

Article

Energy Transition and Carbon Emissions in NICs: Evidence from the CS-ARDL Approach and Dynamic ARDL Simulation

Rui Zhou 

The Institute for Chinese Modernization, Jiangsu Provincial Academy of Social Sciences, Nanjing 210004, China; zhourui@jsass.org.cn

Abstract

Newly Industrialized Countries (NICs) represent the most dynamic economic clusters globally and drive the marginal growth of global carbon emissions, rendering their carbon mitigation performance pivotal to delivering the climate targets pledged under the Paris Agreement. Grounded in the Environmental Kuznets Curve (EKC) hypothesis, this study applies the cross-sectional augmented autoregressive distributed lag (CS-ARDL) framework to the panel data from NICs for the 1990–2022 period and incorporates dynamic autoregressive distributed lag simulation methods to investigate the dynamic relationship between energy transition and CO₂ emissions across these economies. The CS-ARDL estimation results suggest that the conventional inverted U-shaped Environmental Kuznets Curve (EKC) hypothesis is invalid under the conditions of cross-sectional dependence and slope heterogeneity for NICs. Per capita GDP growth is found to exert a significant negative impact on CO₂ emissions in these economies. In both the long and short run, rising per capita non-renewable energy consumption substantially increases CO₂ emissions, whereas a higher share of renewable energy in total final energy consumption yields a significant CO₂ mitigation effect. Estimations conducted via the Augmented Mean Group (AMG), Common Correlation Effect Mean Group (CCEMG), and Dynamic Common Correlation Effect Mean Group (DCCEMG) estimators yield consistent findings with the CS-ARDL model. Dynamic ARDL simulation results reveal that positive shocks to per capita non-renewable energy consumption and renewable energy share in total final energy consumption induce heterogeneous dynamic response trajectories of CO₂ emissions across countries. Nevertheless, rising per capita non-renewable energy consumption triggers an overall sustained growth in CO₂ emissions, while a higher proportion of renewable energy achieves long-term mitigation of CO₂ emissions.

Keywords: energy transition; newly industrialized countries; CO₂ emissions



Academic Editor:
Nikolaos Koukouras

Received: 29 June 2026
Revised: 30 July 2026
Accepted: 31 July 2026
Published: 4 August 2026

Copyright: © 2026 by the author.
Licensee MDPI, Basel, Switzerland.
This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

Global warming has become a formidable threat to global sustainable development. It triggers frequent extreme weather phenomena, sea-level rise and biodiversity depletion, while imposing substantial adverse repercussions on global agricultural productivity and public health. To curb the continuous growth of global greenhouse gas emissions, the 1997 Kyoto Protocol instituted the world's first legally binding international climate treaty, which formally specified quantified emission reduction obligations for Annex I economies, including the United States, the European Union, and Japan. Building on advances in global climate governance, the 2015 Paris Agreement established a long-term core target of limiting global temperature increases to well below 2 °C relative to pre-industrial levels,

with an aspirational objective of constraining global warming to 1.5 °C. The Agreement further mandates all signatory parties to develop nationally appropriate mitigation targets and practical strategies tailored to their domestic economic and ecological endowments.

Anthropogenic activities serve as the primary source of greenhouse gas emissions and the leading driver of contemporary global warming and climate change [1]. Among various greenhouse gases, carbon dioxide (CO₂) contributes approximately 60% of total global emissions, rendering it the most predominant climate-forcing agent [2–4]. Accordingly, CO₂ abatement has become a core priority of global climate mitigation agendas. Since the Industrial Revolution, fossil fuels including coal and crude oil have underpinned global industrial production and residential energy consumption. Widely regarded as the “lifeblood of industry”, crude oil plays an irreplaceable role in fostering modern industrial systems, advancing urbanization processes, and sustaining long-term global economic growth. Nevertheless, the extensive and unsustainable exploitation and combustion of fossil fuels have released enormous carbon reserves sequestered via millions of years of natural photosynthesis into the atmosphere within merely a few centuries. Such unprecedented carbon release substantially surpasses the absorptive capacity of natural ecosystems, disrupting the global carbon cycle, triggering continuous atmospheric CO₂ accumulation, and ultimately exacerbating climate degradation.

The 1960s and 1970s witnessed a profound restructuring of the global division of labor, whereby developed countries gradually relocated labor- and resource-intensive industries to developing economies. The substantial inflow of international capital effectively bridged the domestic savings gap in recipient countries, while the introduction of advanced technologies and sophisticated managerial expertise facilitated the upgrading of local labor quality and the maturation of industrial support systems. These external benefits enabled developing economies to rapidly establish export-oriented industrial structures, thereby accelerating economic transformation and sustaining long-term national income growth [5]. The Encyclopaedia Britannica defines NICs as economies that underwent large-scale industrialization from the late twentieth to the early twenty-first centuries but have yet to achieve the developmental benchmarks of advanced economies. Currently, there exists no universal, officially recognized roster of NICs worldwide, as authoritative institutions adopt heterogeneous classification standards tailored to their respective research objectives. The United Nations Industrial Development Organization (UNIDO) categorizes NICs principally based on manufacturing performance and national income levels, with its NIC list subject to annual dynamic revisions that result in cross-year compositional variations. In comparison, World Population Review and WorldData.info emphasize the long-term trajectory of economic structural transition, generating more stable classification results. Their consistent framework identifies Brazil, China, India, Indonesia, Malaysia, Mexico, the Philippines, South Africa, Thailand, and Turkey as typical NICs. Given that an in-depth investigation into the linkage between energy transition and CO₂ emissions necessitates long-term time series analysis, this study adopts the latter stable classification scheme to select its research sample.

The geographical relocation of manufacturing activities entails not only the spatial restructuring of global production division of labor but also the cross-border transfer of CO₂ emissions. Industries relocated from developed economies to NICs are predominantly low- and mid-end manufacturing sectors featuring high energy consumption, high carbon emissions, and low value added. While the manufactured outputs are primarily supplied to consumer markets in developed countries, the carbon emissions generated throughout the production process are entirely retained in recipient NICs. Ma and Zhang [6] revealed that, since 1985, technological advancement and industrial structure optimization have steered developed economies onto a downward trajectory of carbon emissions, whereas

the industrial expansion in NICs has driven a continuous surge in their CO₂ output. Meng et al. [7] further points out that the shift in production activities from the ‘Global North’ to the ‘Global South’ in the early 21st century actually led to an increase rather than a decrease in total global carbon emissions, as the carbon intensity of production in the recipient countries (particularly China and India) was significantly higher than that in the countries from which production was shifted. Accordingly, the restructuring of the global production system has rendered NICs the predominant contributors to contemporary global CO₂ emissions. Four of the world’s top five carbon-emitting economies belong to NICs, with China and India alone accounting for more than 40% of global total emissions (Figure 1).

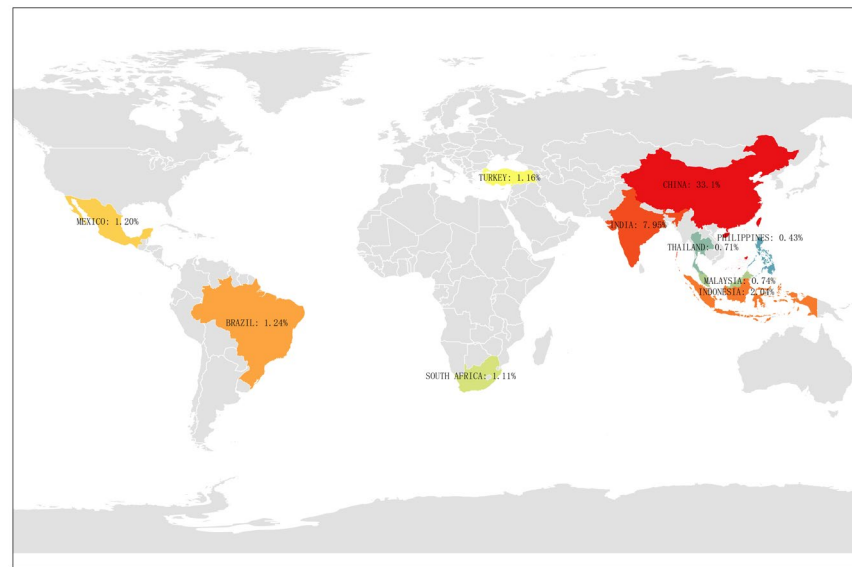


Figure 1. Share of NICs in global CO₂ emissions (Source: EDGAR).

In response to mounting global carbon reduction pressures, NICs have strengthened their participation in global climate governance and proactively promoted the implementation of the Paris Agreement over recent decades. Major NICs have formulated ambitious national climate action targets. Specifically, China aims to cap carbon emissions before 2030 and achieve carbon neutrality by 2060, India pledges to attain economy-wide net-zero emissions by 2070, and Mexico targets full carbon neutrality by 2050. To fulfill these climate commitments, NICs have generally prioritized energy transition as a core strategic approach, with solar, wind, hydropower and other renewable energy sources becoming key pillars of their domestic energy systems. Driven by supportive policy frameworks and large-scale industrial investment, renewable energy consumption across NICs has grown rapidly. In line with the growth forecasts presented in the International Energy Agency (IEA)’s Renewables 2025 report, the share of renewables in the overall energy mix of major NICs is projected to increase significantly by 2030, with particularly remarkable growth in China, India, Mexico, South Africa and Turkey (Figure 2).

Against this backdrop, this study selects NICs as its research subjects to examine the dynamic relationship between energy transition and CO₂ emissions, primarily due to their pivotal position in the global carbon emission landscape and their distinctive developmental stage. First, NICs have undergone rapid economic expansion, steady industrial progress, and increasingly deep integration into the global division of labor. Second, their development path, which heavily relies on industrial relocation from developed economies, has fostered high fossil fuel dependence throughout their industrialization process. This renders NICs the dominant contributors to contemporary global CO₂ emissions, such that their emission trajectories substantially determine the feasibility of achieving global climate

goals. Third, NICs are experiencing the simultaneous advancement of economic and energy transitions. Their economic structure is gradually transforming from low- and medium-end manufacturing toward high-end manufacturing and modern service sectors, while their energy systems are promoting energy substitution by scaling up renewable energy use. These three distinctive features make NICs the most representative and policy-relevant research context for evaluating the emission reduction effectiveness of energy transition, providing critical evidence for clarifying whether energy system transformation can deliver genuine carbon mitigation outcomes.

