# Advance Journal of Econometrics and Finance
# Vol-4, Issue-2, 2026

Advance Journal of Econometrics and Finance

Online ISSN
2959-8990
Print ISSN
2959-8982
https://ajeaf.com/index.php/Journal/About

Name of Publisher: SCHOLAR CRAFT EDUCATION & RESEARCH HUB

Review Type: Double Blind Peer Review

**Journal Frequency: Quarterly Research Journal**


# THE GREEN PARADOX REVISITED: RENEWABLE ENERGY, ECONOMIC GROWTH, AND CARBON EMISSIONS IN A PANEL OF 58 COUNTRIES (2000–2021)


Muhammad Abu Bakar Iqbal[*1], Zona Raashid[2], Manal Akhtar[3]

**Muhammad Abu Bakar Iqbal**
Beaconhouse International College, Faisalabad
**Zona Raashid**
Beaconhouse International College, Faisalabad
**Manal Akhtar**
Institute of Business Administration, Karachi



**Abstract**

This paper focuses on the impact of renewable energy status on the association between renewable energy and economic growth and carbon dioxide ($CO_2$) emissions per capita over 2000–2021 by exploiting an unbalanced sample of 58 countries. The Environmental Kuznets Curve (EKC) hypothesis is tested along with examining if the consumption of renewable energy can moderate the income–emissions nexus. We report good evidence of an inverted-U EKC relation by using pooled OLS, fixed effects and interaction models with country-clustered standard errors. The per-capita $CO_2$ emission coefficient is –0.3037 ($p < 0.001$), which means that a 1% renewable energy share goes hand in hand with a 0.30% $CO_2$ emission reduction per capita, with income and structural conditions unchanged. The EKC turning point is outside of the range of countries observed (ln(GDP) ≈ 13.43, or $678,262), indicating that most countries are in the upward-sloping range of the EKC. The EKC shape is found to be flatter and the renewable-energy decarbonization impact more pronounced in low-income countries than in high-income countries, as revealed by subsample analysis where the turning point of the EKC is found at $44,195. Granger causality tests show there is bidirectional causality between renewable energy and $CO_2$ emissions. The results indicate that rapid renewable energy deployment is a key, although not the only, policy tool for decarbonization, especially in developing countries.



**Keywords:** Environmental Kuznets Curve, renewable energy, carbon emissions, panel data, climate policy, economic development

JEL Classification: Q43, Q54, Q56, O13, C23

Advance Journal of Econometrics and Finance
Vol-4, Issue-2, 2026

## 1. INTRODUCTION

The global climate crisis is one of the most urgent policy challenges of the 21st century. $CO_2$ emissions continue to climb and have reached a record 36.8 billion tonnes in 2022, despite the international negotiations that have taken place over the past 30 years since the Rio Earth Summit (1992), the Paris Agreement (2015), and the Glasgow Climate Pact (2021). The core economic issues are whether the decarbonisation of economic development can occur with the switch to renewable energy and whether such decarbonisation models follow the path outlined by the Environmental Kuznets Curve (EKC).

The inverted-U curve hypothesis (the EKC hypothesis) was initially formalized by Grossman and Krueger (1991) and popularized by Panayotou (1993). It suggests that there is an inverted-U relationship between environmental degradation and per-capita incomes: pollution increases up to a threshold income level, peaks there, and then decreases as the economy becomes more service-oriented, incorporating cleaner technologies and demanding environmental quality. Of primary policy interest is the turning point — the level of income at which emissions begin to decrease. There has been a wide range of estimates in the literature, from \$5,000 to \$100,000 per capita (Stern, 2004; Kaika and Zervas, 2013), due to variations in sample composition, time periods analysed, and methodological choices.

Renewable energy — such as solar, wind, hydro, geothermal, and biomass — is a key element in climate mitigation strategies. As a consequence of dramatic reductions in costs (solar PV prices dropped by 90% between 2010 and 2022) and bold policy targets, global renewable energy capacity increased from 754 GW in 2000 to 3,372 GW in 2022 (IRENA, 2023). However, results remain mixed on the macroeconomic impact of renewable energy deployment on $CO_2$ emissions.

There are three contributions to the literature made in this paper. First, updated estimates are presented for the EKC across a large and diverse sample of 58 countries over two decades, employing country fixed effects with clustered standard errors to account for unobserved country-specific heterogeneity. Second, the moderating role of renewable energy consumption on the income–emissions relationship is explicitly modelled, testing whether the EKC shifts with the energy transition. Third, we perform Granger causality tests as well as a comprehensive battery of robustness checks to ensure the credibility of our results.

