—factors often neglected in traditional panel unit root tests. As a result, it provides a more robust assessment of stationarity, particularly for time series influenced by common shocks or similar trends across countries.

The standard form of the Augmented Dickey-Fuller (ADF) test for panel data is expressed as follows:

$$\Delta y_{it} = \alpha_i + \beta_i y_{it} + \sum_{k=1}^{p_i} \gamma_{ik} \Delta y_{it-k} + \epsilon_{it}$$

In this formulation, Y_{it}, represents the observation for unit i at time t, α_i, is the individual fixed effect, β_i, is the coefficient of the lagged level term (the speed of adjustment), γ_{ik}, are the coefficients of the lagged differences, ϵ_{it}, is the error term.

Pesaran's CADF test incorporates cross-sectional dependence and is specified as follows:

$$\Delta y_{it} = \alpha_i + \beta_i y_{it} + \sum_{k=1}^{p_i} \gamma_{ik} \Delta y_{it-k} + \epsilon_{it} + \delta \bar{y} t - 1 + \epsilon it$$

Here, $\bar{y} t - 1$, denotes the cross-sectional mean at time $t - 1$.

The results of the unit root test are presented in Table 4.

Table 4. Panel Unit Root Test Results (Pesaran CADF).

Variable	t-bar	5% Critical Value	Z[t-bar]	*p*-Value	Order of Stationarity
ln_GDP	−3.608	−2.340	−6.024	0.000 ***	I(1) (stationary at first difference)
D.ENERGYUSE	−3.127	−2.340	−3.588	0.000 ***	I(1) (stationary at first difference)
D.CO_2	−2.998	−2.340	−3.257	0.001 ***	I(1) (stationary at first difference)
renewabletotalIM	−2.503	−2.340	−1.985	0.024 **	I(0) (stationary at level)

Note: ** and *** indicate statistical significance at the 5% and 1% levels, respectively.

The panel unit root test results were analyzed using the Cross-Section Augmented Dickey-Fuller (CADF) test developed by Pesaran (2007)[41] to determine the stationarity properties of the variables. As shown in Table 4, the variables ln_GDP, ENERGYUSE, and CO_2 are not stationary at the level but become statistically significant and stationary after first differencing. This indicates that these three variables are integrated of order one, I(1). On the other hand, the variable renewabletotalIM is found to be stationary at the level at the 5% significance level, indicating that it is integrated of order zero, I(0).

Considering this structural feature, it is evident that the variables in the panel are not uniformly integrated. In addition, the previously conducted cross-sectional dependence (CD) and slope heterogeneity tests confirmed the presence of interdependence among units and variation in slope coefficients across countries. Therefore, the Augmented Mean Group (AMG) estimator was chosen for the empirical analysis, as it accounts for mixed integration orders, cross-sectional dependence, and slope heterogeneity. The AMG method is one of the second-generation panel data techniques. It provides reliable estimates of long-run relationships in complex panel structures such as the one used in this study.

4.4. Augmented Mean Group (AMG) Estimation Results

The Augmented Mean Group (AMG) estimator, developed by [42] is designed to estimate long-run relationships in heterogeneous panel datasets. This approach extends the conventional Mean Group (MG) estimator by incorporating a common dynamic process that accounts for cross-sectional dependence.

In a panel data model, where y_{it} denotes the dependent variable and x_{it} is a vector of explanatory variables, the general specification is given as follows:

$$y_{it} = \alpha_i + \beta_i' x_{it} + u_{it}$$

Here; $i = 1,\ldots, N$ denotes the countries, and $t = 1,\ldots,$ T represents the time periods. α_i captures the country-specific fixed effects, while β_i is a $k \times 1$ vector of coefficients for each country. u_{it} denotes the error term.

To account for cross-sectional dependence, the error term u_{it} is modeled as follows:

$$u_{it} = \lambda_i f_t + \varepsilon_{it}$$

In this formulation, λ_i represents the country-specific factor loadings, while f_t denotes the unobserved common factors (common dynamic process), and ϵ_{it} is the idiosyncratic error term.

The AMG estimator expands the error term u_{it} by incorporating a common dynamic process (R_c) into the model to account for cross-sectional dependence:

$$y_{it} = \alpha_i + \beta_i' x_{it} + \gamma_i R_c + \varepsilon_{it}$$

Here, R_c represents the common dynamic process, which is associated with the unobserved factors f_{tf}.

