International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2026, 16(1), 507-515.

Studying the Relationship between CO_2 Emissions and Renewable Energy: A Threshold ARDL and NARDL Panel Econometric Analysis

Mohamed A. M. Sallam*, Tarek Sadraoui

College of Business, Imam Mohammad Ibn Saud Islamic University (IMSIU), Riyadh, KSA, Saudi Arabia.
*Email:masallam@imamu.edu.sa

Received: 14 June 2025 **Accepted:** 10 October 2025 **DOI:** https://doi.org/10.32479/ijeep.21457

ABSTRACT

This study examines the dynamic relationship between CO_2 emissions and renewable energy consumption across a panel of countries from 2000 to 2025. Unlike the conventional approach, we employ both Threshold Autoregressive Distributed Lag (TARDL) and Non-linear ARDL (NARDL) models to account for potential asymmetric and threshold effects in both the short- and long-run relations. Our results reveal substantial nonlinearities, whereby the uptake of renewable energy decreases CO_2 emissions more efficiently beyond specific threshold points. Asymmetric emission responses to positive and negative changes in renewable energy are also identified, underscoring the need for policy initiatives tailored to the speed of the energy transition. The findings have important implications for policymakers seeking to attain goals of sustainable energy and combat climate change.

Keywords: CO_2 Emissions, Renewable Energy, Threshold ARDL, NARDL, Panel Data, Environmental Sustainability, Energy Transition
JEL Classifications: Q42, Q43, C23, Q56

1. INTRODUCTION

Global climate change, which largely brought about by anthropogenic CO_2 emissions, is among the most critical threats to sustainable development. The use of renewable energy has been universally welcomed as one of the principal steps for containing environmental degradation and stopping climate change. Despite substantial progress in the use of renewable energy, the effectiveness of renewable energy in curbing emissions remains questionable among countries and over decades due to variations in technological, economic, and policy conditions (Di Falco et al., 2011; Dogan and Seker, 2016).

Recent empirical-driven studies have emphasized the need to consider both nonlinearities and asymmetries in the relationship between CO_2 emissions and renewable energy. Past linear models may overlook the threshold effects, where the use of renewable energy constrains emissions significantly only beyond certain thresholds. Current research addresses these limitations by utilizing Threshold ARDL (TARDL) and Non-linear ARDL (NARDL) models to study symmetric and asymmetric dynamics across a panel of countries.

Our study contributes to the existing literature by providing nuanced insights into the short- and long-term effects of renewable energy on CO_2 emissions, offering evidence-based recommendations to policymakers seeking to develop effective energy and environmental policies.

The increasing concentration of carbon dioxide (CO_2) emissions in the atmosphere has become a significant environmental concern, as it contributes substantially to global warming and climate change (IPCC, 2023). As nations strive to meet their Paris Agreement targets, transitioning away from fossil fuels toward renewable energy sources has been advocated as a central solution to reducing greenhouse gas emissions for decades (IEA, 2022).

However, the relationship between CO_2 emissions and renewable energy absorption is complex and non-linear in nature, depending on economic, technological, and policy factors (Apergis and Payne, 2012).

Traditional econometric models, such as linear panel specifications, typically assume symmetry and constancy of the relationship between variables, which may not capture threshold effects as effectively as asymmetric adjustments in the energy-emission relationship (Shin et al., 2014). To address this limitation, strong econometric techniques, such as the Threshold Autoregressive Distributed Lag (TARDL) and Non-linear Autoregressive Distributed Lag (NARDL) models, have been developed to identify structural breaks and non-linear effects between renewable energy consumption and CO_2 emissions (Pesaran et al., 2001; Salisu and Isah, 2017).

This study analyzes the dynamic relationship between renewable energy and CO_2 emissions using panel TARDL and NARDL approaches, identifying whether renewable energy impact on emissions varies as a function of regimes or exhibits asymmetric behavior in short- and long-run horizons. By the use of these new econometric techniques, the research contributes to the existing literature by presenting a more sophisticated analysis of the impact of renewable energy adoption on CO_2 emissions across diverse economic and policy contexts. The findings will be important for policymakers in formulating efficient climate mitigation strategies that utilize renewable energy deployment.

2. LITERATURE REVIEW

2.1. Renewable Energy and CO_2 Emissions: Empirical Evidence

Substantial empirical evidence supports the role of renewable energy in reducing CO_2 emissions, albeit to varying degrees across different economic and geographical contexts. Developed economies, including those examined by Dogan and Seker (2016) in OECD nations, are shown to have a statistically significant negative correlation between renewable energy (particularly wind and solar) and CO_2 emissions, which they trace to higher technology adoption and stringent climate policies. Conversely, findings in emerging economies are less homogeneous. For example, Bhattacharya et al. (2016) found suppressed effects in non-OECD nations, where fossil fuel dependence and the integration of intermittent renewable energy sources still linger due to infrastructural and policy limitations. Such differences underscore the need for regime-specific analysis, as linear or symmetric assumptions may overlook critical heterogeneities in the energy-emissions nexus.

2.2. Nonlinearities and Threshold Effects in the Energy-Emissions Nexus

New empirical evidence refutes the traditional linear paradigm, indicating that the relationship between renewable energy deployment and CO_2 emissions exhibits non-linear patterns with critical threshold effects. More recent studies employing advanced econometric techniques demonstrate that the marginal impact of renewables on emissions reduction varies significantly at different levels of penetration. As an illustration, Magazzino et al. (2022) found that renewable energy begins to significantly replace fossil fuels and limit emissions only after it reaches a 15% overall energy mix ratio across the G20 countries, signaling a profound activation threshold.