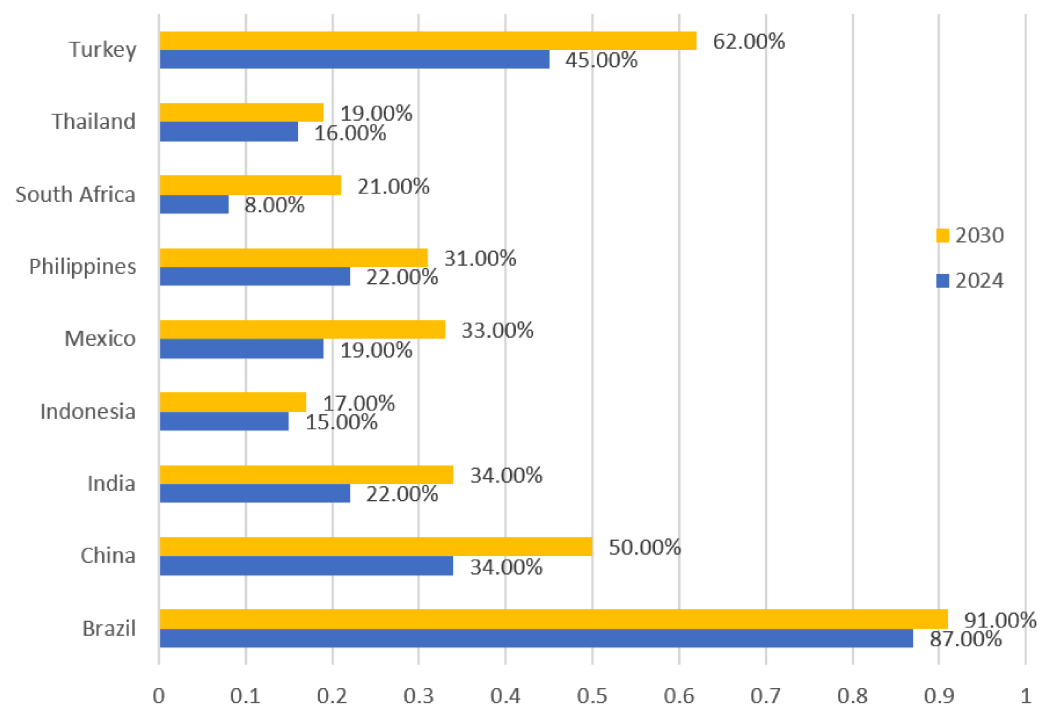


Figure 2. Share of Renewable Energy in Power Generation of Representative NICs (Source: IEA).

Compared with the existing literature, this paper delivers three key marginal contributions. First, it specifically focuses on the nexus between energy consumption and CO₂ emissions within the context of NICs, expanding and enriching the empirical evidence on how energy transition reshapes the carbon emission trajectories of this particular economic group. Second, based on the extended Environmental Kuznets Curve (EKC) hypothesis, this paper constructs a comprehensive analytical framework that integrates economic growth, renewable energy consumption, and non-renewable energy consumption. Furthermore, it adopts the dynamic autoregressive distributed lag (ARDL) model to intuitively capture the time-varying dynamic effects of renewable and non-renewable energy use on CO₂ emission levels. Third, to address the cross-sectional dependence and slope heterogeneity inherent in panel data analysis, this study employs the cross-sectionally augmented ARDL (CS-ARDL) method for core empirical estimation, with Augmented Mean Group (AMG), Common Correlated Effects Mean Group (CCEMG), and Dynamic Common Correlated Effects Mean Group (DCCMG) estimators utilised for robustness validation.

This paper is structured into eight chapters. Section 1 elaborates on the research background, significance, objectives, and marginal contributions of the study. Section 2 presents a literature review that systematically summarizes existing studies on the interactive relationships among economic growth, renewable energy consumption, non-renewable energy consumption, and CO₂ emissions, along with a critical evaluation of current research. Section 3 specifies the research data and preliminary tests, covering variable definitions, data sources, and descriptive statistics, as well as pre-estimation examinations including

multicollinearity, cross-sectional dependence, slope heterogeneity, unit root, and cointegration tests. Section 4 defines the econometric specification and empirical strategy, in which the CS-ARDL approach is constructed based on the extended EKC hypothesis. Section 5 reports the core estimation results derived from the CS-ARDL model. Section 6 conducts robustness checks via the AMG, CCEMG, and DCEMG estimators. Section 7 further adopts dynamic ARDL simulation to capture the dynamic evolutionary characteristics of CO₂ emission effects driven by energy transition. Finally, Section 8 concludes the entire study by summarizing the key empirical results, proposing targeted policy implications, and outlining potential directions for future research.

2. Literature Review

2.1. Economic Growth and CO₂ Emissions

The nexus between economic growth and CO₂ emissions has long been a core research theme in environmental economics. Proposed by Grossman and Krueger [8], the EKC hypothesis provides a classic theoretical framework for explaining this relationship. It suggests that pollutant emissions increase alongside economic expansion in the early stage of development. Once income exceeds a certain threshold, however, emissions will gradually decline as the economy continues to grow. To examine the validity of the EKC conjecture, numerous existing studies have employed a wide range of econometric methods using time-series or cross-country panel data across different economies.

A large number of empirical studies have lent support to the EKC hypothesis, with most analyses concentrating on emerging markets, developing economies and regions experiencing rapid industrialization. Adopting panel data and the generalized method of moments, Apergis and Ozturk [1] detected the EKC trajectory among 11 Asian economies. Subsequent scholarship has continued to validate this proposition across varied samples and empirical frameworks. To illustrate, Liu et al. [9] found evidence of the EKC effect in four ASEAN countries, and Khan and Ozturk [10] confirmed its validity using a panel dataset of 88 developing economies. Similar outcomes have likewise been documented for 180 countries worldwide [11], MENA economies [12], 10 NICs [13], 58 middle-income economies [14], and the world's five largest carbon-emitting nations [15]. Moreover, national-level case studies also support the EKC hypothesis. Based on time-series data, Tang and Tan [16] established the EKC pattern for Vietnam over 1980–2012, and Khan et al. [17] verified its existence in Pakistan for the 1972–2018 period.

Conversely, some studies have rejected the validity of the EKC hypothesis, with empirical evidence primarily drawn from developed economies, resource-based countries, and low-income developing economies. In a sample of 19 European countries, Acaravci and Ozturk [18] found that the EKC hypothesis held only for Denmark and Italy, while it was invalid for all other sampled economies. Examining 12 countries across the Middle East and North Africa (MENA) region, Arouri et al. [19] revealed that, despite most sampled economies satisfying the long-run coefficient conditions for the EKC hypothesis, the corresponding inflection points varied substantially across countries, providing poor evidence in support of the EKC hypothesis. Analyzing 106 economies with diverse income levels, Antonakakis et al. [20] further indicated that sustained economic growth tends to exacerbate greenhouse gas emissions. Focusing on 24 emerging economies, Hove and Tursoy [21] detected no empirical support for the EKC hypothesis. For resource-dependent economies, Badeeb et al. [22] argued that due to the “resource curse” mechanism, the EKC pattern does not follow the traditional EKC pattern. Du et al. [23] examined the relationship between economic growth and CO₂ emissions in both developed and developing countries separately and concluded that the EKC does not hold in either group of countries. Employing Bayesian model averaging and LASSO regression to examine

84 advanced and emerging economies, Gravina and Lanzafame [24] additionally suggested that the linkage between economic growth and CO₂ emissions conforms to an inverted N-shaped curve, rather than the conventional inverted U-shaped EKC pattern.

2.2. Non-Renewable Energy Consumption and CO₂ Emissions

Non-renewable energy, including coal and oil, has long served as the dominant energy consumption for industrial production and residential use, and CO₂ emitted from their combustion constitutes a major source of carbon emissions. Consequently, it is widely accepted that there is a positive correlation between non-renewable energy consumption and CO₂ emissions. Nevertheless, the magnitude of this impact differs substantially across countries and industrial sectors.

Cross-country empirical studies universally identify non-renewable energy consumption as a key driver of rising CO₂ emissions. Focusing on BRICS economies over the 1990–2015 period, Mahalik et al. [25] confirmed that non-renewable energy consumption is the primary factor behind CO₂ emission growth, whose explanatory power considerably exceeds that of others. Based on panel data spanning both developed and developing economies, Rai et al. [26] verified that non-renewable energy consumption serves as the predominant driver of growing carbon emissions. In line with these findings, Almulhim et al. [27] highlighted that increased fossil fuel consumption directly elevates consumption-based carbon emissions across BRICS countries, with this boosting effect being particularly prominent within high-emission quantiles.

Single-country studies also provide consistent evidence for the positive effect of non-renewable energy consumption on carbon emissions. Liu et al. [9] verified that non-renewable energy consumption constitutes the primary driving factor of carbon emission growth across Southeast Asian economies. Khan et al. [28] analyzed Pakistan's time-series data from 1982 to 2018 and validated that oil consumption exerts a significant positive influence on CO₂ emissions in both the short and long run. Similarly, Idroes et al. [29] revealed that the combustion of coal, oil, and natural gas dominates CO₂ emission growth in Indonesia based on long-run time-series data covering 1965–2022. Using Malaysian data spanning 1970–2020, Ahmat et al. [30] further demonstrated that non-renewable energy consumption persistently raises CO₂ emission growth in both short-run and long-run scenarios.

Furthermore, emerging evidence suggests that the emission impacts of non-renewable energy consumption present obvious sectoral heterogeneity. Using panel data for 27 EU member states, Yeasmin et al. [31] found that non-renewable energy consumption in the electricity, steam and gas supply sectors is the primary source of carbon emissions, followed by manufacturing and transportation. Building on these sectoral results, Zhang et al. [32] performed a macro analysis of the transportation sector across 188 countries and regions. Their study shows that while transportation-related carbon emission characteristics vary greatly among economies at different development stages, non-renewable energy consumption remains a predominant driver of CO₂ emissions in the transportation sector.

2.3. Renewable Energy Consumption and CO₂ Emissions

Renewable energy consumption mitigates CO₂ emissions by substituting traditional fossil fuel consumption. However, the magnitude of such abatement effects is contingent on multiple contextual factors, including the proportion of renewables in the overall energy mix and the stage of economic development across individual economies.

Cross-country empirical research generally verifies the carbon reduction benefits brought by rising renewable energy penetration. Focusing on regional economic blocs, Bekun et al. [33] examined 16 EU economies, while Ikram et al. [34] investigated SAARC

member countries, and both studies documented a significant negative relationship between renewable energy consumption and CO₂ emissions. Ben Jebli et al. [35] further extended the research scope to a global panel of 120 economies with diverse income levels. Their heterogeneous analysis indicated that renewable energy consumption contributes to substantial carbon emission reduction across most economies, with low- and middle-income countries serving as the primary exceptions. Several recent empirical studies have drawn similar conclusions on the decarbonization effect of renewable energy consumption [25–27]. Attanayake et al. [36] employed linear and nonlinear regression methods using panel data of 138 countries from 1995 to 2021. Their results strongly confirm that renewable energy consumption effectively curbs CO₂ emissions for most economies, and stress that high-emission countries need to accelerate their energy transition urgently. Similarly, Pakrooh et al. [37] used panel data of 53 countries over 1965–2021 and pointed out that sustainable energy transition is a core strategy for carbon abatement.

Consistent with cross-country evidence, country-specific studies also confirm the decarbonization function of renewable energy. Taking BRICS economies as the sample, Khattak et al. [38] found that renewable energy consumption delivers significant CO₂ mitigation effects in Russia, India and China, while no statistically meaningful abatement effect is detected in Brazil. Targeting India's economic and energy transition from 1990 to 2024, Fernandes et al. [39] quantified the emission reduction performance of renewables. The results indicate that a 1% rise in renewable energy consumption leads to roughly a 1.14% drop in carbon emissions.

2.4. Research Gaps and Motivations of the Study

Previous studies have thoroughly investigated the complex relationships between economic growth, renewable energy use, non-renewable energy consumption and CO₂ emissions, and reached several widely acknowledged conclusions. First, while the validity of the EKC hypothesis is still debated in different scenarios, the inverted U-shaped linkage between economic growth and emissions generally holds for most emerging and developing economies. Second, non-renewable energy consumption is confirmed to be a major driver of rising carbon emissions, and its impacts show remarkable cross-country and cross-sectoral heterogeneity. Third, expanding renewable energy consumption can effectively reduce carbon emissions, and it has been widely recognized as a core strategy for global decarbonization.