The AMG estimator is a method that simultaneously accounts for heterogeneity and cross-sectional dependence in panel data analysis. While the traditional Mean Group (MG) estimator considers cross-country heterogeneity, it overlooks cross-sectional dependence. The AMG approach addresses this limitation by incorporating a common dynamic process into the model, thereby capturing the dependence structure among units. The AMG estimation results are presented in Table 5.

Table 5. AMG Estimation Results (Dependent Variable: CO_2 Emissions).

Variable	Coefficient	Std. Error	*z*-Value	*p*-Value	95% Confidence Interval
ln_GDP	−0.514	0.138	−3.72	0.000 ***	[−0.786, −0.243]
ln_REImport	0.019	0.011	1.73	0.084 *	[−0.003, 0.041]
ENERGYUSE	0.00082	0.00035	2.30	0.022 **	[0.00012, 0.00151]
Constant (_cons)	13.907	3.707	3.75	0.000 ***	[6.642, 21.172]

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

According to the AMG estimation results, a statistically significant and negative relationship is observed between per capita income (ln_GDP) and CO_2 emissions ($p < 0.01$). This finding supports the Environmental Kuznets Curve (EKC) hypothesis, which suggests that growth may contribute to reductions in environmental degradation beyond a certain level of economic development.

The coefficient for renewable energy equipment imports (ln_REImport) is positive, yet statistically significant only at the 10% level ($p \approx 0.084$). This implies that imports of clean energy technologies may not yet be effective in reducing CO_2 emissions, or alternatively, may be associated with a temporary increase in emissions during the infrastructure installation phase.

A positive and statistically significant relationship is found between energy use (ENERGYUSE) and CO_2 emissions ($p < 0.05$). This result indicates that energy consumption in the sampled countries remains largely dependent on fossil fuels, directly contributing to higher carbon emissions.

Overall, when the results are evaluated in conjunction with the structure of national economies and patterns of energy use, it becomes clear that renewable energy imports alone are not sufficient to mitigate emissions. These findings underscore the necessity of complementary energy transition strategies to ensure meaningful environmental outcomes.

The country-specific AMG estimation results are presented in Appendix A. The interpretations of these results are discussed in detail in the discussion section of the study.

4.5. The Common Correlated Effects Mean Group (CCEMG) Estimator

The Common Correlated Effects Mean Group (CCEMG) estimator, introduced by [43], is another second-generation panel data technique that accounts for both cross-sectional dependence and slope heterogeneity. Unlike traditional estimators that assume cross-sectional independence, CCEMG addresses unobserved common factors by augmenting the regression equation with cross-sectional averages of the dependent and independent variables. This approach allows for consistent estimation even in the presence of complex correlation structures among panel units.

The general form of the model can be specified as follows:

$$y_{it} = \alpha_i + \beta_i x_{it} + \gamma_i' \bar{X}_t + \delta_i \bar{y}_t + \varepsilon_{it}$$

In this specification, $\bar{X}_t$ and $\bar{y}_t$ denote the cross-sectional means of the explanatory variables and the dependent variable, respectively. These terms serve as proxies for unobserved common factors that may simultaneously affect all units in the panel. The coefficients γ_i and δ_i capture the sensitivity of each country to these common influences, while ε_{it} is the idiosyncratic error term.

By controlling cross-sectional dependence through cross-sectional averages, the CCEMG estimator provides robust and consistent long-run parameter estimates, particularly in panels where unobserved global shocks or spillover effects are present. Moreover, it allows for heterogeneous slope coefficients across countries, making it well-suited for empirical research involving structurally diverse economies.

The CCEMG results complement the AMG findings and serve as a robust check for the long-run relationships estimated in the previous section. The estimation results are presented in Table 6.

Table 6. CCEMG (Robust) Estimation Results Dependent Variable: CO_2 Emissions (Mt CO_2e).

Variable	Coefficient	Std. Error	*z*-Value	*p*-Value	95% Confidence Interval
ln_GDP	−0.361	0.178	−2.03	0.043 **	[−0.711, −0.012]
ln_REImport	0.001	0.014	0.08	0.937	[−0.026, 0.028]
ENERGYUSE	0.00033	0.00007	4.95	0.000 ***	[0.00020, 0.00046]
Constant	7.249	0.695	10.43	0.000 ***	[5.887, 8.611]
Mean RMS Error	0.0154				
Wald χ^2 (3)	28.62			0.000 ***	

Note: ** and *** indicate statistical significance at the 5% and 1%, levels, respectively.