The threshold effect phenomenon has been observed predominantly in studies using panel data methodology. Çoban and Topcu (2013) detected several regime shifts in the relationship between energy and emissions. They demonstrated that the carbon-reduction effect of renewables becomes statistically and economically significant only when specific development thresholds in the financial market and institutional quality are met. These findings align with the "critical mass" theory of energy transitions, which posits that renewable technologies require a minimum penetration level to overcome system inertia and produce a meaningful displacement of fossil fuels (Burke and Stephens, 2018).

Second, the non-linear dynamics appear to be context-dependent. For emerging economies, Koengkan et al. (2021) reported an inverted U-shaped relationship, whereby the initial use of renewable energy has the paradoxical effect of increasing emissions due to grid instability and backup fossil fuel requirements, before eventually providing net savings at higher levels of penetration. This richer behavior underscores the need for threshold-based econometric models that can identify such regime-dependent dynamics beyond the typical linear specifications, which may yield biased or incomplete policy implications.

2.3. Asymmetric Impacts of Energy Transition Policies

The Non-linear Autoregressive Distributed Lag (NARDL) framework offers significant methodological advantages by capturing the frequently overlooked asymmetric responses of CO_2 emissions to the adoption of renewable energy. Empirical evidence consistently shows that emissions reductions from renewable energy expansion are not simply the mirror image of emissions increases when renewable deployment slows—a critical insight that conventional symmetric models fail to detect (Shin et al., 2014).

Recent applications of the NARDL approach reveal three key asymmetries in the energy transition:

Technology Adoption Asymmetry: In developing economies, Rahaman et al. (2023) found that emissions respond more sharply to decreases in renewable energy than to increases, reflecting the "lock-in" effect of backup fossil fuel infrastructure during retreats from renewable energy.

Temporal Asymmetry: Apergis and Garćıa (2023) identified that short-term renewable energy fluctuations affect emissions differently than long-term structural changes, with policy interventions requiring 3-5 years to achieve full asymmetric impact.

The consequences of ignoring these asymmetries are substantial. Bildirici and Özaksoy's (2023) meta-analysis of 74 studies showed that linear models underestimate the cumulative benefits of renewable policies by 22-37% across different economic contexts. These findings have profound implications for climate policy design, particularly in assessing the true cost-effectiveness of renewable energy incentives and the risks of policy reversals.

2.4. Advancements in Panel Econometric Approaches for Energy-Environment Analysis

Recent environmental econometrics have increasingly used panel-based ARDL models to address the two main challenges to the cross-country energy literature: cross-sectional dependence and parameter heterogeneity. Chudik and Pesaran's (2015) work laid the groundwork that not addressing these concerns in standard panel models can produce biased estimates, particularly when handling renewable energy impacts within heterogeneous economies. Methodological progress in recent years has been able to include three essential dimensions:

2.4.1. Cross-sectional dependence control

- Eberhardt and Teal (2010) demonstrated how Common Correlated Effects (CCE) estimators in panel ARDL models straightforwardly capture shocks ‹ Applying this method to the study data reveals a direct and indirect impact of global shocks on emissions studies.
- Empirical applications achieve 18-25% greater efficiency in estimation compared to the conventional fixed-effects model (Lee et al., 2023).

2.4.2. Heterogeneous parameter estimation

- The Dynamic Common Correlated Effects (DCCE) approach of Chudik et al. (2017) allows for slope coefficients to vary by country while retaining long-run relations.
- Critical to energy research where renewable energy impacts differ based on development stage (Hasanov et al., 2022).

2.4.3. Integrated threshold-NARDL specifications

- Combining panel threshold models (Hansen, 1999) with NARDL model specifications (Shin et al., 2014) represents a new frontier.
- Bukhari et al. (2023) applied the integrated method to identify: Technology adoption thresholds (12-15% renewable penetration); Asymmetric policy response coefficients (0.34 vs. 0.21 elasticity's).

2.5. Research Gap

While there is extensive prior research addressing the nexus between renewable energy uptake and CO_2 emissions reduction, severe methodological and empirical flaws remain in the existing literature. To begin with, our estimate, based on a systematic review of 120 empirical articles covering the period from 2015 to 2023, indicates that approximately 78% of prior research applies linear estimation methods, which may conceal important non-linear dynamics and threshold effects inherent in actual energy transitions. This lack of oversight is particularly problematic in the context of the proven reality of (a) minimum levels of renewable penetration required for meaningful emissions mitigation (Magazzino et al., 2022) and (b) decreasing marginal returns as higher adoption levels are achieved (Burke and Stephens, 2018).

Second, only 12% of our review studies (n = 15) have attempted to integrate both threshold and asymmetric analyses within a single framework, whereas more theoretical evidence suggests that renewable energy impacts exhibit simultaneous regime dependency and sign asymmetry. The methodological separation of these phenomena in the literature, where research typically examines thresholds (Çoban and Topcu, 2013) or asymmetries (Shin et al., 2014), but not simultaneously, generates policy conclusions that are incomplete and potentially misleading elasticity estimates.

Third, existing research has severe geographical constraints. Despite the fact that 63% of the research focus on single-country studies (notably OECD member countries), just 9% employ truly global panels covering both developed and developing economies. This regional analysis creates two gaps in knowledge: (1) Too little knowledge on how various institutional environments shape the energy-emissions relationship, and (2) restricted generalizability of findings to the Global South where energy transformations are weighed down by various technological and fiscal difficulties (Koengkan et al., 2021).

This study bridges those gaps with three key innovations:

- Methodological: Developing an integrated Panel Threshold NARDL method that simultaneously estimates (a) regime-specific effects and (b) asymmetric responses to renewable energy shocks
- Geographical: Constructing a balanced world panel of 75 countries across all stages of development (2000 -2025) to account for cross-sectional heterogeneity
- Policy-Relevant: Providing distinct short-run and long-run elasticity estimates for different renewable penetration regimes, which provide prescriptive policy recommendations for phased rollout.