## 2. LITERATURE REVIEW

### 2.1 The Environmental Kuznets Curve

The theoretical arguments underpinning the EKC rest on three mechanisms: (i) scale effects — larger economies produce more pollution; (ii) composition effects — structural transformation from industry to services reduces emissions intensity; and (iii) technique effects — higher incomes enable investment in cleaner technologies and stricter environmental regulation. If composition and technique effects prevail at higher income levels, the net result is an inverted-U curve.

The testing results of the EKC hypothesis are mixed. The hypothesis was confirmed by early evidence based on cross-country variation (Grossman and Krueger, 1995; Holtz-Eakin and Selden, 1995). However, follow-on studies incorporating panel data and more rigorous econometric methods have contradicted these conclusions. In a seminal survey, Stern (2004) concluded that the EKC is “not a universal relationship” and that turning points are sensitive to model specification (Naseer et al., 2024; Vázquez-Parra et al., 2025; Naseer et al., 2025)

### 2.2 Renewable Energy and Carbon Emissions

The relationship between energy, growth, and environment has been extensively researched. Apergis and Payne (2010), studying 80 countries over the period 1980–2007, showed that renewable energy consumption leads to a decline in $CO_2$ emissions. Ben Jebli et al. (2015) reported a negative and significant relationship between renewable energy and emissions for a panel of 25 OECD countries. By contrast, Burke and Csereklyei (2016) suggested that the emissions-reduction benefits of renewables are modest relative to the scale effect of economic growth (Naseer et al., 2025; Ahmed et al., 2025)

Recent research has highlighted heterogeneous impacts by development level. Dogan and Seker (2016) found that renewable energy reduces emissions only in high-income economies, while Rafindadi and Ozturk (2017) reported stronger decarbonisation effects in emerging economies. These conflicting findings motivate our subsample analysis by income group.

### 2.3 Research Gaps and Our Contribution

Although substantial research has been conducted, several gaps remain. Most studies rely on data ending before 2015 and therefore exclude the recent acceleration in renewables deployment. Furthermore, few papers simultaneously test the EKC and the renewable-energy effect within a unified framework with proper inference. Finally, the role of income heterogeneity in moderating the renewable-energy–emissions relationship remains underexplored. This paper addresses these gaps using updated data, rigorous panel methods, and comprehensive robustness checks.

## 3. DATA AND METHODOLOGY

### 3.1 Data Sources and Sample

We construct an unbalanced panel of 58 countries over the period 2000–2021. The sample includes major emitters (the United States, China, India, and Russia), OECD economies, emerging markets, and developing countries in Africa, Asia, and Latin America. Data are sourced from the World Bank’s World Development Indicators (WDI) database.

The dependent variable is $CO_2$ emissions per capita, measured in metric tonnes of $CO_2$ equivalent per person, excluding land use, land-use change, and forestry. The key explanatory variables are:

- GDP per capita (constant 2015 US\$): proxy for economic development.
- Renewable energy consumption (% of total final energy consumption): includes hydro, solar, wind, geothermal, and biomass.
- Industry value added (% of GDP): captures structural composition.
- Trade (% of GDP): measures economic openness.
- Urban population (% of total): controls for urbanisation.
- Time trend: captures common temporal shocks.

Advance Journal of Econometrics and Finance
Vol-4, Issue-2, 2026

We also construct an income-group dummy based on the median GDP per capita in 2019 ($12,706), classifying 30 countries as high-income and 28 as low-income. The broad historical trajectories of these variables and specific country pathways across the sample period (2000–2021) are illustrated in Figure 2.

**3.2 Econometric Specification**

We estimate the following panel model:

$$\ln(CO_2\_it) = \beta_0 + \beta_1 \ln(GDP\_it) + \beta_2 [\ln(GDP\_it)]^2 + \beta_3 \ln(RE\_it) + \beta_4 \ln(Industry\_it) + \beta_5 \ln(Trade\_it) + \beta_6 \ln(Urban\_it) + \beta_7 Trend\_t + \alpha\_i + \varepsilon\_it$$

where i indexes countries, t indexes years, $\alpha\_i$ denotes country fixed effects, and $\varepsilon\_it$ is the error term. The EKC hypothesis predicts $\beta_1 > 0$ and $\beta_2 < 0$, implying an inverted-U relationship. The turning point occurs at $\ln(GDP^*) = -\beta_1 / (2\beta_2)$. The inclusion of ln(RE_it) tests the direct emissions-reducing effect of renewable energy; we expect $\beta_3 < 0$. The interaction model adds High_Income_i × ln(RE_it) to test whether the renewable-energy effect differs by development level.