The robust version of the Common Correlated Effects Mean Group (CCEMG) estimator, developed by Pesaran (2006) [43], provides significant insights into the effects of certain variables on CO_2 emissions. Notably, the logarithm of real GDP per capita (ln_GDP) is found to be negative and statistically significant at the 5% level. This finding supports the Environmental Kuznets Curve (EKC) hypothesis, indicating that economic growth may reduce environmental degradation beyond a certain threshold. Similarly, ENERGYUSE—per capita energy consumption—is positively associated with CO_2 emissions and statistically significant at the 1% level. This suggests that increased energy use, which is still largely dependent on fossil fuels, is a key contributor to higher carbon emissions.

On the other hand, ln_REImport, the logarithm of renewable energy equipment imports, carries a positive coefficient but is not statistically significant. This result implies that the import of renewable energy technologies does not yet have a direct mitigating effect on emissions—possibly due to the incomplete or delayed impact of technological adoption and integration. These findings are largely consistent with the results obtained from the AMG model. In both models, ln_GDP is negative and significant, ENERGYUSE is positive and significant, and ln_REImport is statistically insignificant.

Therefore, the results from both estimation methods reinforce each other and enhance the structural reliability of the model. The overall validity of the CCEMG model is supported by the Wald χ^2 test, which indicates that the model is statistically significant ($p < 0.01$). Furthermore, the low root mean squared error (RMS error = 0.0154) supports the precision and robustness of the estimates. These findings underscore the necessity of structural reforms in energy policy and highlight the critical role of energy consumption patterns in determining environmental outcomes.

4.6. Robustness Checks: Endogeneity and Multicollinearity Diagnostics

4.6.1. Durbin-Wu-Hausman (DWH) Test

In panel data models, particularly those analyzing macroeconomic and environmental variables such as GDP, energy use, and CO_2 emissions, the risk of endogeneity poses a serious threat to the validity of causal inference.

Endogeneity may arise due to reverse causality, omitted variables, or measurement errors, especially when economic growth and energy consumption not only affect carbon emissions but may also be influenced by them over time. Although the AMG and CCEMG estimators effectively address cross-sectional dependence and slope heterogeneity, they do not inherently correct for potential endogeneity among regressors.

To address this concern, the Durbin-Wu-Hausman (DWH) [44–46] test is employed to formally examine whether the explanatory variables in the model are exogenous. This test compares the consistency of ordinary least squares (OLS) and instrumental variable (IV) estimators. A statistically significant result would indicate that one or more regressors are endogenous and that IV-based estimators should be used to avoid biased coefficient estimates. This study conducts the DWH test to ensure that underlying endogeneity problems do not undermine the long-run relationships identified through AMG and CCEMG estimators.

Table 7 shows that, according to the IV fixed effects model results based on the Durbin–Wu–Hausman test, no significant endogeneity problem is associated with the ln_GDP variable when analyzing its effect on CO_2 emissions (p = 0.263). Therefore, treating ln_GDP as an exogenous regressor is considered appropriate. This result also supports the validity of the instrumental variables used in the model (ENERGYUSE and ln_REImport), thereby reinforcing the reliability of the baseline regression estimates.

Table 7. Endogeneity Test Results (Durbin–Wu–Hausman Test).

Model	Endogenous Variable	Instruments	Coefficient	Std. Error	*z*-Value	*p*-Value	Conclusion
IV-FE (xtivreg)	ln_GDP	ENERGYUSE, ln_REImport	−0.0297	0.0266	−1.12	0.263	No endogeneity detected

Note: The Durbin–Wu–Hausman test is used to determine whether ln_GDP is endogenous with respect to the model. A non-significant *p*-value indicates that endogeneity is not present.

4.6.2. Multicollinearity Test (Variance Inflation Factors—VIF)

Multicollinearity refers to the presence of strong linear correlations among two or more explanatory variables in a regression model. When multicollinearity exists, it becomes difficult to isolate the individual effect of each independent variable on the dependent variable, which may lead to inflated standard errors, unstable coefficient estimates, and misleading statistical inference.