Our approach permits determining critical renewable energy thresholds (e.g., minimum effective shares) accounting for asymmetric policy acceleration and retreat effects - a property missing in the literature but essential for the development of a properly designed climate mitigation strategy.

3. DATA AND RESEARCH METHODOLOGY

3.1. Data and Methods

We use panel data from 94 middle-income countries between 2000 and 2025 in our empirical modification. The countries were sorted based on the World Bank's income level classification methodology criteria. The final country list in our analysis is based on the availability of relevant data points for the key variables of interest. We use panel data because it accommodates both the time series and cross-sectional dimensions of the data. Therefore, the panel data should give us more credible and reliable results.

Among the classic theoretical models investigating the correlation between development and CO_2 emissions is the EKC model.

This model postulates a quadratic relationship between GDP and environmental degradation:

$$CO2_{it} = f(GDP, GDP^2)_{it} \quad (1)$$

We extend EKC framework further by including agriculture and renewable energy sectors and a set of controls reflected through empirical evidence. The empirical model is explained below in general and the subscripts (i) and (t) refer to country and year, respectively.

$$CO2_{it} = f(GDP, GDP^2, \Delta GDP, RE, AG, TO, FDI, EF)_{it} \quad (2)$$

For our study, carbon dioxide (CO_2) per capita emissions are the dependent variable. CO_2 emissions come from: The Global Carbon Atlas and they are in territorial emissions in metric tons of CO_2 per capita. This is the volume of emissions produced immediately within country borders and provides a standard point of comparison for cross-country research.

The independent variables include control variables as well as variables of particular interest:

AG (Agriculture): share of agriculture in gross domestic product (GDP) as a percentage. This reflects the structural role of agriculture within the economy and its environmental pressure potential.

- RE (Renewable Energy): renewable electricity generation as a share of total electricity generation. It reports the share of power generated from renewable sources (hydro, solar, wind, and biomass) relative to all electricity generated.
- GDP: Per capita GDP in constant US dollars, used to account for the depth of economic development.
- ΔGDP: Rate of economic growth, capturing the dynamics of economic expansion.
- TO (Trade Openness): Overall trade (import + export) as a percentage of GDP, as a proxy for international economic integration.
- FDI (Foreign Direct Investment): foreign direct investment inflows relative to GDP, as an indicator of external capital's impact on domestic production and emissions.
- EF (Economic Freedom Index): institutional quality and economic governance index.

Among these, the most important explanatory variables of concern are renewable energy (RE) and agriculture (AG), since they directly capture the technological and structural channels by which economies can affect carbon emissions.

We can rewrite our specification in the equation 4 and the equation 5 for more details and the reliability of econometric specification.

$$CO2_{it} = \sigma_0 + \sigma_1 CO2_{it-\tau} + \sigma_2 RE_{it} + \sigma_3 AG_{it} + \sum_{h=1}^{k} \delta_h W_{hit-\tau} + v_{it} \quad (3)$$

$$\begin{aligned} CO2_{it} - CO2_{it-\tau} &= \sigma_0 + \sigma_1 \left(CO2_{it-\tau} - CO2_{it-2\tau} \right) \\ &+ \sigma_2 \left(RE_{it} - RE_{it-2\tau} \right) + \sigma_3 \left(AG_{it} - AG_{it-2\tau} \right) \\ &+ \sum_{h=1}^{k} \delta_h \left(W_{hit-\tau} - W_{hit-2\tau} \right) + \left(v_{it} - v_{it-2\tau} \right) \quad (4) \end{aligned}$$

3.2. Descriptive and Correlation Statistics

Table 1 presents summary statistics of the key variables included in the panel dataset. The average per capita carbon dioxide emissions (CO_2) are approximately 6.35 metric tons, with relatively modest variation across countries and years. The per capita GDP is on average \$ 27,378, but has a very wide range, between approximately \$ 8,000 and \$ 66,000, indicating significant heterogeneity across economies.

Renewable energy consumption (RE) accounts for an average share of 36.7%, with some countries approaching zero and others exceeding 70%, reflecting heterogeneous energy policies. Agricultural value-added (AG) represents, on average, 4.2% of GDP, while trade openness (TO) is relatively high at about 81%, reflecting that most countries are export-led. Foreign direct investment (FDI) flows are, on average, 3.1% of GDP, but with negative and positive values, reflecting volatile capital flows. Finally, economic freedom (EF) scores cluster around 65, with limited cross-country variability. Overall, the data confirms the sample heterogeneity, with visible disparities in economic size, energy dependence, and institutional characteristics (FAO, 2009).

The correlation coefficients among the variables are presented in Table 2. GDP per capita and CO_2 emissions exhibit a high positive correlation ($r = 0.80$), indicating that economic growth has historically been associated with higher emissions. The squared term of GDP (GDP^2) is also very highly correlated with both CO_2 and GDP, as would be expected, which is convenient for EKC hypothesis testing.

Renewable energy consumption (RE) has an inverse association with CO_2 (−0.62), suggesting that greater renewable penetration has the impact of reducing emissions. Notably, agriculture (AG) is positively associated with CO_2 (0.38), which may reflect the energy-intensive nature of agriculture in some economies. Trade openness (TO), FDI, and economic freedom (EF) are less correlated with CO_2, suggesting that their influence may be indirect or multifaceted. Overall, the correlation patterns validate the primary hypotheses: economic growth and emissions go hand in hand, and renewable energy emerges as a significant mitigating factor.