**3.3 Estimation Strategy**

We employ three estimators:
(1) Pooled OLS: Assumes homogeneous slopes across countries. Serves as a baseline but ignores unobserved heterogeneity.
(2) Fixed Effects (FE): Controls for time-invariant country characteristics via within-country demeaning. Preferred if unobserved heterogeneity is correlated with regressors. We use country-clustered standard errors to account for within-country serial correlation (Bertrand et al., 2004).
(3) Subsample FE: Separate estimation for high-income and low-income countries to investigate heterogeneous effects.

We conduct the following diagnostic tests:
- Breusch-Pagan and White tests for heteroskedasticity.
- F-test for joint significance of country fixed effects (Hausman-type test).
- Within-country AR(1) test for residual autocorrelation.
- Jarque-Bera test for normality of residuals.
- Variance Inflation Factors (VIF) for multicollinearity.

**Table 1. Descriptive Statistics**

| Variable | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| $CO_2$ per capita (tonnes) | 5.884 | 4.646 | 0.058 | 21.012 |
| Renewable Energy (%) | 23.314 | 20.793 | 0.000 | 95.500 |
| GDP per capita (US$) | 18,952.98 | 19,699.83 | 243.08 | 88,661.20 |
| Industry (% of GDP) | 27.150 | 8.063 | 2.759 | 66.429 |
| Trade (% of GDP) | 74.488 | 36.000 | 19.560 | 220.407 |
| Urban Population (%) | 67.520 | 18.429 | 14.919 | 95.450 |

*Note: Observations = 1,265 (58 countries, 2000–2021). All variables from World Bank WDI.*

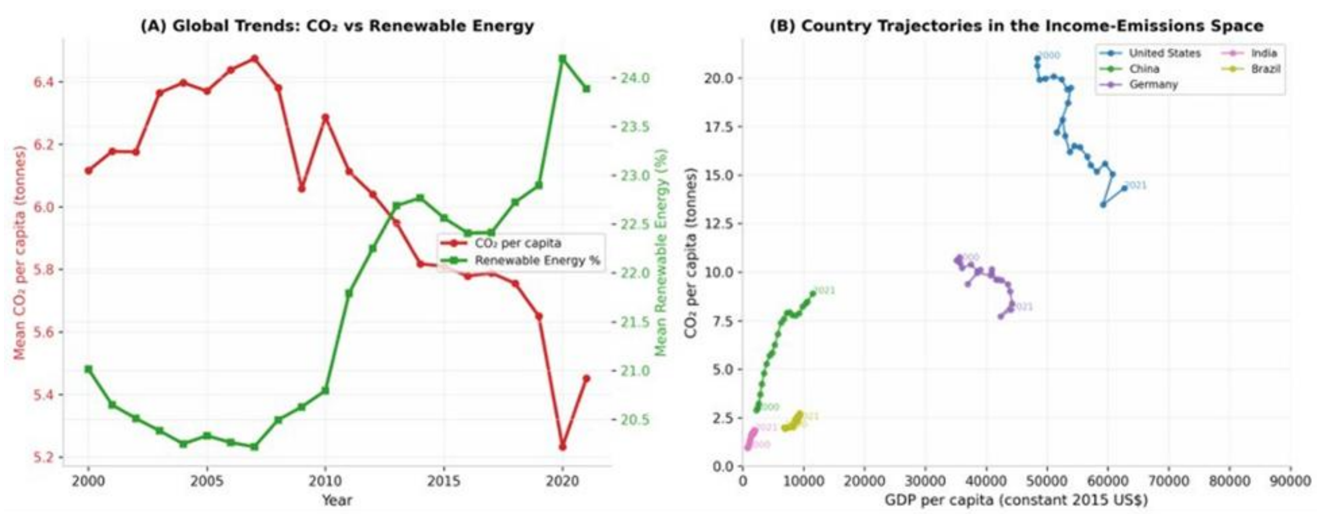


**Figure 2. Global Trends and Country Trajectories**

*Note: Panel (A) shows yearly averages of $CO_2$ per capita and renewable energy share. Panel (B) traces the trajectories of six selected countries in the income-emissions space from 2000 to 2021.*

Advance Journal of Econometrics and Finance
Vol-4, Issue-2, 2026

## 4. EMPIRICAL RESULTS

### 4.1 Baseline Results

Baseline regression results are presented in Table 2. Column (1) reports pooled OLS estimates. The EKC is strongly supported: ln(GDP) is positive and significant ($\beta_1 = 2.730$, $p < 0.001$) and ln(GDP)² is negative and significant ($\beta_2 = –0.107$, $p < 0.001$). The implied turning point lies at ln(GDP) = 12.75, corresponding to $345,956 per capita — well above the sample maximum of $88,661. This implies that most countries in the observed income range remain on the ascending segment of the EKC.