Given the economic nature of the variables used in this study—such as per capita GDP, energy consumption, and renewable energy imports—which may be conceptually and empirically correlated, it is essential to assess whether multicollinearity poses a threat to the model's reliability. For this purpose, the Variance Inflation Factor (VIF) test is conducted. VIF values exceeding the commonly accepted threshold (typically 10, or in more conservative analyses, 5) indicate a high degree of multicollinearity, while lower values suggest that collinearity is not a major concern [47].

In the following section, the results of the VIF test are presented and interpreted to evaluate the independence of the explanatory variables included in the panel regression model.

Table 8 shows that, according to the Variance Inflation Factor (VIF) results, all variables have VIF values well below 2. This indicates that multicollinearity is not a concern in the model. Consequently, the estimated coefficients are statistically reliable, and the interpretability of the regression results is significantly enhanced.

Table 8. Multicollinearity Test Results (Variance Inflation Factors—VIF)

Variable	VIF	1/VIF
ln_REImport	1.64	0.6099
ln_GDP	1.56	0.6406
ENERGYUSE	1.14	0.8803

Note: A VIF value below 5 is generally considered acceptable, suggesting that the explanatory variables do not exhibit problematic levels of multicollinearity.

4.7. Panel Granger Causality Test

To further examine the direction of influence between the explanatory variables and CO_2 emissions, a panel Granger non-causality test was conducted using the [48] methodology. This test is well-suited for heterogeneous panels and allows for individual-specific causal relationships across cross-sectional units. In contrast to traditional time-series

Granger tests, the Dumitrescu–Hurlin approach accommodates variations in both the size and structure of the panel, making it particularly appropriate for macroeconomic and environmental datasets involving developing countries.

The purpose of this test is to assess whether changes in variables such as per capita income, renewable energy imports, and energy use systematically precede changes in CO_2 emissions across countries, thereby implying a predictive or causal link. Identifying such causal pathways strengthens the empirical validity of the baseline results and contributes to the formulation of more targeted policy interventions. The test results are presented in Table 9.

Table 9. Panel Granger Causality Test Results (Dumitrescu–Hurlin, 2012).

Causality Direction	Lag	Z-bar	*p*-Value	Conclusion
ln_GDP ⟶ CO_2	1	5.3463	0.0000 ***	Causality exists
ln_REImport ⟶ CO_2	1	3.0137	0.0026 ***	Causality exists
ENERGYUSE ⟶ CO_2	1	1.1900	0.2341	No causality detected

Note: *** indicates statistical significance at the 1% level.

The *ln_GDP* variable is found to Granger-cause CO_2 emissions, indicating that economic growth exerts a causal influence on environmental pressures. In other words, changes in income levels are statistically significant predictors of variations in carbon emissions at the panel level.

Similarly, *ln_REImport* also exhibits Granger causality with respect to CO_2 emissions. This finding suggests that renewable energy equipment imports are associated with environmental outcomes, offering evidence that such technological investments may influence emission levels—particularly in the context of developing countries.

In contrast, the *ENERGYUSE* variable does not Granger-cause CO_2 emissions, implying that total energy consumption does not significantly explain short-run fluctuations in carbon emissions. This suggests the absence of a direct and immediate causal relationship between energy use and emissions in the short term.

Overall, these findings are largely consistent with the results obtained from the AMG and CCEMG models, particularly regarding the effects of income and imports. Testing the direction of causality strengthens the internal validity of the model and enhances the policy relevance of the results by allowing for causal interpretation of the estimated relationships.

5. Discussion

This study examined the environmental impacts of renewable energy equipment imports and energy use within the economic growth processes of seven developing economies—Türkiye, Brazil, Indonesia, Mexico, India, Vietnam, and South Africa—from 2000 to 2021. The use of second-generation panel estimators, namely the Augmented Mean Group (AMG) and Common Correlated Effects Mean Group (CCEMG), was motivated by the heterogeneity and cross-sectional dependence inherent in the data.

The AMG results for the full panel revealed three key patterns. First, real GDP per capita (ln_GDP) displayed a statistically significant negative relationship with CO_2 emissions, supporting the later phase of the Environmental Kuznets Curve (EKC) hypothesis. This suggests that beyond a certain income level, structural economic changes and technological improvements contribute to emission reductions. Second, renewable energy equipment imports (ln_REImport) showed a positive but only weakly significant effect on CO_2 emissions, indicating that the environmental benefits of such imports may depend on how effectively these technologies are integrated into domestic energy systems. Third, energy use (ln_EnergyUse) was strongly and positively associated with emissions, reflecting the fossil fuel–intensive nature of energy consumption patterns in the sample countries. Robustness checks using CCEMG estimations confirmed these relationships.