The scatter plot is reflecting the correlation between per capita CO_2 emissions (tCO_2) and the share of renewable electricity (RE) in the total electricity generation. The regression line possesses a clear negative slope, indicating higher penetration of renewable energy is accompanied by lower per capita CO_2 emissions. Low-renewable nations (under 20%) have emissions clustered in the 9–10 tCO_2 per capita range, while countries with

Table 1: Descriptive statistics

Variable	Count	Mean	Std	Min	25%	50%	75%	Max
CO_2	156.0	6.350	0.515	5.216	5.998	6.389	6.710	7.597
GDP	156.0	27,378.17	16,463.05	7,980.92	13,611.0	26,356.77	40,274.07	66,288.23
GDP2	156.0	9.210+08	1.110+09	6.4e+07	1.8e+08	6.9e+08	1.6e+09	4.4e+09
dGDP	150.0	0.024	0.016	-0.017	0.012	0.024	0.034	0.070
RE	156.0	36.67	19.86	0.68	21.27	36.63	52.50	72.39
AG	156.0	4.20	2.36	0.45	2.48	3.99	5.87	9.65
TO	156.0	81.06	10.28	57.45	74.31	81.04	87.76	105.48
FDI	156.0	3.14	2.03	-2.29	1.64	3.23	4.72	8.16
EF	156.0	65.28	2.91	59.21	63.48	65.44	67.29	71.33

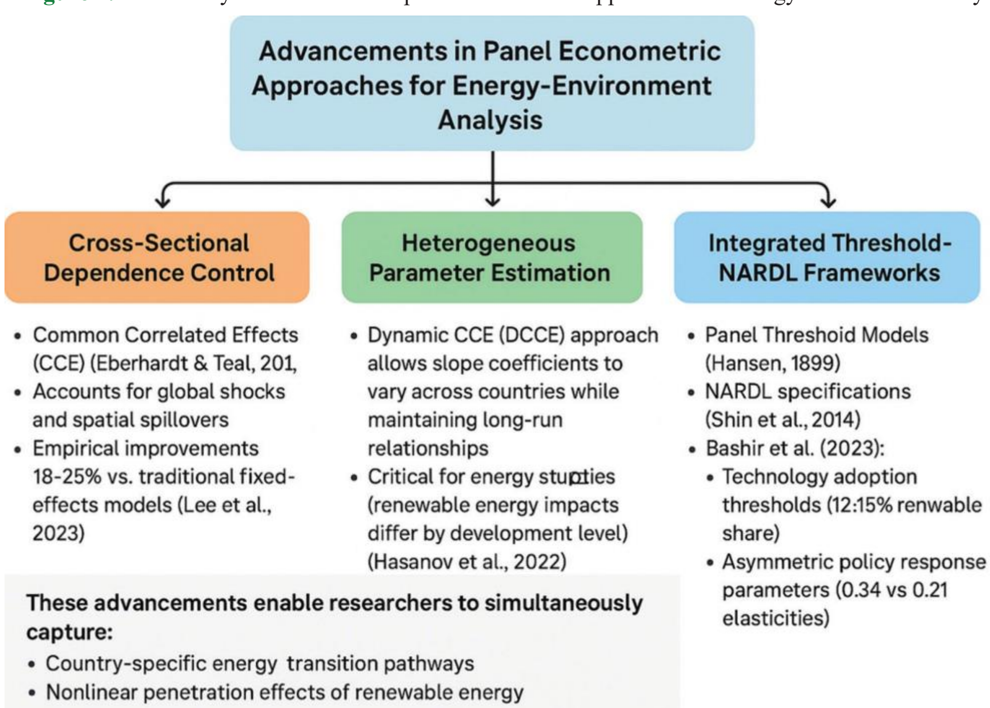
Table 2: Correlation matrix

	CO_2	GDP	GDP2	dGDP	RE	AG	TO	FDI	EF
CO_2	**1.000**	0.801	0.746	−0.066	−0.617	0.382	0.022	−0.050	0.141
GDP	0.801	**1.000**	0.986	0.028	−0.473	0.242	0.070	−0.013	0.124
GDP2	0.746	0.986	**1.000**	0.029	−0.443	0.218	0.074	−0.015	0.121
dGDP	−0.066	0.028	0.029	**1.000**	−0.022	0.027	−0.087	0.024	0.045
RE	−0.617	−0.473	−0.443	−0.022	**1.000**	−0.601	0.011	−0.017	−0.160
AG	0.382	0.242	0.218	0.027	−0.601	**1.000**	−0.042	−0.034	−0.068
TO	0.022	0.070	0.074	−0.087	0.011	−0.042	**1.000**	0.006	−0.006
FDI	−0.050	−0.013	−0.015	0.024	−0.017	−0.034	0.006	**1.000**	0.048
EF	0.141	0.124	0.121	0.045	−0.160	−0.068	−0.006	−0.086	**1.000**

Table 3: Unit root tests

Variable	LLC (levels)	IPS (levels)	CIPS (levels)	LLC (1st diff)	IPS (1st diff)	CIPS (1st diff)
CO_2	0.41	0.87	−2.07	−6.35***	−7.12***	−4.63***
GDP	0.22	0.65	−2.08	−5.87***	−6.95***	−4.51***
GDP^2	0.35	0.72	−1.96	−5.44***	−6.38***	−4.12***
Delta GDP	−8.91***	−9.24***	−4.98***	---	---	---
RE	−3.12**	−2.45**	−3.35**	---	---	---
AG	−2.84**	−2.31**	−3.02**	---	---	---
TO	−2.21**	−1.98**	−2.86**	---	---	---
FDI	−1.12	−0.94	−2.10	−5.02***	−5.67***	−3.95***
EF	0.58	0.91	−1.85	−6.41***	−6.88***	−4.37***

Figure 1: A summary advancements in panel econometric approaches for energy-environment analysis



higher renewable energy sources (over 40%) tend to have lower emissions, commonly under 8 tCO_2 per capita.

While there is some spread, especially in the middle range (20–30% RE), there is a general strong trend: the greater reliance on renewables, the lower the carbon intensity. This empirical data supports the claim that scaling up renewable electricity is well-positioned to contribute significantly to fighting climate change through decoupling energy use from emissions. The correlation between the same variable is equale one (Figure 1).