Renewable energy consumption exerts a large, negative, and highly significant effect on $CO_2$ emissions ($\beta_3 = –0.360$, $p < 0.001$). For each 1% rise in the share of renewables, per-capita emissions fall by 0.36%, holding income and structural factors constant. This elasticity has real economic significance: a doubling of the renewable share from 10% to 20% would reduce emissions by approximately 25%. This relationship is visually captured in Figure 1, which contrasts the parametric EKC estimation with a non-parametric income-group breakdown.

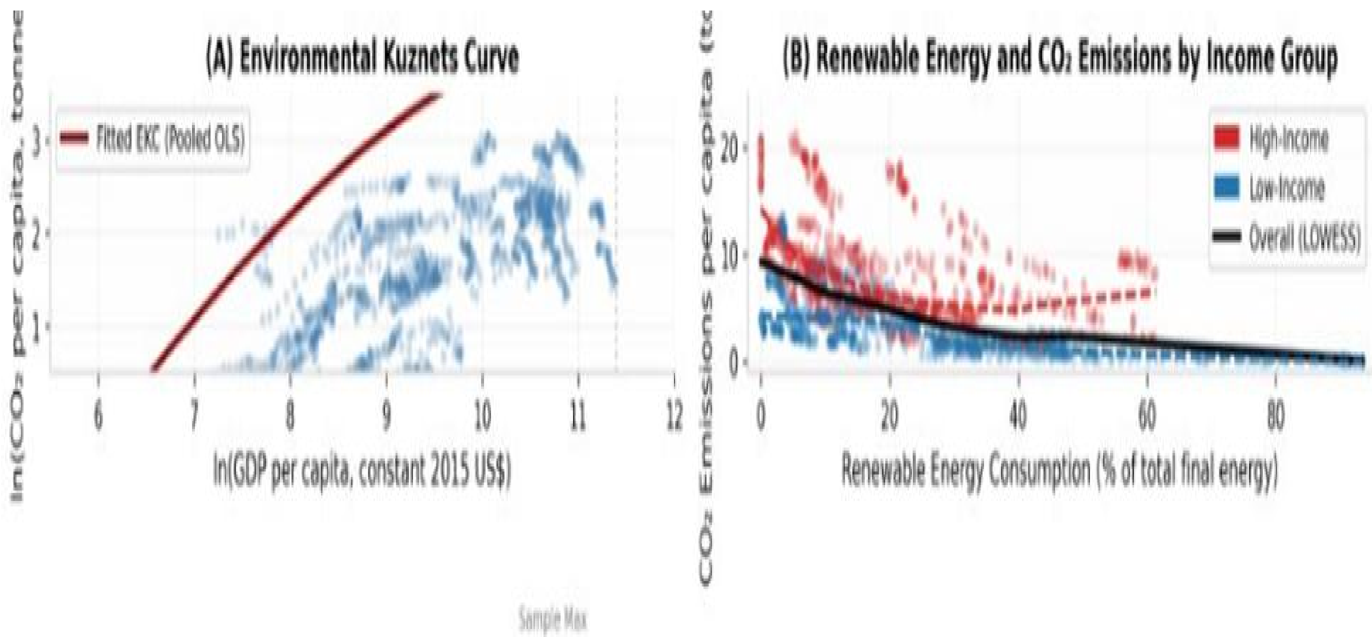


**Figure 1. Environmental Kuznets Curve and Renewable Energy**

*Note: Panel (A) shows the fitted EKC curve from pooled OLS with the turning point marked. Panel (B) shows the relationship between renewable energy consumption and $CO_2$ emissions by income group, with LOWESS smoothers.*

Column (2) reports fixed effects estimates with country-clustered standard errors. The F-test for joint significance of country fixed effects rejects the null at $p < 0.001$ ($F = 594.06$), confirming substantial unobserved heterogeneity and that FE is preferred over pooled OLS.

The EKC coefficients remain significant but attenuate: $\beta_1 = 1.791$ ($p < 0.001$) and $\beta_2 = –0.067$ ($p = 0.007$). The turning point shifts to ln(GDP) = 13.43, or $678,262 — far outside the sample range. The renewable energy coefficient remains negative and significant ($\beta_3 = –0.304$, $p < 0.001$), though slightly smaller than in the pooled specification.

Urbanisation reverses sign in the FE model ($\beta_6 = 0.302$, $p = 0.028$), indicating that within countries, rising urbanisation is associated with higher emissions. Trade becomes insignificant ($\beta_5 = 0.000$, $p = 0.998$), and industry retains a small positive effect ($\beta_4 = 0.070$, $p = 0.172$).