Despite the abundant existing literature, several research gaps still require further exploration. In terms of research samples, country groups differ substantially in economic development stages, resource endowments, industrial structures, and energy transition trajectories. Such structural heterogeneity may generate cross-group variations in both the direction and magnitude of energy consumption's impacts on CO₂ emissions. However, most existing studies focus on either single-country case analyses or general cross-country panels, with insufficient efforts to refine sample classification and conduct targeted examinations according to systematic disparities in economic and energy structures. In terms of research content, prior studies predominantly evaluate the emission effects of renewable and non-renewable energy consumption separately. Even the limited studies that integrate both energy types within a unified empirical framework seldom adopt counter-factual simulation approaches to capture the dynamic response pathways of CO₂ emissions under diverse energy consumption structures. Methodologically, conventional cross-country panel analyses generally neglect cross-sectional dependence and slope heterogeneity, largely relying on traditional first-generation panel econometric techniques. This methodological limitation may induce estimation bias by failing to account for global economic shocks, cross-border technological spillovers, and regional interdependence. Furthermore, overre-

liance on a single estimation method, without multidimensional cross-validation across alternative model specifications, weakens the overall robustness of existing empirical findings. Consequently, taking NICs as an example, this paper estimates the dynamic relationship between energy transition and CO₂ emissions using a CS-ARDL model within an extended EKC framework, based on tests for cross-sectional dependence and slope heterogeneity. Robustness analyses were conducted using the AMG, CCEMG and DCEMG estimators. Furthermore, the dynamic response path of the energy transition's impact on CO₂ emissions was characterized using dynamic ARDL simulation. The structure of the study is illustrated in Figure 3.

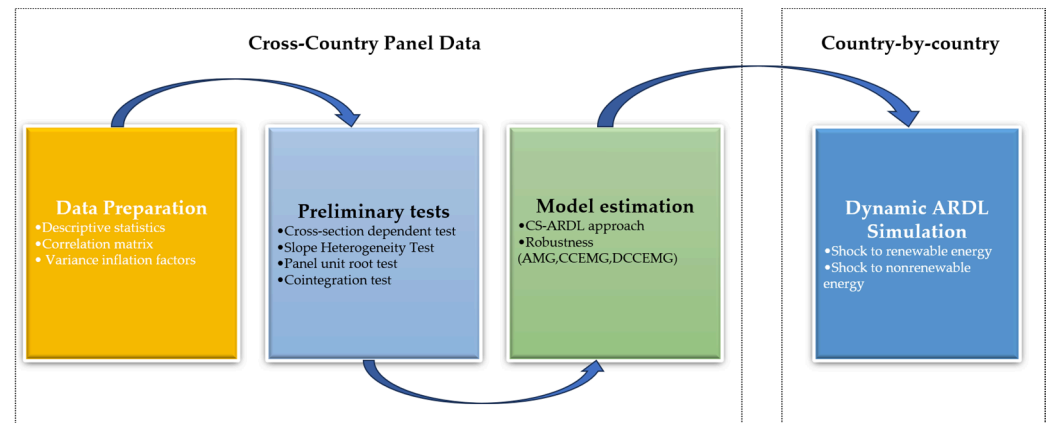


Figure 3. Framework for empirical research.

3. Data and Preliminary Tests

3.1. Variables and Data Explanations

This study investigates the dynamic relationship between energy transition and CO₂ emissions across NICs within the canonical EKC hypothesis framework. It assumes a quadratic function between economic growth and environmental pollution. To capture the ongoing energy transition process, this study adopts per capita non-renewable energy consumption and the share of renewable energy in total final energy consumption as core energy indicators. These energy variables are introduced into the standard EKC model as critical explanatory factors, forming an extended EKC specification that incorporates energy transition. The concrete empirical equation is set out below:

$$\ln CO2_{it} = f \left[\ln GDP_{it}, (\ln GDP_{it})^2, \ln NRE_{it}, \ln RE_{it} \right] \quad (1)$$

In this equation, $\ln CO2$, $\ln GDP$, $(\ln GDP)^2$, $\ln NRE$, and $\ln RE$ represent the logarithm of per capita CO₂ emissions, the logarithm of GDP per capita, the logarithm of the square of GDP per capita, the logarithm of per capita non-renewable energy consumption, and the logarithm of the share of renewable energy in total final energy consumption, respectively. Here, subscript i stands for the cross-sectional country dimension ($i = 1, 2, \dots, N$), while subscript t denotes the time dimension ($t = 1, 2, \dots, T$). Table 1 provides detailed definitions and data sources for all variables contained in Equation (1); the sample spans the 1990–2022 period.

Table 1. Variables explanations and Data sources.

Variables	Explanations	Unit	Sources
$\ln CO_2$	The logarithm of Carbon dioxide (CO ₂) emissions excluding LULUCF per capita	Metric tons	WDI
$\ln GDP$	The logarithm of GDP per capita	Constant 2015 US dollar	WDI
$(\ln GDP)^2$	The logarithm of the square of GDP per capita	Constant 2015 US dollar	WDI
$\ln NRE$	The logarithm of Non-renewable energy consumption	Kg of oil equivalent per capita	Calculated based on WDI data: $(1 - RE) \times$ energy use
$\ln RE$	The logarithm of the share of renewable energy in total final energy consumption	Percent (%)	WDI

3.2. Basic Statistical Description

Table 2 reports the descriptive statistics of all variables. For the sample NICs, the average per capita CO₂ emissions stand at 3.677 tons, ranging from a minimum of 0.666 tons to a maximum of 9.546 tons, which points to large cross-country gaps in the CO₂ emission. Measured in constant 2015 US dollars, the average per capita GDP amounts to 5383.688 USD, with a median of 5396.990 USD and a standard deviation of 3160.390, reflecting prominent heterogeneity in economic development among NICs. The average per capita non-renewable energy consumption equals 251.994 kg of oil equivalent, alongside a standard deviation of 131.942, suggesting notable cross-country differences in fossil fuel usage volume. The average share of renewable energy in total final energy consumption is 24.876%, with a median of 21.950% and a minimum of only 2.000%. These statistical features reveal that most NICs still have relatively low renewable energy penetration, leaving substantial room for green energy transition. Furthermore, Jarque–Bera test results for all variables strongly reject the null hypothesis of normal distribution at the 1% significance level. Given this non-normal distribution property, appropriate econometric treatments are required in subsequent panel estimations to guarantee accurate and robust empirical outcomes.

Table 3 presents the correlation matrix of all log-transformed variables used in this research. The correlation coefficients of per capita CO₂ emissions with per capita GDP and its squared term stand at 0.732 and 0.730, respectively, both statistically significant at the 1% confidence level. This result verifies a strong positive correlation between economic growth and carbon emissions among NICs. Meanwhile, the correlation coefficient between the renewable energy share of total final energy consumption and per capita CO₂ emissions is -0.810 , also statistically significant at the 1% confidence level, indicating that higher renewable energy penetration is tightly associated with lower carbon emissions. By contrast, the correlation between per capita non-renewable energy consumption and per capita CO₂ emissions lacks statistical significance. This correlation may arise from omitted conditional factors and unobserved cross-country heterogeneity, which necessitates further empirical examination via regression analysis in the following sections. Furthermore, the strong significant correlation between per capita GDP and its squared term originates from

their intrinsic quadratic mathematical relationship, which captures the nonlinearity of the environmental Kuznets curve.

Table 2. Descriptive statistics.

	<i>CO2</i>	<i>GDP</i>	<i>NRE</i>	<i>RE</i>
Mean	3.677	5383.688	251.994	24.876
Median	3.134	5396.990	214.216	21.950
maximum	9.546	14,273.57	689.623	59.20
Std. Dev	2.438	3160.390	131.942	14.904
Skewness	0.736	0.300	1.437	0.363
Kurtosis	2.343	2.102	4.762	1.914
Jarque–Bera	30.23 *** (0.000)	34.37 *** (0.000)	64.97 *** (0.000)	77.33 *** (0.000)
Observation	330	330	330	330

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

Table 3. Correlation matrix.

	<i>lnCO2</i>	<i>lnGDP</i>	$(\ln GDP)^2$	<i>lnNRE</i>	<i>lnRE</i>
<i>lnCO2</i>	1.000				
<i>lnGDP</i>	0.732 *** (0.000)	1.000			
$(\ln GDP)^2$	0.730 *** (0.000)	0.999 *** (0.000)	1.000		
<i>lnNRE</i>	−0.065 (0.242)	0.087 (0.116)	0.082 (0.138)	1.000	
<i>lnRE</i>	−0.810 *** (0.000)	−0.608 *** (0.000)	−0.610 *** (0.000)	0.605 *** (0.000)	1.000

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

To identify potential multicollinearity across explanatory variables, this study performs a variance inflation factor (VIF) test. As presented in Table 4, the raw VIF values for per capita GDP and its squared term reach 391.70 and 387.97, respectively, both substantially exceeding the widely accepted critical threshold of 10, thereby confirming severe multicollinearity between the two variables. Theoretically, such high multicollinearity is an inherent and unavoidable feature of the EKC setup due to the quadratic functional form linking economic growth and environmental pollutants. However, to eliminate estimation bias caused by the multicollinearity, this study applies the mean-centering transformation to both per capita GDP and its squared term. After mean-centering, all VIF values drop below 10, demonstrating that the multicollinearity problem has been effectively alleviated and the adjusted model is statistically valid for subsequent regression estimations.

Table 4. Variance inflation factors.

Variables	Pre-Mean-Centering		Post-Mean-Centering	
	VIF	1/VIF	VIF	1/VIF
<i>lnGDP</i>	391.70	0.003	5.12	0.195
$(\ln GDP)^2$	387.97	0.003	3.72	0.269
<i>lnNRE</i>	5.12	0.195	3.27	0.306
<i>lnRE</i>	3.27	0.306	1.51	0.664

3.3. Cross-Section Dependent Test

In cross-country panel analyses, cross-sectional dependence is prevalent, as sampled economies often share geographical boundaries, participate in unified trade arrangements, and exhibit frequent cross-border flows of capital, goods, services, and labor. Neglecting cross-sectional dependence in empirical estimation may lead to biased and inconsistent regression outcomes [40]. To rigorously identify potential cross-sectional dependence, this study adopts four test methods proposed by Pesaran [41,42], Juodis and Reese [43], Fan et al. [44], and Pesaran and Xie [45]. Specifically, four test statistics, namely CD, CDw, CDw+, and CD*, are employed to examine cross-sectional correlation across all core variables. The detailed definitions and interpretations of these statistics are provided as follows.

CD Test Statistic

$CD = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij}$, where $\hat{\rho}_{ij}$ denotes the residual correlation coefficient between cross-section i and cross-section j , N represents the total number of cross-sectional units, and T refers to the number of time periods. The corresponding null hypothesis is formulated as $H_0 : \rho_{ij} = 0$, indicating the absence of cross-sectional correlation across sample units.

CDw Test Statistic

$CD_w = \sqrt{\frac{1}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^N \frac{\hat{\rho}_{ij}}{\hat{V}(\hat{\rho}_{ij})}}$, where $\hat{V}(\hat{\rho}_{ij})$ represents the asymptotic

variance estimator of ρ_{ij} . By incorporating variance correction, this test statistic substantially enhances estimation accuracy and testing power, particularly for small sample cases.

CDw+ Test Statistic

$CD_{w+} = \sqrt{\frac{2T}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^N \frac{\hat{\rho}_{ij}}{\hat{V}(\hat{\rho}_{ij})}}$. Building on the CDw test, this statis-

tic incorporates a $\sqrt{2T}$ normalization term to further enhance the robustness of cross-sectional dependence.