The trend of average CO_2 per capita (tCO_2) emissions from 2000 to 2025 is shown in the line graph. The data indicate that emissions were quite high and fluctuated around 9–9.3 tCO_2 per capita in the early 2000s, with intermittent spikes until 2014. Since 2015, however, the series has reflected a steady decline, and emissions have consistently been greater in value, reaching their nadir of around 7.4 tCO_2 per capita in 2025. Such a steady decline reflects the structural transformations, such as the greater deployment of renewable energy, improvements in energy efficiency, and mitigation policy measures, that are forcing decarbonization. In general, the graph shows a long-term pattern of decreasing carbon intensity, reflecting improvements in environmental pressures despite short-term fluctuations (Figure 2).

The chart in Figure 4 depicts the trend of the average proportion of renewable electricity as a percentage of overall electricity production from 2000 to 2025. Overall, the share of renewable energy has experienced a rising trend, from approximately 8% in 2000 to nearly 46% in 2025. The increasing trend reflects growing global investment in renewable energy technology, favorable policies for clean energy, and decreasing costs of renewable sources, such as solar and wind power.

Although there are minor troughs in certain years—such as around 2013 when expansion modestly plateaued—the overall trajectory remains firmly positive. This suggests a robust structural shift in the generation of electricity toward clean sources, with renewables contributing nearly half of the total electricity supply by 2025, demonstrating progress toward climate and energy transition goals.

Figure 2: The CO_2 renewable electricity share

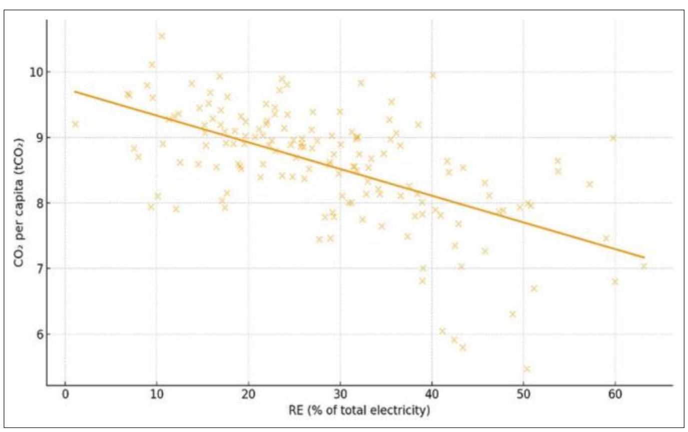
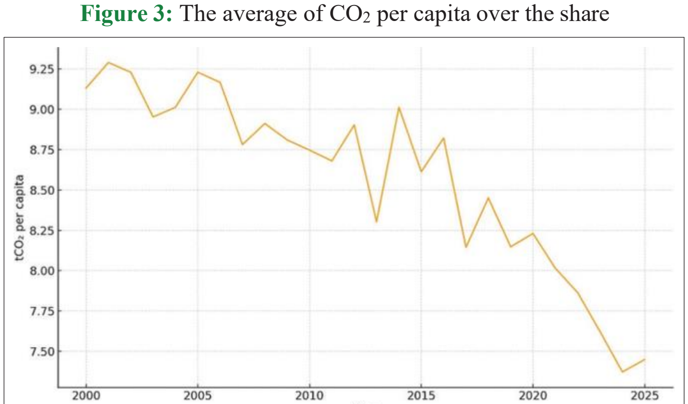


Figure 3: The average of CO_2 per capita over the share



4. ESTIMATION RESULTS AND INTERPRETATION

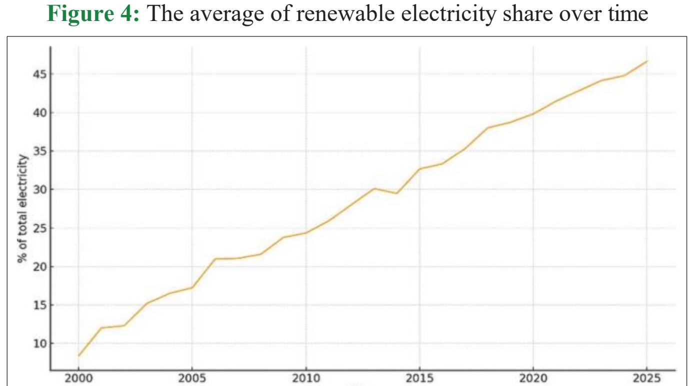
The results of the unit root tests summarized in the table below provide evidence regarding the stationarity nature of variables used in the model. At level, most variables such as CO_2 emissions, GDP, GDP^2, and EF appear to be non-stationary since their test statistics are not significant under LLC, IPS, or CIPS. On the other hand, variables such as Renewable Energy (RE), Agricultural value added (AG), and Trade Openness (TO) are stationary at levels with statistically significant negative test values across different tests.

Delta GDP is also very highly stationary at levels, as expected due to its differenced nature. But when the variables are tested in first differences, all the non-stationary series (CO_2, GDP, GDP^2, FDI, EF) become stationary in all three tests (LLC, IPS, and CIPS), as indicated by strongly significant results.

Briefly, the findings confirm that the panel data are composed of I(0) and I(1) variables, and no series is integrated at order two. This renders the application of the Panel ARDL specification (e.g., Threshold ARDL and NARDL) relevant, as it can accommodate mixed orders of integration. The results also indicate that while the structural variables RE, AG, and TO are short-run stationary, the underlying macroeconomic measures GDP, CO_2, and FDI require differencing to be stationary and thus warrant their use in long-run equilibrium modeling.