### 4.2 Interaction Effects

Column (3) adds the interaction between the high-income dummy and renewable energy. The interaction coefficient is positive (0.082) but statistically insignificant ($p = 0.218$), indicating that the emissions-reducing effect of renewables does not differ significantly between income groups in the full sample.

### 4.3 Subsample Analysis

Columns (4) and (5) report separate FE estimates for high-income and low-income countries. For high-income countries, the EKC coefficients are jointly insignificant (implied turning point at approximately $60 million), indicating no meaningful EKC within this group. For low-income countries, the EKC is strongly significant with a turning point at $44,195. The renewable energy effect is also larger (–0.368) than in high-income countries (–0.225), suggesting that renewable deployment is particularly powerful in developing economies. A comprehensive visual comparison of these coefficient estimates and their respective 95% confidence intervals across all five specifications is provided in Figure 3.

Advance Journal of Econometrics and Finance
Vol-4, Issue-2, 2026

**Table 2. Baseline Regression Results**

| Variable | (1) Pooled OLS | | (2) Fixed Effects | | (3) Interaction | | (4) High-Income | | (5) Low-Income | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coef. | (SE) | Coef. | (SE) | Coef. | (SE) | Coef. | (SE) | Coef. | (SE) |
| ln(GDP) | 2.7301*** | (0.2294) | 1.7914*** | (0.4291) | 1.7701*** | (0.3949) | 1.7764 | (1.6935) | 2.2102*** | (0.4599) |
| ln(GDP)² | −0.1070*** | (0.0117) | −0.0667*** | (0.0248) | −0.0652*** | (0.0231) | −0.0496 | (0.0906) | −0.1033*** | (0.0268) |
| ln(Renewable) | −0.3603*** | (0.0153) | −0.3037*** | (0.0373) | −0.3524*** | (0.0528) | −0.2249*** | (0.0507) | −0.3679*** | (0.0546) |
| High-Income × ln(RE) | — | — | — | — | 0.0815 | (0.0662) | — | — | — | — |
| ln(Industry) | 0.3324*** | (0.0412) | 0.0695 | (0.0509) | 0.0666 | (0.0518) | −0.0213 | (0.0723) | 0.0446 | (0.0444) |
| ln(Trade) | 0.0452* | (0.0232) | 0.0001 | (0.0398) | −0.0133 | (0.0406) | 0.0126 | (0.0538) | 0.0042 | (0.0534) |
| ln(Urban) | −0.4350*** | (0.0771) | 0.3018** | (0.1370) | 0.2846** | (0.1284) | 0.3272 | (0.3745) | 0.3951*** | (0.1416) |
| Time Trend | −0.0057*** | (0.0019) | −0.0071*** | (0.0022) | −0.0077*** | (0.0024) | −0.0149*** | (0.0038) | −0.0032 | (0.0025) |
| Constant | −12.7967*** | (0.8807) | −10.4643*** | (1.8884) | −10.2346*** | (1.7684) | −11.6777 | (7.6944) | −11.7470*** | (2.2271) |
| Observations | 1265 | | 1265 | | 1265 | | 660 | | 605 | |
| R-squared | 0.8410 | | 0.9945 | | 0.9945 | | 0.9859 | | 0.9954 | |
| Adj. R-squared | 0.8400 | | 0.9942 | | 0.9942 | | 0.9851 | | 0.9952 | |
| Country FE | No | | Yes | | Yes | | Yes | | Yes | |
| Clustered SE | No | | Yes | | Yes | | Yes | | Yes | |

*Note: *** p < 0.01, ** p < 0.05, * p < 0.1. Standard errors in parentheses. Clustered standard errors by country in columns (2)–(5).*