CD* Test Statistic

$CD^* = \sqrt{\frac{T}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij} \sqrt{\frac{T}{1 - \hat{\rho}_{ij}^2}}}$, which incorporates the term $\sqrt{\frac{T}{1 - \hat{\rho}_{ij}^2}}$ to

mitigate disturbance of residual serial autocorrelation on test outcomes, rendering the test applicable to panel data characterized by serial correlation.

The empirical outcomes reported in Table 5 reveal significant cross-sectional dependence throughout the full panel dataset. For $\ln CO_2$, the CD statistic is 26.50 with a p -value close to 0, strongly rejecting the null hypothesis of no cross-sectional correlation at the 1% confidence level. Meanwhile, the corresponding CDw, CDw+, and CD* statistics are all statistically significant at the 1% confidence level, verifying the robust cross-sectional dependence of carbon emission variables. For $\ln GDP$ and $\ln RE$, the CD, CDw and CDw+ statistics deliver significant results at the 1% confidence level, even though the CD* statistic lacks statistical significance. Taken together, these findings still substantiate cross-sectional dependence for the two variables. As for $(\ln GDP)^2$ and $\ln NRE$, the standard CD statistic cannot reject the null hypothesis, yet significant results from CDw, CDw+ and CD* statistic uniformly confirm cross-sectional dependence exists for both variables.

Table 5. Results of cross-sectional dependence tests.

Variable	Pesaran [41,42]	Juodis, Reese [43]	Fan et al. [44]	Pesaran, Xie [45]
	CD	CDw	CDw+	CD*
$\ln CO_2$	26.50 *** (0.000)	−3.10 *** (0.002)	176.44 *** (0.000)	3.75 *** (0.000)
$\ln GDP$	35.65 *** (0.000)	−3.02 *** (0.003)	242.18 *** (0.000)	−1.10 (0.269)
$(\ln GDP)^2$	−1.47 (0.141)	−3.64 *** (0.000)	171.82 *** (0.000)	5.64 *** (0.000)
$\ln NRE$	1.02 (0.309)	−3.12 *** (0.002)	133.42 *** (0.000)	3.26 *** (0.001)
$\ln RE$	20.93 *** (0.000)	−2.04 ** (0.041)	138.20 *** (0.000)	−0.24 (0.814)

Note: *** indicates significance at the 1% confidence level, ** indicates significance at the 5% confidence level.

3.4. Slope Heterogeneity Test

Given the substantial cross-country disparities in economic development stages, institutions, and resource endowments across NICs, the marginal impact of explanatory variables on CO₂ emissions presents prominent cross-national heterogeneity, which implies that the slope coefficients vary systematically across national characteristics. Ignoring such slope heterogeneity would generate biased and inconsistent estimation results when applying traditional fixed-effects and random-effects models. To address this issue, this study employs the slope heterogeneity test proposed by Pesaran and Yamagata [46], which develops the standardized Δ statistic and the small-sample adjusted $\hat{\Delta}_{adj}$ statistic. Compared with the conventional Swamy [47] test, this method possesses better asymptotic properties for large-N and large-T panel data and achieves higher robustness in the presence of residual cross-sectional dependence and serial correlation. When the Δ and $\hat{\Delta}_{adj}$ statistics exceed the critical values at the given statistically significant level, the null hypothesis of slope homogeneity is formally rejected, confirming the existence of slope heterogeneity across panel units. As reported in Table 6, the calculated Δ and $\hat{\Delta}_{adj}$ statistics are 11.036 and 12.392, with p -values of 0.0001 and 0.0002, respectively. At the 1% confidence level, both statistics strongly reject the null hypothesis of homogeneous slopes, verifying significant slope heterogeneity across NICs.

Table 6. Slope Heterogeneity Test.

Test	Statistic	p -Value
$\hat{\Delta}$	11.036 ***	0.000
$\hat{\Delta}_{adj}$	12.392 ***	0.000

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

3.5. Panel Unit Root Test

Panel unit root tests are indispensable to prevent spurious regression in empirical analysis. In the presence of cross-sectional dependence and slope heterogeneity, the traditional first-generation panel unit root tests, such as the Breitung, ADF-Fisher, and PP-Fisher tests, tend to produce biased and misleading stationarity inferences [40,42]. To address these limitations, the second-generation panel unit root tests have been developed to allow for cross-sectional dependence and slope heterogeneity across panel units [48–50]. Accordingly, this study adopts two classic second-generation stationarity tests proposed by Pesaran [50],

namely the covariate-augmented Dickey–Fuller (CADF) test and the cross-sectionally augmented IPS (CIPS) test. The corresponding empirical results are presented in Tables 7 and 8. The findings indicate that all variables are non-stationary at the level form. Nevertheless, after first-order differencing, all variables yield significant statistics at the 1% confidence level, confirming that all series follow a stationary process after differencing and satisfy the fundamental stationarity prerequisites for subsequent econometric regressions.

Table 7. Results of CADF Test.

Variables	Level			1st Difference		
	T-Bar	Z [t-Bar]	p-Value	T-Bar	Z [t-Bar]	p-Value
<i>lnCO2</i>	−2.008	1.191	0.883	−2.480 ***	−2.335	0.009
<i>lnGDP</i>	−1.980	1.293	0.902	−2.783 ***	−3.376	0.000
$(\ln GDP)^2$	−1.685	2.354	0.991	−2.448 **	−2.249	0.012
<i>lnNRE</i>	−1.895	1.597	0.945	−2.450 **	−2.254	0.012
<i>lnRE</i>	−2.373	−0.118	0.453	−2.418 **	−2.148	0.016

Note: *** indicates significance at the 1% confidence level, ** indicates significance at the 5% confidence level.

Table 8. Results of CIPS Test.

	Level		1st Difference	
	Statistic	Critical Value (1%)	Statistic	Critical Value (1%)
<i>lnCO2</i>	−2.035	−3.06	−4.684 ***	−3.06
<i>lnGDP</i>	−2.194	−3.06	−4.026 ***	−3.06
$(\ln GDP)^2$	−2.099	−3.06	−4.233 ***	−3.06
<i>lnNRE</i>	−2.061	−3.06	−4.745 ***	−3.06
<i>lnRE</i>	−2.326	−3.06	−4.037 ***	−3.06

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

3.6. Cointegration Test

Panel cointegration tests are utilized to verify the existence of long-run stable equilibrium relationships among non-stationary panel variables, which serves as a fundamental procedure to eliminate spurious regression. Given that the sample in this study consists of cross-country panel data characterized by “small N and moderate T” ($N = 10$, $T = 33$), and that cross-sectional dependence and slope heterogeneity are present, the Hadri–Kurozumi–Rao panel cointegration test (hereinafter referred to as the HKR test) [51] is adopted in this study. This method can handle any form of cross-sectional dependence, allows for slope heterogeneity across cross-sectional units, and performs better under finite-sample conditions than the earlier Westerlund panel cointegration test [52]. The HKR test assumes as its null hypothesis that “all cross-sectional units exhibit a cointegration relationship.” As shown in Table 9, the p -values corresponding to the panel statistics S_k and $\tilde{S}_k$ are both far greater than 10%; therefore, the test results do not statistically reject the null hypothesis, indicating that a long-run panel cointegration relationship exists among the variables.

Table 9. Hadri–Kurozumi–Rao Panel Cointegration Test.

Pooled Statistic	Value	p-Value
S_k	−1.518	0.936
$\tilde{S}_k$	−0.762	0.777

Note: S_k represents the uncorrected autocovariance, and $\tilde{S}_k$ represents the bias-corrected autocovariance.

To further examine the robustness of the cointegration relationship across cross-sections, Table 10 presents the results of individual tests for each cross-sectional unit. Among all 10 cross-sectional units, only Units 5 and 7 rejected the null hypothesis at the 10% confidence level; however, at the stricter 5% confidence level, none of the individual units could reject the null hypothesis of cointegration. The p -values for the remaining 8 cross-sections were all well above 0.1, strongly supporting the cointegration relationship. Overall, the results of the individual tests are highly consistent with the panel statistics, indicating that the cointegration relationship is not driven by a small number of cross-sections but exhibits strong consistency across cross-sections, with no significant individual outliers.

Table 10. Hadri–Kurozumi–Rao Unit-specific Cointegration Tests.

Unit	S_k	$\tilde{S}_k$	p -Value	Unit	S_k	$\tilde{S}_k$	p -Value
1	−1.579	−1.522	0.936	6	−1.142	−0.915	0.820
2	0.744	0.964	0.168	7	1.025	1.500	0.067 *
3	−0.835	−0.526	0.701	8	0.808	1.106	0.134
4	−1.112	−0.960	0.832	9	−1.091	−0.952	0.830
5	1.057	1.389	0.082 *	10	−1.050	−0.628	0.735

Note: * indicates significance at the 10% confidence level. S_k represents the uncorrected autocovariance, and $\tilde{S}_k$ represents the bias-corrected autocovariance.

4. Model Specification and Econometric Strategy

Building on the aforementioned data description and preliminary empirical tests, this study employs the CS-ARDL approach developed by Chudik et al. [53]. This approach effectively accommodates three key panel data features identified in the sample, namely slope heterogeneity, cross-sectional dependence, and mixed variable integration orders [54]. Unlike the conventional ARDL framework, the CS-ARDL approach introduces cross-sectional averages of dependent and independent variables to capture unobserved common shocks, thereby eliminating estimation bias caused by cross-sectional dependence. The panel CS-ARDL empirical specification is formulated as follows:

$$\begin{aligned} \ln CO2_{it} = & \alpha_i + \sum_{j=1}^p \phi_{ij} \ln CO2_{i,t-j} + \sum_{k=0}^q \beta_{1ik} \ln GDP_{i,t-k} + \sum_{k=0}^q \beta_{2ik} (\ln GDP_{i,t-k})^2 \\ & + \sum_{k=0}^q \beta_{3ik} \ln NRE_{i,t-k} + \sum_{k=0}^q \beta_{4ik} \ln RE_{i,t-k} + \sum_{l=0}^g \gamma'_{i,l} \bar{Z}_{t-l} \\ & + \delta_i \tau + \varepsilon_{i,t} \end{aligned} \quad (2)$$

In particular, the vector $\bar{Z}_t = (\overline{\ln CO2_t}, \overline{\ln GDP_t}, \overline{(\ln GDP_t)^2}, \overline{\ln GDP_t^2}, \overline{\ln NRE_t}, \overline{\ln RE_t})'$ captures common correlated factors, where each term corresponds to the cross-sectional average of the respective variable, calculated as $N^{-1} \sum_{i=1}^N \ln CO2_{it}$, $N^{-1} \sum_{i=1}^N \ln GDP_{it}$, $N^{-1} \sum_{i=1}^N (\ln GDP_{it})^2$, $N^{-1} \sum_{i=1}^N \ln NRE_{it}$, $N^{-1} \sum_{i=1}^N \ln RE_{it}$. In this specification, $\gamma_{i,l}$ denotes the factor loadings for individual country i ; α_i refers to the country-specific intercept; τ represents the time trend; j , k , l denote the lag order; and $\varepsilon_{i,t}$ is the idiosyncratic disturbance term. Additionally, ϕ_{ij} , β_{1ik} , β_{2ik} , β_{3ik} , β_{4ik} and δ_i denote the coefficients to be estimated.