However, the country-specific AMG results, presented in Appendix A, highlight substantial heterogeneity in the magnitude, sign, and significance of these relationships, underlining the need for tailored policy strategies. For instance, in Brazil, higher GDP per capita was associated with a substantial decline in emissions, while energy use exerted a strong positive effect, suggesting that efficiency gains in production and structural transformation have started to offset some environmental pressures, yet fossil fuel reliance remains a challenge. In India, both GDP growth and renewable energy equipment imports showed significant effects, the latter being positive, which may reflect the reliance on imported components without sufficient domestic integration. In Indonesia, renewable energy imports exerted a significant positive effect, potentially due to transitional inefficiencies or the carbon intensity of installation processes. Mexico exhibited the strongest positive effect of renewable energy imports on emissions, highlighting possible mismatches between imported technology and the existing energy mix. In South Africa, the positive and significant coefficient for the common dynamic process indicates that regional or global shocks have amplified domestic emission trends, while GDP growth consistently reduced emissions. Türkiye and Vietnam showed similar patterns, with GDP negatively and energy use positively affecting emissions, but renewable energy imports playing no statistically significant role, suggesting untapped potential in technology transfer and integration.

These differences can be linked to variations in energy policy frameworks, industrial capabilities, and technological readiness across countries. For example, nations with higher technological absorption capacity and stronger institutional frameworks, such as Brazil and South Africa, appear to reap greater emission-reducing benefits from economic growth, while countries still reliant on carbon-intensive energy sources, such as Indonesia and Mexico, experience weaker or even adverse impacts from renewable energy imports.

Furthermore, the heterogeneity underscores that renewable energy imports alone do not guarantee emission reductions. Without supportive infrastructure, skilled labor, and policies promoting local manufacturing and adaptation, the environmental impact of such imports may remain limited or even counterproductive. Similarly, the strong positive association between energy use and emissions across most countries signals the urgent need to decouple energy consumption from fossil fuel dependency through efficiency gains and accelerated renewable integration.

Overall, the findings suggest that while aggregate panel results provide valuable general insights, country-level differences must be accounted for to design effective green growth policies. A one-size-fits-all approach is unlikely to succeed; instead, strategies must be adapted to each country's structural characteristics, energy mix, and policy environment.

6. Policy Recommendations

The findings of this study underscore the need for policy frameworks that integrate economic growth objectives with environmental sustainability in a way that is sensitive to country-specific conditions (Appendix A). The limited environmental gains from renewable energy equipment imports indicate that trade policies should be coupled with technology transfer agreements, local manufacturing incentives, and capacity-building programs to ensure that renewable technologies are imported, adapted, produced, and maintained domestically. At the same time, the strong positive link between energy use and CO_2 emissions highlights the urgency of improving energy efficiency through cleaner industrial technologies, incentives for energy-saving practices in households and businesses, and the deployment of smart grids to optimize consumption patterns. Introducing carbon pricing instruments, supported by green financing mechanisms, can further encourage a shift toward low-carbon energy sources while mobilizing private investment in renewable energy, storage solutions, and sustainable transport infrastructure. Ensuring a just transition remains crucial, with retraining programs, social protection measures, and targeted support for vulnerable communities to enhance public acceptance and political feasibility. Ultimately, aligning trade, industrial, environmental, and energy policies within a coherent framework, and fostering regional cooperation in technology sharing and harmonized standards, will be essential to bridge the gap between current practices and the goal of sustainable, inclusive and low-carbon development.

7. Conclusions

This study provides empirical evidence on the interplay between economic growth, renewable energy equipment imports, energy use, and CO_2 emissions in seven emerging economies over 2000–2021, applying second-generation panel estimators to account for heterogeneity and cross-sectional dependence. The findings reveal that GDP per capita exerts a significant negative impact on CO_2 emissions, supporting the Environmental Kuznets Curve hypothesis, while energy use remains a strong positive driver of emissions. The effect of renewable energy equipment imports is weaker and more context-dependent, highlighting the importance of complementary policies to enhance their environmental effectiveness.