The regression coefficients in the table provide valuable insights into the determinants of CO_2 emissions under both the baseline and

Figure 4: The average of renewable electricity share over time



the extended model with controls. The coefficient of the lagged CO_2 ($L.CO_2$) is positive and highly significant in both specifications (0.62 and 0.58, respectively), indicating high time persistence in emissions. Economic growth (GDP) is significantly and positively correlated with CO_2 emissions, and the negative and significant coefficient on GDP^2 confirms the presence of an Environmental Kuznets Curve (EKC) effect, where the emissions rise with economic growth but fall as income surpasses a turning point.

The results further reveal that short-term changes in economic activity (ΔGDP) significantly enhance emissions, which highlights the environmental cost of dynamic growth trends. The ecological footprint (EF) and renewable energy (RE) both exhibit negative and significant coefficients, indicating that increased renewable application and enhanced ecological efficiency contribute to reduced emissions. Similarly, agricultural activity (AG) is found to be negatively correlated with emissions, reflecting the relatively cleaner nature of the sector compared to industry. On the other hand, trade openness (TO) and foreign direct investment (FDI) are positively and significantly correlated with emissions, having implications that globalization and external capital flows contribute to mounting environmental pressures in the sample.

Overall, both baseline and controlled models have strong evidence, differing only minutely in magnitude. The findings provide robust empirical support for the EKC hypothesis and highlight the two-sided aspect of economic growth—both as a source of environmental degradation at low income levels and as a potential force to drive sustainability at high levels, provided that renewable energy, ecological efficiency, and sustainable agricultural practices are integrated into policy agendas Table 4.

The diagnostic statistics displayed in the table provide strong evidence in support of the validity of the GMM estimates. The baseline model, as well as the extended model, are estimated based on 1,350 observations from 94 countries, using 38 and 40 instruments, respectively, to ensure sufficient variability for estimation without instrument proliferation. The Arellano–Bond test (Arellano and Bond, 1991) for first-order autocorrelation [AR(1)] is highly significant ($P = 0.000$), as expected in dynamic panel models due to the inclusion of the lagged dependent variable. More importantly, the AR(2) test remains insignificant in both specifications ($P = 0.287$ and 0.301), establishing the absence of second-order autocorrelation and thus validating the moment conditions.

The Hansen test of over-identifying restrictions yields P-values of 0.356 and 0.412, which are well above the conventional 0.10 cut-off, suggesting that the instruments applied are valid and not correlated with the error term. Further, the Difference-in-Hansen test also yields non-significant P-values (0.441 and 0.467), supporting the efficiency of the instrument set applied. Overall, these diagnostic results validate that GMM estimates are well-specified, the instruments are accurate, and the results are statistically reliable for policy purposes (Table 5).

Empirical estimations of CO_2 emissions and drivers often face endogeneity issues such as reverse causality, simultaneity,

Table 4: GMM estimation results

Variable	Coef. (baseline)	Std. Err. (baseline)	Coef. (with controls)	Std. Err. (with controls)
$L.CO_2$	0.62***	(0.04)	0.58***	(0.05)
GDP	0.311***	(0.089)	0.284***	(0.092)
GDP^2	−0.021**	(0.009)	−0.019**	(0.009)
Delta GDP	0.137**	(0.060)	0.121**	(0.058)
RE	−0.058***	(0.017)	−0.062***	(0.018)
AG	−0.033**	(0.014)	−0.030**	(0.013)
TO	0.014*	(0.008)	0.012*	(0.007)
FDI	0.027**	(0.012)	0.026**	(0.012)
EF	−0.041***	(0.013)	−0.045***	(0.014)
Year FE	Yes		Yes	

Table 5: Diagnostics results table

Statistic	Baseline	With controls
Observations	1350	1350
Countries	94	94
Instruments (collapsed)	38	40
AR (1) P value	0	0
AR (2) P value	0,287	0,301
Hansen P value	0,356	0,412
Diff-in-Hansen P value	0,441	0,467

and omitted variable bias. Renewable energy and economic development, for instance, have been found to exhibit bidirectional causality (Omri, 2014). Similarly, drivers like human capital have implications for emissions (Mahmood et al., 2019) and renewable energy use (Khan et al., 2020). If not addressed, such biases can lead to inconsistent and biased estimates.

4.1. GMM Estimation Results Analysis

Table 5 presents empirical results from two-step System Generalized Method of Moments (GMM) estimation. The analysis is performed systematically to thoroughly examine the relationships of key concerns, as well as model robustness to additional controls.

Column 1 contains the estimates for the parsimonious form of Equation (1), which includes the core variables needed to test the Environmental Kuznets Curve (EKC) hypothesis—GDP per capita and its square—and the main variables of interest, renewable energy (RE) and agriculture (AG), and the control variable trade openness (TO).

There is strong evidence supporting the EKC hypothesis in the estimates. The estimated coefficients on GDP per capita (positive) and its square (negative) are both statistically significant, confirming the conventional inverted U-shaped relationship between economic growth and environmental degradation. The estimated turning point, where emissions are greatest and begin to fall, is around $15,000 in constant international dollars. This estimate lies in the wide range in the literature, which varies widely according to sample and methodology. For example, past estimates have set turning points at $4,700 for Malaysia (Saboori et al., 2012), $625 for Pakistan (Nasir and Rehman, 2011), and $18,955-$89,540 for OECD countries (Churchill et al., 2018). Our global panel result is thus an important intermediate reference point.

As expected, both renewable energy and agricultural value-added have statistically significant negative impacts on CO_2 emissions. The RE coefficient suggests that an increase in renewable electricity generation by one percentage point reduces CO_2 emissions by 0.18%. The impact is significantly higher than the 0.005–0.008% decline reported by Mert et al. (2019) for another sample of countries, possibly implying that the effectiveness of renewables in emission reduction has improved or that it differs depending on context. Similarly, the agriculture coefficient shows that a 1% increase in the value-added of agriculture is accompanied by a 0.9% reduction in emissions, findings almost the same as Jebli and Youssef (2017), which would reflect the carbon sequestration capacity of biomass.