In dynamic empirical specifications, the inclusion of lagged dependent variables in the CS-ARDL framework gives rise to endogeneity bias. Specifically, the lagged dependent variable $\ln CO2_{i,t-1}$ incorporated in the model is correlated with the error term. This relationship violates the core orthogonality assumption of ordinary least squares (OLS), which requires strict independence between regressors and stochastic disturbances, thereby inducing endogenous bias in the lagged variable. Failure to account for such endogeneity would generate biased and inconsistent coefficient estimates and undermine the reliability

of empirical results. To address this problem, Chudik and Pesaran [53,55] propose a correction procedure that sets the augmentation lag order g as a strictly positive value calculated as $\sqrt[3]{T}$. Moreover, the optimal lag orders p and q of the model are determined based on the Akaike Information Criterion (AIC). However, during specific empirical research, including excessive lagged cross-sectional mean terms can markedly reduce degrees of freedom. With limited samples, there is no rigid requirement that $g = \sqrt[3]{T}$, and suitable adjustments should be made in light of the degrees of freedom. Following the methodological framework of Ditzen [56], this study converts the established CS-ARDL specification into an error correction model (ECM) specification and reparametrizes Equation (2) accordingly.

$$\begin{aligned} \Delta \ln CO2_{it} = & \phi_i \left[\ln CO2_{i,t-1} - \theta_{0i} - \theta_{1i} \ln GDP_{it} - \theta_{2i} (\ln GDP_{it})^2 - \theta_{3i} \ln NRE_{it} - \theta_{4i} \ln RE_{it} \right] \\ & + \sum_{j=1}^{p-1} \alpha_{ij} \Delta \ln CO2_{i,t-j} + \sum_{k=0}^{q-1} \beta_{1ik} \Delta \ln GDP_{i,t-k} + \sum_{k=0}^{q-1} \beta_{2ik} \Delta (\ln GDP_{i,t-k})^2 \\ & + \sum_{k=0}^{q-1} \beta_{3ik} \Delta \ln NRE_{i,t-k} + \sum_{k=0}^{q-1} \beta_{4ik} \Delta \ln RE_{i,t-k} + \sum_{l=0}^g \gamma'_{i,l} \bar{Z}_{t-l} \\ & + \delta_i \tau + \mu_{i,t} \end{aligned} \quad (3)$$

In Equation (3), the parameter vector θ captures long-run effects, while the coefficient α and parameter vector β reflect short-run effects. Δ refers to the first-difference operator, and the term enclosed in parentheses denotes the error correction term. In addition, ϕ_i measures the adjustment speed at which the economic system converges to its long-run equilibrium after exogenous shocks.

5. Estimation Results of the CS-ARDL Approach

5.1. Short-Run Dynamic Effects

In Table 11, the short-run estimation results of the CS-ARDL approach indicate that energy consumption structure dominates short-run CO₂ emission fluctuations across NICs. In terms of short-run parameters, the current-period coefficient of per capita non-renewable energy consumption is 0.710 and significantly positive at the 1% confidence level. This result aligns well with the inherent development features of NICs. These countries are experiencing continuous expansion of industrial and energy-intensive sectors, and their economic growth remains heavily reliant on traditional fossil fuel inputs such as coal and oil, leading to a rigid energy consumption structure. Accordingly, short-run increases in fossil fuel consumption directly raise carbon emissions, rendering non-renewable energy consumption the primary driver of short-run emission growth. Conversely, the current-period coefficient of the share of renewable energy consumption in total final energy consumption is −1.049 and statistically significant at the 1% confidence level. This outcome suggests that the ongoing low-carbon transitions in sample countries enable effective clean energy substitution, which substantially curbs CO₂ emissions. Renewable energy deployment can offset the emission pressure caused by rising fossil fuel consumption, thereby achieving a prominent short-run carbon mitigation effect.

With respect to the short-run effects of economic growth, neither contemporaneous per capita GDP nor its squared term exhibits a statistically significant impact on CO₂ emissions. This indicates that instantaneous economic expansion does not intensify short-run carbon emissions. In contrast, the coefficient of the one-period lagged $\ln GDP$ is significantly negative, indicating that NICs have achieved initial low-carbon progress through enhanced industrial energy efficiency, refined production management, and stricter environmental regulations. The remaining lagged variables show no statistical significance. Overall, these findings confirm that short-run carbon emission fluctuations are mainly dominated by the

current energy consumption structure, while the lagged influence of economic development is limited.

Table 11. The estimated results of CS-ARDL approach.

Variable	Short-Run Results		
	Coef.	Std. Err	$p > z $
$D.\ln GDP$	−0.305	0.218	0.162
$D.(\ln GDP)^2$	0.157	0.144	0.276
$D.\ln NRE$	0.710 ***	0.132	0.000
$D.\ln RE$	−1.049 ***	0.148	0.000
$D.\ln CO_2(-1)$	−0.124	0.088	0.162
$D.\ln GDP(-1)$	−0.544 **	0.245	0.026
$D.(\ln GDP)^2(-1)$	0.163	0.207	0.430
$D.\ln NRE(-1)$	0.002	0.088	0.980
$D.\ln RE(-1)$	−0.045	0.142	0.751
ECT	−1.124 ***	0.088	0.000
Long-Run Results			
$\ln GDP$	−0.921 *	0.531	0.083
$(\ln GDP)^2$	0.408	0.393	0.299
$\ln NRE$	0.702 ***	0.191	0.000
$\ln RE$	−0.997 ***	0.112	0.000

Note: *** indicates significance at the 1% confidence level, ** indicates significance at the 5% confidence level, * indicates significance at the 10% confidence level. By comparing CS-ARDL estimation results under $g = 1$, $g = 2$ and $g = 3$, it was found that $g = 1$ delivers sufficient degrees of freedom, so $g = 1$ was chosen to ensure estimation efficiency. The lag order of p and q is 1.

In addition, the coefficient of the error correction term (ECT) is estimated at −1.124 and is statistically significant at the 1% confidence level. With an absolute value between 1 and 2, this coefficient suggests that the CO₂ emission system of NICs features a strong dynamic convergence mechanism with a damped oscillatory adjustment path. Specifically, short-term fluctuations in energy consumption structure and economic activities may drive CO₂ emissions away from their long-run equilibrium. In response, the system promptly corrects such deviations and even generates reverse overshooting, wherein the short-term correction magnitude exceeds the equilibrium level by approximately 12.4%. The system then undergoes period-by-period attenuated oscillations and eventually converges to a stable long-term equilibrium path. Although short-term cyclical fluctuations exist, the significantly negative ECT coefficient firmly verifies the presence and overall stability of the long-term cointegration relationship among the research variables.

5.2. Long-Run Dynamic Effects

The long-run equilibrium estimation results in Table 11 further indicate that NICs do not conform to the traditional inverted-U-shaped EKC. Instead, the long-run evolution of CO₂ emissions is predominantly determined by energy transition rather than economic growth scale. Specifically, the long-run coefficient of per capita GDP is significantly negative at the 10% confidence level, while its squared term is statistically insignificant. This finding suggests that, as their economies have expanded, NICs have progressively prioritized low-carbon development within their growth agendas. These economies are actively promoting industrial restructuring, shifting away from energy-intensive, high-emission sectors toward mid-to-high-end manufacturing and modern service industries. Meanwhile, the widespread diffusion of green and low-carbon production technologies, coupled with the continuous refinement of environmental regulatory frameworks, has enabled long-run economic growth to decouple from the high-pollution, high-emission development

paradigm. Taking China as a case in point, data from the 2025 Statistical Bulletin on National Economic and Social Development, published by the National Bureau of Statistics of China, shows that equipment manufacturing contributed 36.8% to the value added of industrial enterprises above designated size. Within this sector, high-tech manufacturing and digital product manufacturing accounted for 17.1% and 12.5% of value-added output, respectively. Driven by industrial green and low-carbon transition, China has effectively realized the decoupling of sustained economic growth from the high-pollution, high-emission development paradigm.

In terms of the long-run effects of energy transition, the long-run coefficient of per capita non-renewable energy consumption is significantly positive, confirming that fossil fuel dependence constitutes a key driver of sustained CO₂ emission growth in NICs. This phenomenon is largely attributable to the ongoing industrialization and urbanization processes in these countries. The construction of industrial systems and the expansion of infrastructure remain heavily reliant on conventional fossil energy consumption, and the continued consumption of fossil fuels persistently elevates overall CO₂ emissions over the long-run. In contrast, the long-run coefficient of the share of renewable energy in total final energy consumption is significantly negative, underscoring the critical role of renewable energy penetration in facilitating the low-carbon transition of NICs. The large-scale substitution of fossil fuels with renewable energy effectively reduces the economy's dependence on traditional energy sources, thereby contributing to a steady and sustained decline in long-run CO₂ emissions. For example, comparing China's 2015 and 2025 Statistical Bulletins on National Economic and Social Development, we observe a dramatic upgrade to the country's energy consumption structure. In the past ten years, coal accounted for a shrinking share of total primary energy consumption, dropping from 64.0% to 51.4%, while clean energy expanded rapidly from 17.9% to 30.4%. Such energy transition is a key force behind the persistent fall in China's carbon dioxide emission intensity.

6. Robustness

To validate the robustness of the core empirical results, we adopt AMG, CCEMG and DCEMG estimators for re-estimation. As reported in Table 12, all three alternative specifications yield consistent estimation outcomes, with the coefficient of $\ln NRE$ being significantly positive and that of $\ln RE$ significantly negative at the 1% confidence level. These findings are highly consistent with the baseline results derived from the CS-ARDL model, thereby confirming the reliability and robustness of the core conclusions. Specifically, per capita non-renewable energy consumption consistently drives CO₂ emissions upward, whereas the share of renewable energy in total final energy consumption exerts a stable and statistically significant emission-mitigation effect across all model specifications. Such cross-model consistency indicates that the underlying mechanism—whereby fossil energy consumption increases CO₂ emissions while renewable energy substitution reduces them—is insensitive to the choice of estimation method. Accordingly, the dominant role of energy structure in shaping CO₂ emission variations in NICs is empirically well supported.

In terms of the economic growth-emission nexus, the AMG, CCEMG and DCEMG estimators yield insignificant coefficients for $\ln GDP$ and its squared term. This divergence suggests that the conventional EKC relationship is susceptible to confounding influences from cross-sectional dependence and Slope Heterogeneity. Among these, unobserved multidimensional common factors lead to increase cross-sectional dependence. For NICs, these latent cross-country synchronous systemic shocks can be grouped into six dimensions: (1) cyclical variations in global fossil fuel prices and aggregate demand; (2) worldwide cycles of low-carbon and industrial technology diffusion and breakthroughs; (3) synchronized global climate governance and environmental policy cycles; (4) long-run structural

transformations of global value chains and trade globalization; (5) cross-border cycles of green capital flows, international financing costs and green investment risk appetite; and (6) shared regional trends in industrialization phases, environmental governance institutional capacity and public environmental awareness. Once those systematic cross-country confounding effects are eliminated, the typical EKC pattern no longer holds. This finding further corroborates the long-run evidence from the CS-ARDL model, demonstrating that the EKC hypothesis is not tenable for NICs when common factor disturbances are fully controlled for.

Table 12. The results of AMG, CCEMG and DCCEMG Estimators.

	AMG	CCEMG	DCCEMG
$\ln CO_2(-1)$			0.103 * (0.081)
$\ln GDP$	−0.138 (0.598)	−0.091 (0.654)	−0.375 (0.254)
$(\ln GDP)^2$	−0.168 (0.439)	0.030 (0.795)	−0.033 (0.906)
$\ln NRE$	0.708 *** (0.000)	0.682 *** (0.000)	0.676 *** (0.000)
$\ln RE$	−1.064 *** (0.000)	−0.986 *** (0.000)	−0.956 *** (0.000)
Constant	−0.498 (0.247)	−0.785 (0.153)	

Note: *** indicates significance at the 1% confidence level, * indicates significance at the 10% confidence level.