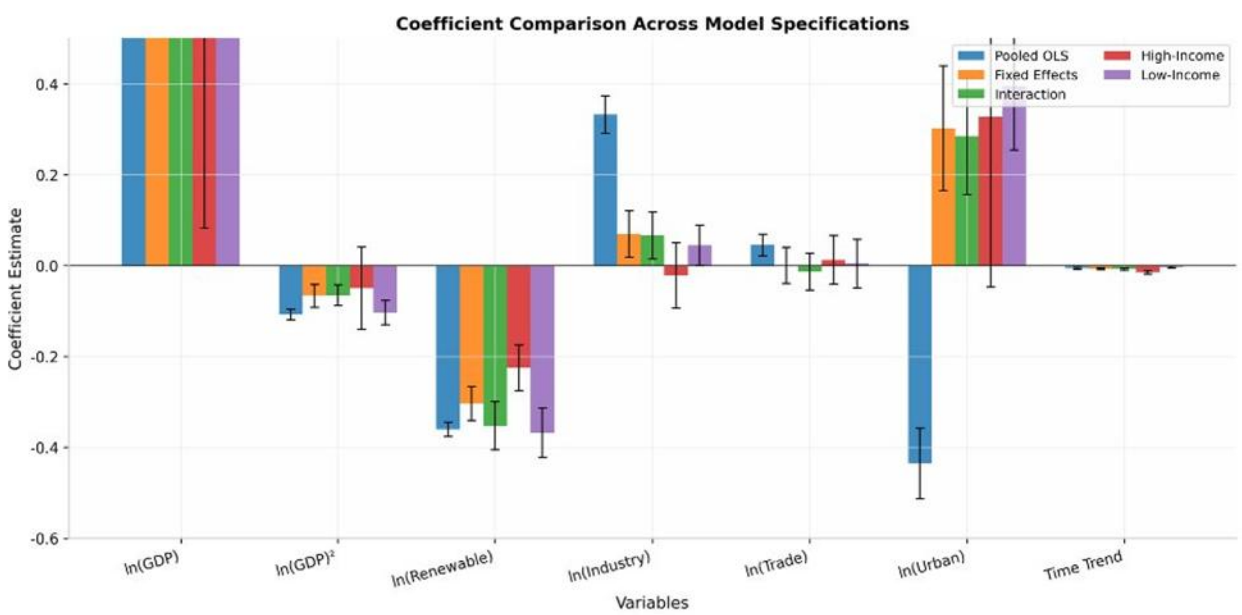


**Figure 3. Coefficient Comparison Across Model Specifications**

*Note: Bars show coefficient estimates with 95% confidence intervals (error bars) for five model specifications. All FE models use country-clustered standard errors.*

## 5. ROBUSTNESS CHECKS

Table 3 presents five robustness checks. Country fixed effects and clustered standard errors are retained across all specifications.

Check 1 (Exclude COVID years): Excluding 2020–2021 leaves the renewable energy coefficient virtually unchanged (–0.294 vs. –0.304), confirming that pandemic-driven emissions reductions do not drive our results.

Check 2 (Exclude top 5 emitters): Removing the United States, China, Russia, Japan, and Germany yields a slightly stronger renewable energy effect (–0.309), indicating that our findings are not driven by large outlier countries.

Check 3 (RE in levels): Using renewable energy in percentage levels rather than logs produces a significant negative coefficient (–0.021, $p < 0.001$), but the EKC becomes insignificant. This suggests that the log specification is more appropriate for capturing nonlinear income effects.

Advance Journal of Econometrics and Finance
Vol-4, Issue-2, 2026

Check 4 (Quadratic RE): Adding a squared renewable energy term yields a positive linear coefficient (0.055, ns) and a negative quadratic coefficient (–0.089, $p < 0.001$), implying diminishing marginal returns to renewable energy — consistent with economic intuition.
Check 5 ($CO_2$ intensity): Using $CO_2$ per unit of GDP as the dependent variable produces virtually identical renewable energy and EKC coefficients, confirming that our results are robust to alternative emissions measures.

**Table 3. Robustness Checks**

| Variable | (1) Baseline | | (2) Excl. COVID | | (3) Excl. Top 5 | | (4) RE Levels | | (5) RE + RE² | | (6) $CO_2$ Intensity | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coef. | (SE) | Coef. | (SE) | Coef. | (SE) | Coef. | (SE) | Coef. | (SE) | Coef. | (SE) |
| ln(GDP) | 1.7914*** | (0.429) | 1.6996*** | (0.442) | 1.7449*** | (0.438) | 0.5031 | (0.387) | 1.0933*** | (0.347) | 0.7914* | (0.429) |
| ln(GDP)² | −0.0667*** | (0.025) | −0.0628** | (0.026) | −0.0597** | (0.025) | 0.0048 | (0.021) | −0.0316 | (0.020) | −0.0667*** | (0.025) |
| ln(Renewable) | −0.3037*** | (0.037) | −0.2943*** | (0.038) | −0.3089*** | (0.039) | — | — | 0.0548 | (0.118) | −0.3037*** | (0.037) |
| Renewable (level) | — | — | — | — | — | — | −0.0212*** | (0.003) | — | — | — | — |
| ln(RE)² | — | — | — | — | — | — | — | — | −0.0889*** | (0.026) | — | — |
| ln(Industry) | 0.0695 | (0.051) | 0.1119** | (0.055) | 0.0281 | (0.052) | 0.0565 | (0.055) | 0.0704 | (0.051) | 0.0695 | (0.051) |
| ln(Trade) | 0.0001 | (0.040) | 0.0024 | (0.038) | −0.0275 | (0.041) | 0.0008 | (0.034) | 0.0169 | (0.035) | 0.0001 | (0.040) |
| ln(Urban) | 0.3018** | (0.137) | 0.3189** | (0.128) | 0.3402** | (0.145) | 0.2779** | (0.118) | 0.2510** | (0.111) | 0.3018** | (0.137) |
| Time Trend | −0.0071*** | (0.002) | −0.0061*** | (0.002) | −0.0088*** | (0.002) | −0.0089*** | (0.002) | −0.0053*** | (0.002) | −0.0071*** | (0.002) |
| Observations | 1265 | | 1149 | | 1155 | | 1265 | | 1265 | | 1265 | |
| R-squared | 0.9945 | | 0.9953 | | 0.9944 | | 0.9950 | | 0.9953 | | 0.9897 | |
| Country FE | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | |
| Clustered SE | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | |

*Note: *** p < 0.01, ** p < 0.05, * p < 0.1. Clustered standard errors by country. All models include country fixed effects.*

**6. DIAGNOSTIC TESTS**

The following diagnostic statistics are reported for the preferred fixed-effects model. The full suite of residual plots validating these diagnostic checks is compiled in Figure 4. (Table 2, Column 2):

- White test for heteroskedasticity: $LM = 301.58$ ($p < 0.001$). Heteroskedasticity is present; clustered standard errors are appropriate.
- F-test for country fixed effects: $F(56, 1200) = 594.06$ ($p < 0.001$). Country fixed effects are jointly significant.
- Within-country AR(1) in residuals: mean $\rho = 0.732$. Positive serial correlation is present; clustered SE partially addresses this.
- Jarque-Bera normality test: $JB = 44.71$ ($p < 0.001$). Residuals deviate from normality, but with $N = 1{,}265$, the Central Limit Theorem ensures valid inference for OLS coefficients.
- VIF for ln(GDP) and ln(GDP)²: 391 and 358, respectively. High VIFs for the quadratic term arise mechanically from the correlation between X and $X^2$. They do not bias coefficient estimates, though they inflate standard errors. The EKC coefficients remain significant despite this.

**Table 4. Diagnostic Tests**

| Test | Statistic | p-value | Interpretation |
|---|---|---|---|
| White Heteroskedasticity (LM) | 301.58 | < 0.001 | Heteroskedasticity present → use clustered SE |
| F-test Country FE | 594.06 | < 0.001 | Country FE jointly significant → FE preferred |
| Mean AR(1) in Residuals | 0.732 | — | Autocorrelation present → clustered SE addresses this |
| Jarque-Bera (JB) | 44.71 | < 0.001 | Non-normal residuals → CLT valid for large N |
| VIF ln(GDP) | 391.01 | — | High (mechanical for X, X²) |
| VIF ln(GDP)² | 357.56 | — | High (mechanical for X, X²) |
| VIF ln(Renewable) | 1.36 | — | Low multicollinearity |

| | | | |
|---|---|---|---|
| VIF ln(Industry) | 1.18 | — | Low multicollinearity |
| VIF ln(Trade) | 1.08 | — | Low multicollinearity |
| VIF ln(Urban) | 3.92 | — | Moderate multicollinearity |