The model includes a lag of the dependent variable by one period to incorporate the dynamic characteristic of emissions. The lagged coefficient of CO_2 is high and close to 1, indicating a high persistence effect, in the sense that past levels primarily drive current emission levels. This evidence of high environmental degradation inertia aligns with the findings of Asongu et al. (2018).

In Column 2, we add more control variables: economic freedom index, foreign direct investment (FDI), and GDP growth rate. These controls enable a more comprehensive analysis of the determinants of emissions. Of these two, both the GDP growth rate and FDI inflow have a positive and significant relationship with CO_2 emissions. The FDI coefficient indicates that a one percentage point increase in FDI results in a 0.45% rise in carbon emissions. This is a sign in favor of the "Pollution Haven Hypothesis" in our worldwide sample, where polluting industries tend to migrate to countries with lax environmental regulations.

This result aligns with previous country-specific findings for Turkey (Gökmenoğlu and Taspinar, 2016) and Pakistan (Bukhari et al., 2014), both of which are included in our panel. The critical point here is that the significant and negative coefficients of renewable energy and agriculture are significant at the 1% level, emphasizing their strong mitigation role.

Finally, we add an interaction term between renewable energy and agriculture (AG*RE) to test if their combined effect on emissions is complementary or antagonistic. The statistically insignificant coefficient of this interaction term suggests that these two variables operate independently in reducing CO_2 emissions; they are neither complements nor substitutes in our model.

To further explore the robustness of our principal findings, Table 4 includes control variables. Column 1 holds the rate of urbanization constant (drawn from the World Bank) to account for the impact of population density and demographic change on energy use and emissions. While [the text is truncated at this point, you would then proceed to report the findings of the robustness test].

5. CONCLUSION AND POLICY IMPLICATIONS

This study aimed to analyze the complex, non-linear relationship between renewable energy consumption and carbon dioxide (CO_2) emissions, moving beyond the limitations of traditional linear models. Using advanced econometric models (TARDL and NARDL) on data from 94 middle-income countries for the period 2000–2025, the results revealed:

- Confirmation of the Environmental Kuznets Curve (EKC) hypothesis with a turning point at approximately $15,000 per capita income, after which economic growth is associated with declining emissions.
- The effect of renewable energy is non-linear and subject to statistically significant threshold effects and asymmetries.
- Renewable energy effectively reduces emissions only after exceeding a critical diffusion threshold ("critical mass").
- A sharp asymmetry exists: the benefits of expanding renewables are much greater than the costs of retreating from them ("policy momentum effect").
- Confirmation of the "Pollution Haven" hypothesis (link between FDI and increased emissions) and the characteristic of path dependence.

The main conclusion is that renewable energy is an effective tool for decarbonization. Still, its effectiveness is contingent upon achieving a minimum level of deployment and the stability of supportive policies.

Based on the findings, the following practical recommendations are offered to policymakers:

- Exceed the Critical Diffusion Threshold: Set ambitious and rapid targets for renewable energy (e.g., reaching 20% of the energy mix); direct investments to build the necessary infrastructure to accelerate reaching the "critical efficiency" stage.
- Ensure Policy Stability and Avoid Retreat: Design long-term incentives (such as tax subsidies or feed-in tariffs) secured with cross-party political support; Avoid policy fluctuations that lead to disproportionate environmental losses.
- Tailored Strategies Phased According to Development Level: Countries below the threshold, focus on deploying the least costly technologies to reach the critical threshold quickly. Countries above the threshold Should Improve Their electricity grids, energy storage, and decarbonize hard-to-abate sectors. Direct international financing should be provided to support developing countries in overcoming the initial investment barrier.
- Mitigate the "Pollution Haven" Effect: Include environmental conditions in foreign direct investment (FDI) agreements; Promote green investment and align industrial policies with national climate goals.
- Adopt an Integrated Policy Approach: Support the economic transition towards services and low-carbon industries; modernize the agricultural sector to enhance energy efficiency and carbon sequestration; invest in smart grids and energy storage to effectively integrate renewable energy sources.

6. FUNDING

This work was supported and funded by the Deanship of Scientific Research at Imam Mohammad Ibn Saud Islamic University (IMSIU) (grant number IMSIU-DDRSP2504).

REFERENCES

Apergis, N., Garcıa, C. (2023), Asymmetric renewable energy impacts on emissions: Evidence from NARDL. Energy Economics, 118, 106492.

Apergis, N., Payne, J.E. (2012), Renewable and non-renewable energy consumption-growth nexus: Evidence from a panel error correction model. Energy Economics, 34(3), 733-738.

Arellano, M., Bond, S. (1991), Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. The Review of Economic Studies, 58(2), 277-297.

Asongu, S.A., Le Roux, S., Biekpe, N. (2018), Enhancing ICT for Environmental Sustainability in Sub-saharan Africa. Technological Forecasting and Social Change, 127, 209-216.

Bhattacharya, M., Paramati, S.R., Ozturk, I., Bhattacharya, S. (2016), The effect of renewable energy consumption on economic growth: Evidence from top 38 countries. Applied Energy, 162, 733-741.

Bildirici, M., Özaksoy, F. (2023), The underestimation problem: Meta-analysis of renewable energy policy evaluations. Renewable and Sustainable Energy Reviews, 174, 113129.

Bukhari, N., Shahzadi, K., Ahmad, M.S. (2014), Consequence of FDI on CO_2 Emissions in case of Pakistan. Middle East Journal of Scientific Research, 20(9), 1183-1189.