7. Further Research: A Novel Dynamic ARDL Simulation

7.1. Basic Settings for the Dynamic ARDL Simulation Model

Autoregressive distributed lag (ARDL) models are widely used in social science research and can test a range of propositions of significant theoretical importance. However, because this model may generally involve complex dynamic specifications—including multiple lags, first-order differences, and first-order differences with lags—it becomes more difficult to interpret the effects of changes in independent variables [57]. To overcome this drawback, they developed the Dynamic ARDL Simulation model. This approach draws on ARDL-estimated parameters and employs counterfactual simulation to generate the multi-period dynamic adjustment path of the dependent variable triggered by a unit shift or standardized shock to a chosen regressor, with all simulated trajectories available for visual plotting.

In this study, the parameter settings for Dynamic ARDL Simulation are defined as follows: the lag order is set to 1, each variable incorporates one contemporaneous first-difference term, the exogenous shock to $\ln RE$ or $\ln NRE$ is imposed at the 10th period of the simulation scenario, and the total simulated scenario spans 30 periods. The detailed implementation procedure of the Dynamic ARDL Simulation is outlined below. First, 1000 sets of parameter vectors are randomly drawn from the multivariate normal asymptotic distribution of the estimated coefficient vector. Second, the dynamic multiplier trajectories over the predefined forecast horizon are computed for each sampled parameter vector. Third, the 2.5th and 97.5th percentiles of the 1000 simulated multiplier paths are extracted to construct

a 95% confidence band for the impulse response function. The specification of the dynamic ARDL Simulation model is shown below:

$$\begin{aligned}\Delta \ln \text{CO}_2_t = & \alpha_0 + \varphi_1 \Delta \ln \text{GDP}_t + \rho_1 \ln \text{GDP}_{t-1} + \varphi_2 \Delta (\ln \text{GDP}_t)^2 \\ & + \rho_2 (\ln \text{GDP}_{t-1})^2 + \varphi_3 \Delta \ln \text{NRE}_t + \rho_3 \ln \text{NRE}_{t-1} + \varphi_4 \Delta \ln \text{RE}_t \\ & + \rho_4 \ln \text{RE}_{t-1} + \vartheta \text{ECT}_{t-1} + \varepsilon_t\end{aligned}\quad (4)$$

In Equation (4), φ_k, ρ_k ($k = 1, 2, 3, 4$) are the parameters to be estimated, ECT is the error correction term estimated by the ARDL model, and ε_t denotes the residual term.

7.2. Results of the Dynamic ARDL Simulation Model

The estimation results derived from the CS-ARDL, AMG, CCEMG, and DCCMG estimators consistently indicate that higher per capita non-renewable energy consumption significantly raises per capita CO₂ emissions, whereas an increased share of renewable energy in total final energy consumption effectively mitigates per capita CO₂ emissions. To visually verify and supplement the above empirical findings from a country-specific perspective, this study adopts the dynamic ARDL simulation approach adopted by Abbasi et al. [58], Udeagha and Breitenbach [59], and Javed et al. [60], to simulate the dynamic effects of $\ln \text{RE}$ and $\ln \text{NRE}$ on per capita CO₂ emissions.

Figure 4 illustrates the dynamic transmission paths of positive $\ln \text{RE}$ shocks on CO₂ emissions across the ten NICs. The simulation results reveal evident cross-country heterogeneous responses. First, Brazil, India, Malaysia, Mexico, and South Africa display significant and persistent reductions in CO₂ emissions. For these economies, a positive shock to $\ln \text{RE}$ triggers an immediate decline in CO₂ emissions, which rapidly converges to a new negative long-term equilibrium. Brazil features a flexible baseload power system predominantly powered by hydropower. Hydropower units deliver superior deep peak-shaving capacity, allowing the marginal output of thermal power to be adjusted downward in near real time when intermittent renewable sources (i.e., wind and solar) are integrated into the grid. Similarly, by expanding the deployment of wind and solar power, India, Mexico, and South Africa have not only partially replaced coal-fired power generation, but a positive shock to $\ln \text{RE}$ would also replace even more fossil fuel consumption, leading to a sustained reduction in CO₂ emissions. Second, CO₂ emissions in China, Thailand, and Turkey continue to grow but exhibit a markedly slower growth rate. This empirical pattern suggests that the current expansion of renewable energy capacity in these economies is inadequate to fully offset the rising carbon emissions driven by overall energy consumption growth. Although China leads the world in installed wind and solar power capacity, coal-fired power generation remains dominant due to the continued growth in electricity demand and the role of coal-fired power in providing baseload power and peak-shaving. For Thailand, emission mitigation is constrained by the lock-in effect of long-term take-or-pay natural gas procurement contracts. For Turkey, the steel and cement industries rely on coke as a chemical reducing agent in production, making full electrification of these high-emission sectors impossible. Given the inelastic nature of fossil fuel consumption, the positive impact of the share of renewable energy in total final energy consumption will slow the rate of increase in CO₂ emissions, rather than lead to an absolute reduction in total emissions. Third, Indonesia shows a distinct response: following the positive $\ln \text{RE}$ shock, CO₂ emissions rise temporarily in the short run before stabilizing at a relatively high equilibrium level, indicative of a potential energy rebound effect. Two key factors account for this phenomenon. Long-standing fossil fuel subsidies in Indonesia have artificially distorted terminal energy prices and incentivized excessive fossil fuel consumption. Meanwhile, the rapid expansion of energy-intensive industries—particularly nickel smelting—has driven up CO₂ emissions. Overall, the simulation results verify that increasing the proportion of

renewable energy in total final energy consumption serves as an effective strategy for CO₂ emission reduction across NICs.

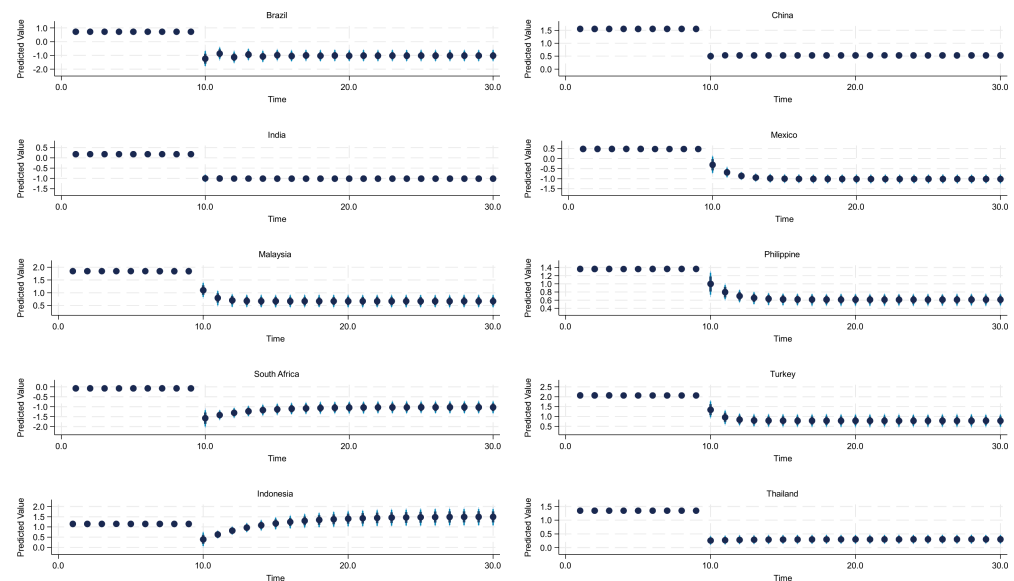


Figure 4. Counterfactual shock in CO₂ emissions and the share of renewable energy consumption using dynamic ARDL simulations.

Figure 5 illustrates the dynamic transmission paths of positive $\ln NRE$ shocks on CO₂ emissions across the ten NICs. The simulation results reveal distinct cross-country response characteristics. First, all sampled NICs exhibit positive long-term emission responses to the $\ln NRE$ shock, confirming that fossil fuel consumption constitutes a rigid and fundamental driving factor of CO₂ emissions in these economies. Second, China and Thailand show unremarkable dynamic adjustment trajectories. Faced with a positive $\ln NRE$ shock, their CO₂ emissions immediately jump and stabilize at the long-run equilibrium level. This feature is attributable to the distinctive energy structures of the two countries: China's energy mix is dominated by coal, while Thailand relies heavily on natural gas. Such structural characteristics create a direct, lag-free transmission link between variations in fossil fuel consumption and subsequent changes in CO₂ emissions. Third, CO₂ emissions in India and Indonesia follow a short-term rising trend before gradual stabilization and convergence. The continued expansions of India's manufacturing sector and Indonesia's mining and smelting industries have generated strong and inelastic demand for fossil fuels. However, India's rapid development in photovoltaic power generation and Indonesia's mandatory B20/B30 biodiesel blending policies have effectively mitigated the immediate surge in carbon dioxide emissions caused by increased fossil fuel consumption, yet this mitigating effect converges over time toward a higher equilibrium level. Fourth, Turkey and Malaysia witness substantially larger long-term increases in CO₂ emissions compared with other sample economies. The economic development of both Turkey and Malaysia relies on high-carbon industries, and non-renewable energy sources play an indispensable role. Therefore, a positive shock to $\ln NRE$ would increase the growth rate of CO₂ emissions, and the emissions level would eventually converge to a higher one in the long run.

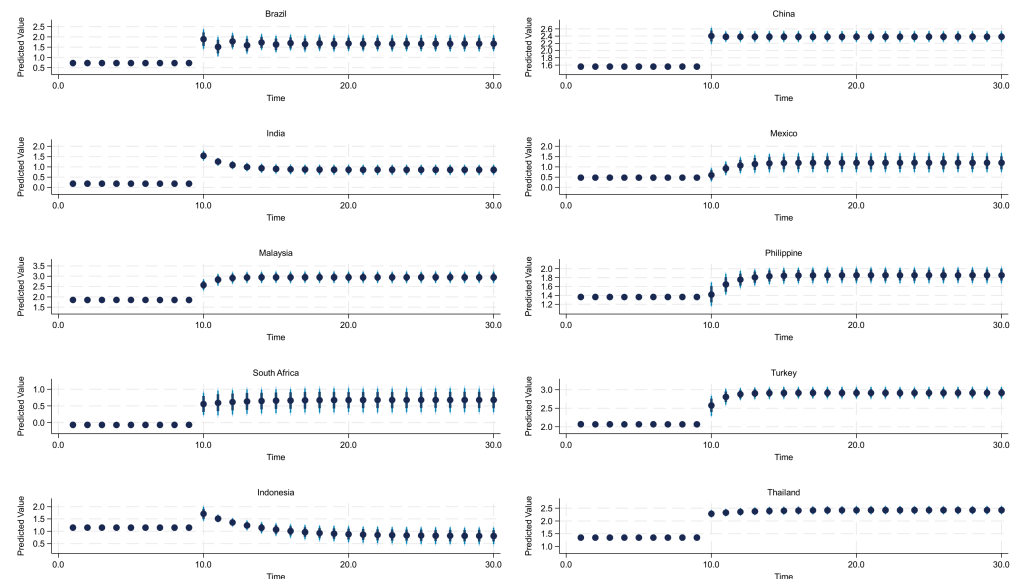


Figure 5. Counterfactual shock in CO₂ emissions and per capita non-renewable energy consumption using dynamic ARDL simulations.