By integrating country-specific AMG results, the study demonstrates substantial heterogeneity in the drivers of emissions, underlining the necessity of tailored policy frameworks that align economic, trade, and environmental priorities. These results contribute to the existing literature by emphasizing that green growth strategies in developing economies must move beyond aggregate indicators and incorporate structural, technological, and policy dimensions. The study thus offers a more nuanced understanding of how trade in renewable energy technologies interacts with domestic energy systems and growth trajectories, providing a foundation for more targeted and effective sustainability policies.

8. Limitations and Future Research

While this study provides robust evidence on the relationship between economic growth, renewable energy equipment imports, energy use, and CO_2 emissions in emerging economies, several limitations should be acknowledged.

First, the analysis focuses on a limited set of seven countries over the period 2000–2021, which constrains the generalizability of the findings. The end year of 2021 was determined by data availability, as detailed import statistics for wind turbines and solar panels at the 4-digit HS code level are not available beyond this year from official international trade databases. Expanding the scope to include a broader range of developing and developed countries and extending the time coverage when more recent data becomes available, could yield a more comprehensive understanding of the dynamics involved. Future research could extend the analysis as newer data become available, incorporate broader country samples, and integrate additional policy-relevant variables—such as carbon pricing schemes, renewable energy incentives, and institutional capacity indicators—to capture the evolving dynamics of low-carbon transitions. Strengthening data availability and comparability will be critical for providing timely, evidence-based guidance to policymakers.

Second, the dataset primarily captures aggregate renewable energy equipment imports without differentiating between technology types, efficiency levels, or end-use applications, potentially obscuring heterogeneous environmental impacts. Incorporating more granular trade data in future research would enable deeper insights into the role of technology composition.

Third, while the econometric methods employed account for heterogeneity and cross-sectional dependence, the model does not explicitly control policy regimes, institutional quality, or carbon pricing mechanisms, which may mediate the observed relationships. Future studies could integrate structural and policy-related variables to better capture the channels through which trade, energy use, and growth affect emissions. Additionally, the country-specific results presented here suggest substantial differences in the determinants of CO_2 emissions; subsequent research should explore these differences through in-depth case studies or regional sub-group analyses.

Finally, the analysis does not address potential non-linearities beyond the EKC framework or the interaction effects between renewable energy imports and domestic production capabilities. Extending the empirical framework to include interaction terms, threshold effects, or dynamic feedback loops could provide richer policy-relevant insights. By addressing these limitations, future research can refine the understanding of how trade in clean technologies interacts with economic and energy systems, thereby informing more effective and context-sensitive sustainability strategies.

Appendix A. Country-Specific Policy Implications Based on AMG Estimates

The country-specific AMG results presented in the tables below reveal notable heterogeneity in the relationships between GDP per capita, renewable energy equipment imports, energy use, and CO_2 emissions across the seven developing economies examined. These variations highlight the need for policy interventions to be tailored to each country's structural characteristics, energy profile, and technological capacity.

Table A1. AMG Estimation Results for Brazil.

Variable	Coefficient	Std. Error	*z*-Value	*p*-Value	95% Confidence Interval
ln_GDP	−1.463375	0.2837886	−5.16	0.0000 ***	[−2.01959; −0.9071594]
ln_REImport	−0.0043658	0.0180595	−0.24	0.809	[−0.0397617; 0.0310301]
ln_EnergyUse	2.081735	0.3758975	5.54	0.0000 ***	[1.34499; 2.818481]
__00000R_c	1.195375	0.9531213	1.25	0.210	[−0.6727081; 3.063459]
_cons	24.93191	5.31164	4.69	0.0000 ***	[14.52129; 35.34254]

Notes: ***, denote statistical significance at the 1%, level.

Table A2. AMG Estimation Results for India.

Variable	Coefficient	Std. Error	*z*-Value	*p*-Value	95% Confidence Interval
ln_GDP	−1.037851	0.0651882	−15.92	0.000 ***	[−1.165617; −0.9100842]
ln_REImport	0.0226034	0.0123002	1.84	0.066 *	[−0.0015044; 0.0467113]
ln_EnergyUse	1.60065	0.1515799	10.56	0.000 ***	[1.303559; 1.897741]
__00000R_c	−0.2383131	0.5428073	−0.44	0.661	[−1.302196; 0.8255696]
_cons	18.8966	1.096579	17.23	0.000 ***	[16.74734; 21.04585]

Notes: ***, and * denote statistical significance at the 1%, and 10% levels, respectively.