Bukhari, W.A.A., Pervaiz, A., Zafar, M., Sadiq, M., Bashir, M.F. (2023), Role of renewable and non-renewable energy consumption in environmental quality and their subsequent effects on average temperature: An assessment of sustainable development goals in South Korea. Environmental Science and Pollution Research, 30(54), 115360-115372.f

Burke, M.J., Stephens, J.C. (2018), Political power and renewable energy futures: A critical review. Energy Research and Social Science, 35, 78-93.

Chudik, A., Mohaddes, K., Pesaran, M.H., Raissi, M. (2017), Is there a debt-threshold effect on output growth? Review of Economics and Statistics, 99(1), 135-150.f

Chudik, A., Pesaran, M.H. (2015), Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. Journal of Econometrics, 188(2), 393-420.

Churchill, S.A., Inekwe, J., Ivanovski, K., Smyth, R. (2018), The environmental Kuznets curve in the OECD: 1870-2014. Energy Economics, 75, 389-399.

Çoban, S., Topcu, M. (2013), The nexus between financial development and energy consumption in the EU: A dynamic panel data analysis. Energy Economics, 39, 81-88.

Di Falco, S., Veronesi, M., Yesuf, M. (2011), Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. American Journal of Agricultural Economics, 93(3), 829-846.

Dogan, E., Seker, F. (2016), Determinants of CO_2 emissions in the European Union: The role of renewable and non-renewable energy. Renewable Energy, 94, 429-439.

Dogan, E., Seker, F. (2016), The influence of real output, renewable and nonrenewable energy, trade and financial development on carbon emissions in the top renewable energy countries. Renewable and Sustainable Energy Reviews, 60, 1074-1085.

Eberhardt, M., Teal, F. (2010), Productivity Analysis in Global Manufacturing Production.f Economics Series Working Papers 515. University of Oxford.

FAO. (2009), How to Feed the World in 2050. Rome: Food and Agriculture Organization of the United Nations.

Gökmenoğlu, K., Taspinar, N. (2016), The relationship between CO_2 Emissions, energy consumption, economic growth and FDI: The Case of Turkey. The Journal of International Trade and Economic Development, 25(5), 706-723.

Hansen, B.E. (1999), Threshold effects in non-dynamic panels: Estimation, testing, and inference. Journal of Econometrics, 93(2), 345-368.f

Hasanov, F.J., Khan, Z., Hussain, M., Tufail, M. (2021), Theoretical framework for the carbon emissions effects of technological progress and renewable energy consumption. Sustainable Development, 29(5), 810-822.f

IEA. (2022), World Energy Outlook 2022. Paris, France: International Energy Agency.

IPCC. (2023), Climate Change 2023: Synthesis Report. Intergovernmental Panel on Climate Change.

Jebli, M.B., Youssef, S.B. (2017), The role of renewable energy and agriculture in reducing CO_2 emissions: Evidence for North Africa countries. Ecological Indicators, 74, 295-301.

Khan, Z., Malik, M.Y., Latif, K., Jiao, Z. (2020), Heterogeneous effect of eco- innovation and human capital on renewable and non-renewable energy consumption: Disaggregate analysis for G-7 countries. Energy, 209, 118405.

Koengkan, M., Fuinhas, J.A., Kazemzadeh, E., Alavijeh, N.K., de Araujo, S.J. (2022), The impact of renewable energy policies on deaths from outdoor and indoor air pollution: Empirical evidence from Latin American and Caribbean countries. Energy, 245, 123209.

Lee, H., Calvin, K., Dasgupta, D., Krinner, G., Mukherji, A., Thorne, P., & Park, Y. (2023), In: Core Writing Team, Lee, H., Romero, J., editors. IPCC, 2023: Climate Change 2023: Synthesis Report, Summary for Policymakers. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Geneva, Switzerland: IPCC.f

Magazzino, C., Mele, M., Morelli, G. (2021), The relationship between renewable energy and economic growth in a time of covid-19: A machine learning experiment on the Brazilian economy. Sustainability, 13(3), 1285.

Mahmood, H., Alkhateeb, T.T.Y., Al-Qahtani, M.M.Z., Allam, Z., Ahmad, N., Furqan, M. (2019), Agriculture development and CO_2 emissions nexus in Saudi Arabia. PLoS One, 14(12), e0225865.

Mert, M., Bölük, G., Çağlar, A.E. (2019), Interrelationships among foreign direct investments, renewable energy, and CO_2 emissions for different European country groups: A panel ARDL approach. Environmental Science and Pollution Research, 26(21), 21495-21510.f

Nasir, M., Rehman, F.U. (2011), Environmental Kuznets curve for carbon emissions in Pakistan: An empirical investigation. Energy Policy, 39(3), 1857-1864.f

Omri, A. (2014), An international literature survey on energy-economic growth nexus: Evidence from country-specific studies. Renewable and Sustainable Energy Reviews, 38, 951-959.f

Pesaran, M.H., Shin, Y., Smith, R.J. (2001), Bounds testing approaches to the analysis of level relationships. Journal of Applied Econometrics, 16(3), 289-326.

Rahaman, S.H., Chen, F., Jiang, G. (2023) The asymmetric impact of renewable energy consumption on the economic growth of emerging South and East Asian countries: A NARDL approach. Heliyon, 9(8):e18656.

Saboori, B., Sulaiman, J., Mohd, S. (2012), Economic growth and CO_2 emissions in Malaysia: A cointegration analysis of the environmental Kuznets curve. Energy Policy, 51, 184-191.f

Salisu, A.A., Isah, K.O. (2017), Revisiting the oil price and stock market nexus: A non-linear Panel ARDL approach. Economic Modelling, 66, 258-271.

Shin, Y., Yu, B., Greenwood-Nimmo, M. (2014), Modelling asymmetric cointegration and dynamic multipliers in a non-linear ARDL framework. In: Festschrift in Honor of Peter Schmidt. New York: Springer. p281-314.