8. Conclusions, Policy Indications and Further Study

8.1. Conclusions

Using panel data covering the 1990–2022 period for NICs, this study empirically investigates the dynamic relationship between energy transition and CO₂ emissions within an extended EKC framework. The CS-ARDL estimation results do not support the conventional inverted U-shaped EKC relationship. Instead, the carbon emission system exhibits a robust error-correction mechanism, enabling rapid convergence toward long-run equilibrium following short-run external shocks.

In both the short and long run, per capita non-renewable energy consumption acts as a significant driver of rising CO₂ emissions, whereas an increased share of renewable energy in total final energy consumption exerts stable and statistically significant CO₂ emission-mitigation effects. These core findings are strongly corroborated by alternative robust estimation techniques, including AMG, CCEMG, and DCCMG, all of which yield consistent coefficient signs and statistical significance across model specifications.

Furthermore, the dynamic ARDL simulation results reveal pronounced cross-country heterogeneity in both the response paths and magnitudes of CO₂ emissions to energy structure shocks. Several sample countries exhibit distinct energy rebound effects during the low-carbon transition, pointing to regional disparities in transition efficiency and emission governance capacity. Nevertheless, energy consumption structure remains the dominant and decisive factor shaping long-run CO₂ emission variations in NICs, outweighing the impact of pure economic scale expansion.

8.2. Policy Implications

Based on the above empirical findings, this study proposes targeted policy implications for accelerating the low-carbon transition and achieving sustainable development in NICs.

First, accelerate the transition toward a green and low-carbon energy structure. NICs should prioritize energy transition as the core lever for CO₂ emission mitigation. These economies should fully capitalize on the dual advantages of renewable energy—namely, its capacity to deliver both immediate short-run CO₂ emission reductions and sustained long-run CO₂ abatement effects—to progressively replace conventional fossil fuels with clean energy alternatives. On the one hand, governments should strictly constrain the

extensive consumption of coal, oil, and other non-renewable energy sources, and rigorously regulate new fossil energy inputs in energy-intensive sectors. Such restrictive measures can effectively reduce fossil fuel dependence across high-emission fields, including industrial manufacturing, power generation, and transportation. On the other hand, countries should scale up the targeted deployment of solar, wind, hydropower, and other renewable energy resources in accordance with local endowment conditions, and actively promote the close coupling of systems such as natural gas systems (NGS) and electric power systems (EPS) to accommodate a diverse range of renewable energy sources and energy carriers [61]. In addition, policy subsidies and industrial support measures should be strengthened to continuously increase the share of renewable energy in final energy consumption, thereby consolidating the foundational advantages of the clean energy transition.

Second, implement targeted and differentiated CO₂ emission reduction policies tailored to cross-country heterogeneity. NICs exhibit significant variations in terms of economic development levels, energy endowments, industrial structures, and reliance on fossil fuels; therefore, carbon emission reduction policies must avoid a “one-size-fits-all” approach and instead adopt a targeted, tiered governance model. For economies with high dependence on fossil fuels and a rigid carbon emissions structure, policy efforts should focus on promoting energy-saving retrofits in industry, implementing dual controls on energy consumption and energy efficiency, and phasing out outdated, energy-intensive industries, while strictly curbing the unregulated expansion of high-carbon sectors. For countries with abundant renewable energy potential and high sensitivity to emissions reduction policies, market access for clean energy should be further liberalized, and targeted fiscal and tax incentive mechanisms should be introduced to accelerate the large-scale replacement of fossil fuels with renewable energy. Building on this foundation, China should fully leverage its global leadership in the new energy sector to deepen South–South cooperation among NICs—utilizing multilateral mechanisms such as BRICS and the Green Belt and Road Initiative to promote policy coordination and technology sharing. Chinese enterprises should be encouraged to transfer clean energy technologies and foster locally based production capacity through overseas manufacturing facilities and joint R&D programs. Such efforts will translate China’s green energy transition experience into global public goods that advance collective low-carbon progress across NICs, ultimately delivering a win–win outcome characterized by the decoupling of economic expansion from CO₂ emissions.

Third, advance industrial transformation, green technological innovation, and institutional improvement. Establishing a long-run CO₂ emission reduction system that integrates industrial upgrading, technological progress, and institutional governance is essential to balancing sustainable industrial development, steady economic growth, and the dual-carbon goals. In terms of industrial optimization, NICs should continuously upgrade their industrial structures by gradually phasing out low-end, energy-intensive manufacturing sectors and actively fostering high-end equipment manufacturing, high-tech industries, and modern service sectors. Such industrial restructuring helps fundamentally decouple economic expansion from the high-carbon emission characteristics inherent in traditional industrialization. In terms of technological empowerment, governments and enterprises should strengthen the research, development, and large-scale application of green and low-carbon technologies, with increased investment in energy conservation, energy storage, and carbon capture, utilization, and storage (CCUS) technologies. Continuous technological progress can effectively improve overall energy utilization efficiency and reduce macro-level carbon emission intensity. In terms of institutional safeguards, it is necessary to refine the supporting institutional systems covering environmental regulation, carbon emission supervision, and green finance, so as to establish a multi-dimensional, long-run, and stable emission reduction mechanism that underpins sustainable low-carbon development.

8.3. Research Limitations and Future Prospects

Despite employing rigorous empirical models to investigate the dynamic nexus among energy transition, economic growth, and carbon emissions in NICs, this study has certain limitations that leave considerable scope for future research extension and improvement. Firstly, the empirical analysis in this study is based on the EKC framework, which fails to capture potential nonlinear relationships and threshold effects among the variables related to energy transition. The impacts of economic growth and energy transition on CO₂ emissions may vary significantly across different stages of development, and such heterogeneous threshold characteristics are not fully explored in the current research. Secondly, this study does not conduct segmented regression analysis or policy effect evaluation targeting key global climate agreements, such as the Paris Agreement. Consequently, it is unable to identify structural changes in energy transition trajectories or differential responses of CO₂ emissions to energy shocks before and after the implementation of major climate policies. Thirdly, it is crucial to exclude borderline countries to ensure the robustness of the estimates; however, since there are currently no established criteria for determining which countries qualify as borderline countries, this study did not conduct heterogeneity estimates after excluding borderline countries. Finally, due to limitations in sample size and degrees of freedom, variables such as trade openness, industrial structure, and institutional quality were not taken into account. Additionally, the fact that only $g = 1$ was selected for the augmentation lag order in the CS-ARDL method may, to some extent, affect the robustness of the CS-ARDL estimates. On this basis, future research could further extend the present study by exploring the nonlinear threshold mechanisms underlying CO₂ emission evolution and conducting segmented policy impact assessments, so as to provide more refined and targeted empirical support for low-carbon governance in NICs.

Funding: This research received no external funding.

Data Availability Statement: Data are available upon request.

Conflicts of Interest: The author declares that there are no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

NICs	Newly Industrialized Countries
EKC	Environmental Kuznets Curve
VIF	Variance inflation factor
CADF	Covariate-augmented Dickey–Fuller
CIPS	Cross-sectionally augmented IPS
CS-ARDL	Cross-sectional augmented autoregressive distributed lag
ECM	Error correction model
AMG	Augmented Mean Group
CCEMG	Common Correlated Effects Mean Group
DCCEMG	Dynamic Common Correlated Effects Mean Group

References

1. Apergis, N.; Ozturk, I. Testing Environmental Kuznets Curve hypothesis in Asian countries. *Ecol. Indic.* **2015**, *52*, 16–22. [[CrossRef](#)]
2. Kaygusuz, K. Energy and environmental issues relating to greenhouse gas emissions for sustainable development in Turkey. *Renew. Sustain. Energy Rev.* **2009**, *13*, 253–270. [[CrossRef](#)]
3. Majeed, M.T.; Mumtaz, S. Happiness and environmental degradation: A global analysis. *Pak. J. Commer. Soc. Sci.* **2017**, *11*, 753–772.
4. Khan, S.; Majeed, M.T. Decomposition and decoupling analysis of carbon emissions from economic growth: A case study of Pakistan. *Pak. J. Commer. Soc. Sci.* **2019**, *13*, 868–891.