Table A3. AMG Estimation Results for Indonesia.

Variable	Coefficient	Std. Error	*z*-Value	*p*-Value	95% Confidence Interval
ln_GDP	−0.6329484	0.0803876	−7.87	0.000 ***	[−0.7905053;−0.4753916]
ln_REImport	0.0291195	0.0147629	1.97	0.049 **	[0.0001848; 0.0580542]
ln_EnergyUse	0.64041	0.1697607	3.77	0.000 ***	[0.3076851; 0.9731348]
__00000R_c	1.395079	0.8933923	1.56	0.118	[−0.3559379; 3.146096]
_cons	12.30522	1.401357	8.78	0.000 ***	[9.558611; 15.05183]

Notes: *** and ** note statistical significance at the 1% and 5% levels, respectively.

Table A4. AMG Estimation Results for Mexico.

Variable	Coefficient	Std. Error	*z*-Value	*p*-Value	95% Confidence Interval
ln_GDP	−0.7543932	0.1560665	−4.83	0.000 ***	[−1.060278; −0.4485084]
ln_REImport	0.1191329	0.0321952	3.70	0.000 ***	[0.0560314; 0.1822344]
ln_EnergyUse	0.816498	0.0930822	8.77	0.000 ***	[0.6340602; 0.9989359]
__00000R_c	0.3695513	0.5799681	0.64	0.524	[−0.7671653; 1.506268]
_cons	12.28172	4.072343	3.02	0.003 ***	[4.300075; 20.26337]

Notes: *** denote statistical significance at the 1%, level.

Table A5. AMG Estimation Results for South Africa.

Variable	Coefficient	Std. Error	*z*-Value	*p*-Value	95% Confidence Interval
ln_GDP	−0.6592443	0.0985221	−6.69	0.000 ***	[−0.852344; −0.4661445]
ln_REImport	0.0359451	0.0193965	1.85	0.064 *	[−0.0020714; 0.0739616]
ln_EnergyUse	0.6057835	0.0757703	7.99	0.000 ***	[0.4572763; 0.7542906]
__00000R_c	1.892619	0.8276232	2.29	0.022 **	[0.2705069; 3.51473]
_cons	12.6567	2.424009	5.22	0.000 ***	[7.90573; 17.40767]

Notes: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively

Table A6. AMG Estimation Results for Türkiye.

Variable	Coefficient	Std. Error	*z*-Value	*p*-Value	95% Confidence Interval
ln_GDP	−0.8494864	0.0760315	−11.17	0.000 ***	[−0.9985054; −0.7004674]
ln_REImport	0.0060551	0.0124095	0.49	0.626	[−0.018267; 0.0303772]
ln_EnergyUse	1.068277	0.1721344	6.21	0.000 ***	[0.7309001; 1.405654]
__00000R_c	−0.3437377	0.5577123	−0.62	0.538	[−1.436834; 0.7493584]
_cons	14.51995	1.071539	13.55	0.000 ***	[12.41977; 16.62013]

Notes: *** denote statistical significance at the 1% level.

Table A7. AMG Estimation Results for Vietnam.

Variable	Coefficient	Std. Error	*z*-Value	*p*-Value	95% Confidence Interval
ln_GDP	−0.0952514	0.2323191	−0.41	0.682	[−0.5505885; 0.3600857]
ln_REImport	−0.0573819	0.0425331	−1.35	0.177	[−0.1407452; 0.0259813]
ln_EnergyUse	1.018274	0.197173	5.16	0.000 ***	[0.6318221; 1.404726]
__00000R_c	−0.1479934	1.193529	−0.12	0.901	[−2.487268; 2.191281]
_cons	−3.568069	5.081757	−0.70	0.483	[13.52813; 6.391992]

Notes: *** denote statistical significance at the 1% level.

Ethics Statement

Not applicable. This study is based on publicly available open-access data and does not involve humans or animals

Informed Consent Statement

Not applicable. This study does not involve human participants.

Data Availability Statement

All data used in this study are publicly available open-access.

Funding

This research received no external funding.

Declaration of Competing Interest

The author declares that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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