5. Grossman, G.; Krueger, A. *Environmental Impacts of a North American Free Trade Agreement*; National Bureau of Economic Research: Cambridge, UK, 1991. [\[CrossRef\]](#)
6. Zhang, Y.; Tian, K.; Liu, Z. Tracking global industry relocation and its economic and environmental impacts 1997–2023. *Struct. Change Econ. Dyn.* **2026**, *77*, 258–273. [\[CrossRef\]](#)
7. Ma, L.; Zhang, L. Spatio-temporal coupling relationship between international manufacturing transfer and CO₂ emissions. *Resour. Sci.* **2017**, *39*, 2408–2419. [\[CrossRef\]](#)
8. Meng, J.; Huo, J.; Zhang, Z.; Liu, Y.; Mi, Z.; Guan, D.; Feng, K. The narrowing gap in developed and developing country emission intensities reduces global trade's carbon leakage. *Nat. Commun.* **2023**, *14*, 3775. [\[CrossRef\]](#) [\[PubMed\]](#)
9. Liu, X.; Zhang, S.; Bae, J. The impact of renewable energy and agriculture on carbon dioxide emissions: Investigating the environmental Kuznets curve in four selected ASEAN countries. *J. Clean. Prod.* **2017**, *164*, 1239–1247. [\[CrossRef\]](#)
10. Khan, M.; Ozturk, I. Examining the direct and indirect effects of financial development on CO₂ emissions for 88 developing countries. *J. Environ. Manag.* **2021**, *293*, 112812. [\[CrossRef\]](#) [\[PubMed\]](#)
11. Farooq, S.; Ozturk, I.; Majeed, M.T.; Akram, R. Globalization and CO₂ emissions in the presence of EKC: A global panel data analysis. *Gondwana Res.* **2022**, *106*, 367–378. [\[CrossRef\]](#)
12. Kostakis, I.; Armaos, S.; Abeliotis, K.; Theodoropoulou, E. The investigation of EKC within CO₂ emissions framework: Empirical evidence from selected cross-correlated countries. *Sustain. Anal. Model.* **2023**, *3*, 100015. [\[CrossRef\]](#)
13. Xu, T.; Feng, C.; Guluzada, E.; Chao, C. Evaluating the advancement of sustainable development objectives in recently industrialized nations by tying gold prices, fossil fuel prices, and energy use. *Energy Strateg. Rev.* **2024**, *56*, 101575. [\[CrossRef\]](#)
14. Dontoh, E.A.; Idun, A.A.A.; Adam, A.M. Financial outreach, total factor productivity, and carbon dioxide emissions: Does ekc hold in middle-income countries? *Environ. Dev. Sustain.* **2026**, 1–27. [\[CrossRef\]](#)
15. Qayoom, A.; Altaf, N. The built environment and the EKC: Evidence from the top five carbon-emitting nations. *Int. J. Constr. Manag.* **2026**, 1–18. [\[CrossRef\]](#)
16. Tang, C.F.; Tan, B.W. The impact of energy consumption, income and foreign direct investment on carbon dioxide emissions in Vietnam. *Energy* **2015**, *79*, 447–454. [\[CrossRef\]](#)
17. Khan, M.K.; Khan, M.I.; Rehan, M. The relationship between energy consumption, economic growth and carbon dioxide emissions in Pakistan. *Financ. Innov.* **2020**, *6*, 1. [\[CrossRef\]](#)
18. Acaravci, A.; Ozturk, I. On the relationship between energy consumption, CO₂ emissions and economic growth in Europe. *Energy* **2010**, *35*, 5412–5420. [\[CrossRef\]](#)
19. Arouri, M.E.H.; Ben Youssef, A.; M'henni, H.; Rault, C. Energy consumption, economic growth and CO₂ emissions in Middle East and North African countries. *Energy Policy* **2012**, *45*, 342–349. [\[CrossRef\]](#)
20. Antonakakis, N.; Chatziantoniou, I.; Filis, G. Energy consumption, CO₂ emissions, and economic growth: An ethical dilemma. *Renew. Sustain. Energy Rev.* **2017**, *68*, 808–824. [\[CrossRef\]](#)
21. Hove, S.; Tursoy, T. An investigation of the environmental Kuznets curve in emerging economies. *J. Clean. Prod.* **2019**, *236*, 117628. [\[CrossRef\]](#)
22. Badeeb, R.A.; Lean, H.H.; Shahbaz, M. Are too many natural resources to blame for the shape of the Environmental Kuznets Curve in resource-based economies? *Resour. Policy* **2020**, *68*, 10169. [\[CrossRef\]](#)
23. Du, C.; Xue, J.; Wang, W.; Tong, J. Revisiting the carbon emissions hypothesis in the developing and developed countries: A new panel cointegration approach. *Environ. Ecol. Stat.* **2022**, *29*, 295–314. [\[CrossRef\]](#)
24. Gravina, A.F.; Lanzafame, M. 'What's your shape?' A data-driven approach to estimating the Environmental Kuznets Curve. *Energy Econ.* **2025**, *148*, 108649. [\[CrossRef\]](#)
25. Mahalik, M.K.; Mallick, H.; Padhan, H. Do educational levels influence the environmental quality? The role of renewable and non-renewable energy demand in selected BRICS countries with a new policy perspective. *Renew. Energy* **2021**, *164*, 419–432. [\[CrossRef\]](#)
26. Rai, P.; Gupta, P.; Saini, N.; Tiwari, A.K. Assessing the impact of renewable energy and non-renewable energy use on carbon emissions: Evidence from select developing and developed countries. *Environ. Dev. Sustain.* **2025**, *27*, 3059–3080. [\[CrossRef\]](#)
27. Almulhim, A.A.; Inuwa, N.; Chaouachi, M.; Samour, A. Testing the Impact of Renewable Energy and Institutional Quality on Consumption-Based CO₂ Emissions: Fresh Insights from MMQR Approach. *Sustainability* **2025**, *17*, 704. [\[CrossRef\]](#)
28. Khan, M.I.; Teng, J.Z.; Khan, M.K. The impact of macroeconomic and financial development on carbon dioxide emissions in Pakistan: Evidence with a novel dynamic simulated ARDL approach. *Environ. Sci. Pollut. Res.* **2020**, *27*, 39560–39571. [\[CrossRef\]](#)
29. Idroes, G.M.; Hardi, I.; Rahman, M.H.; Afjal, M.; Noviany, T.R.; Idroes, R. The dynamic impact of non-renewable and renewable energy on carbon dioxide emissions and ecological footprint in Indonesia. *Carbon Res.* **2024**, *3*, 35. [\[CrossRef\]](#)
30. Ahmat, N.; Christopher, S.; Saputra, J.; Sukemi, M.N.; Nawawi, M.N. The Impact of Energy Consumption, Economic Growth, and Non-Renewable Energy on Carbon Dioxide Emission in Malaysia. *Int. J. Energy Econ. Policy* **2024**, *15*, 143–152. [\[CrossRef\]](#)
31. Yeasmin, F.; Selkani, I. EU27 greenhouse gas emissions and green trade analysis: A reporting study. *Int. J. Export Mark.* **2025**, *7*, 69–88. [\[CrossRef\]](#)

32. Zhang, B.; Kang, J.; Feng, T. Global disparities in CO₂ emissions from mobility sectors of diverse economies: A macroscopic exploration across 188 countries /regions. *Environ. Sustain. Indic.* **2024**, *23*, 100455. [\[CrossRef\]](#)
33. Bekun, F.V.; Alola, A.A.; Sarkodie, S.A. Toward a Sustainable Environment: Nexus between CO₂ Emissions, Resource Rent, Renewable and Nonrenewable Energy in 16-EU Countries. *Sci. Total Environ.* **2019**, *657*, 1023–1029. [\[CrossRef\]](#) [\[PubMed\]](#)
34. Ikram, M.; Zhang, Q.; Sroufe, R.; Ali Shah, S.Z. Towards a Sustainable Environment: The Nexus between ISO 14001, Renewable Energy Consumption, Access to Electricity, Agriculture and CO₂ Emissions in SAARC Country. *Sustain. Prod. Consum.* **2020**, *22*, 218–230. [\[CrossRef\]](#)
35. Ben Jebli, M.; Farhani, S.; Guesmi, K. Renewable Energy, CO₂ Emissions and Value Added: Empirical Evidence from Countries with Different Income Levels. *Struct. Chang. Econ. Dyn.* **2020**, *53*, 402–410. [\[CrossRef\]](#)
36. Attanayake, K.; Wickramage, I.; Samarasinghe, U.; Ranmini, Y.; Ehalapitiya, S.; Jayathilaka, R.; Yapa, S. Renewable Energy as a Solution to Climate Change: Insights from a Comprehensive Study across Nations. *PLoS ONE* **2024**, *19*, e0299807. [\[CrossRef\]](#) [\[PubMed\]](#)
37. Pakrooh, P.; Nammouri, H.; Ben Jabeur, S. Energy Transition and CO₂ Emissions: Fresh Insight from Low, Middle and High-Income Countries. *Res. Int. Bus. Financ.* **2025**, *73*, 102880. [\[CrossRef\]](#)
38. Khattak, S.I.; Ahmad, M.; Khan, Z.U.; Khan, A. Exploring the Impact of Innovation, Renewable Energy Consumption, and Income on CO₂ Emissions: New Evidence from the BRICS Economies. *Environ. Sci. Pollut. Res.* **2020**, *27*, 13866–13881. [\[CrossRef\]](#) [\[PubMed\]](#)
39. Fernandes, K.; Marathe, S.R.; Parab, S.; Amonkar, V.; Vernekar, G.; Pandhre, S.S. Evaluating the Role of Government Expenditure in Promoting Renewable Energy and Economic Growth in India. *Environ. Econ.* **2025**, *16*, 162–172. [\[CrossRef\]](#)
40. Ozturk, I.; Farooq, S.; Majeed, M.T.; Skare, M. An empirical investigation of financial development and ecological footprint in South Asia: Bridging the EKC and pollution haven hypotheses. *Geosci. Front.* **2024**, *15*, 101588. [\[CrossRef\]](#)
41. Pesaran, M.H. Testing weak cross-sectional dependence in large panels. *Econom. Rev.* **2015**, *34*, 1089–1117. [\[CrossRef\]](#)
42. Pesaran, M.H. General diagnostic tests for cross-sectional dependence in panels. *Empir. Econ.* **2021**, *60*, 13–50. [\[CrossRef\]](#)
43. Juodis, A.; Reese, S. The Incidental Parameters Problem in Testing for Remaining Cross-Section Correlation. *J. Bus. Econ. Stat.* **2022**, *40*, 1191–1203. [\[CrossRef\]](#)
44. Fan, J.; Liao, Y.; Yao, J. Power Enhancement in High-Dimensional Cross-Sectional Tests. *Econometrica* **2015**, *83*, 1497–1541. [\[CrossRef\]](#) [\[PubMed\]](#)
45. Pesaran, M.H.; Xie, Y. *A Bias-Corrected CD Test for Error Cross-Sectional Dependence in Panel Data Models with Latent Factors* (Cambridge Working Papers in Economics, CWPE 2158); Faculty of Economics, University of Cambridge: Cambridge, UK, 2021.
46. Pesaran, M.H.; Yamagata, T. Testing slope homogeneity in large panels. *J. Econom.* **2008**, *142*, 50–93. [\[CrossRef\]](#)
47. Swamy, P.A.V.B. Efficient inference in a random coefficient regression model. *Econometrica* **2010**, *38*, 311–323. [\[CrossRef\]](#)
48. Phillips, P.C.B.; Sul, D. Dynamic panel estimation and homogeneity testing under cross section dependence. *Econom. J.* **2003**, *6*, 217–259. [\[CrossRef\]](#)
49. Moon, H.R.; Perron, B. Testing for a unit root in panels with dynamic factors. *J. Econom.* **2004**, *122*, 81–126. [\[CrossRef\]](#)
50. Pesaran, M.H. A simple panel unit root test in the presence of cross-section dependence. *J. Appl. Econom.* **2007**, *22*, 265–312. [\[CrossRef\]](#)
51. Hadri, K.; Kurozumi, E.; Rao, Y. Novel panel cointegration tests emending for cross-section dependence with N fixed. *Econom. J.* **2015**, *18*, 363–411. [\[CrossRef\]](#)
52. Westerlund, J. New simple tests for panel cointegration. *Econom. Rev.* **2005**, *24*, 297–316. [\[CrossRef\]](#)
53. Chudik, A.; Mohaddes, K.; Pesaran, M.H.; Raissi, M. Long-run effects in large heterogeneous panel data models with cross-sectionally correlated errors. In *Essays in Honor of Aman Ullah*; Emerald Group Publishing Limited: Bingley, UK, 2016; Volume 36. [\[CrossRef\]](#)
54. Carvelli, G. The long-run effects of government expenditure on private investments: A panel CS-ARDL approach. *J. Econ. Financ.* **2023**, *47*, 620–645. [\[CrossRef\]](#)
55. Chudik, A.; Pesaran, M.H.; Smith, R.P. *Analysis of Multiple Long-Run Relations in Panel Data Models*; Working Paper No. 2523; Federal Reserve Bank of Dallas: Dallas, TX, USA, 2025. [\[CrossRef\]](#)
56. Ditzén, J. Estimating long-run effects and the exponent of cross-sectional dependence: An update to xtdcce2. *Stata J.* **2021**, *21*, 687–707. [\[CrossRef\]](#)
57. Jordan, S.; Philips, A.Q. Cointegration Testing and Dynamic Simulations of Autoregressive Distributed Lag Models. *Stata J.* **2018**, *18*, 902–923. [\[CrossRef\]](#)
58. Abbasi, K.F.; Adedoyin, F.F.; Abbas, J.; Hussain, K. The impact of energy depletion and renewable energy on CO₂ emissions in Thailand: Fresh evidence from the novel dynamic ARDL simulation. *Renew. Energy* **2021**, *180*, 1439–1450. [\[CrossRef\]](#)
59. Udeagha, M.C.; Breitenbach, M.C. Exploring the moderating role of financial development in environmental Kuznets curve for South Africa: Fresh evidence from the novel dynamic ARDL simulations approach. *Financ. Innov.* **2023**, *9*, 5. [\[CrossRef\]](#)

60. Javed, A.; Rapposelli, A.; Adedoyin, F.F.; Arshad, Z. Examining the Role of Remittances, Technological Innovation, and Foreign Direct Investment on Environmental Quality in Pakistan: Fresh Evidence from a Novel Dynamic ARDL Simulation Approach. *Soc. Indic. Res.* **2025**, *179*, 123–151. [[CrossRef](#)]
61. He, S.; Zhang, S.; Li, Y.; Gu, W.; Chung, C. Physics-informed neural network for dynamic energy flow calculation in integrated electricity and gas systems. *Appl. Energy* **2026**, *407*, 127374. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.