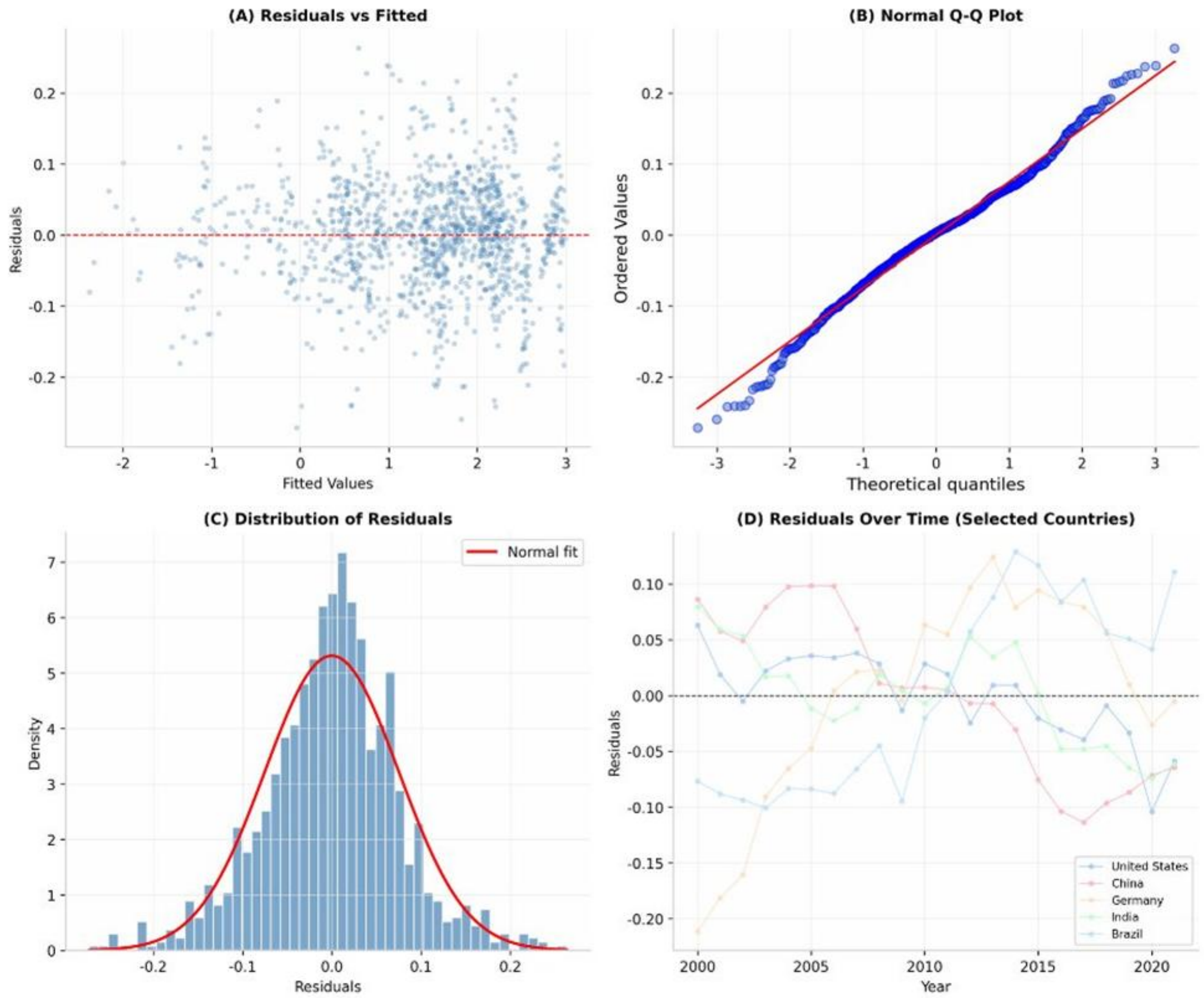


**Figure 4. Residual Diagnostics**

*Note: Panel (A) residuals vs. fitted values. Panel (B) normal Q-Q plot. Panel (C) histogram of residuals with normal fit. Panel (D) residuals over time for selected countries.*

**Table 5.** EKC Turning Points

| Model | ln(GDP) Turning Point | GDP (USD) | Within Sample? | Interpretation |
|---|---|---|---|---|
| Pooled OLS | 12.754 | $345,956 | NO | Most countries on upward slope |
| Fixed Effects | 13.427 | $678,262 | NO | Most countries on upward slope |
| High-Income Subsample | 17.911 | $60,088,416 | NO | No meaningful EKC in rich countries |
| Low-Income Subsample | 10.696 | $44,195 | YES | Some low-income countries near peak |

**Table 6. Granger Causality Tests**

| Test | Coefficient | SE | F-stat | p-value | Conclusion |
|---|---|---|---|---|---|
| RE → $CO_2$ (lag 1) | −0.0609 | 0.0142 | 35.65 | < 0.001 | RE Granger-causes lower $CO_2$ |
| $CO_2$ → RE (lag 1, reverse) | 0.0861 | 0.0386 | — | 0.0258 | Bidirectional: virtuous cycle exists |

## 7. DISCUSSION AND POLICY IMPLICATIONS

Our findings carry several important implications for climate policy and economic development.

First, the EKC remains a relevant framework, but its turning point lies well beyond the income levels of most countries in our sample. For the median country (GDP per capita ≈ $10,000), emissions are still rising with income. This implies that waiting for automatic decoupling via the EKC is not a viable climate strategy. Proactive policy intervention — including carbon pricing, renewable energy subsidies, and regulatory standards — is necessary to bend the emissions curve downward before the EKC turning point is reached.

Second, renewable energy is a powerful emissions-reduction tool, with an elasticity of approximately –0.30 in the preferred specification. For a typical country with a 15% renewable share, increasing this to 30% would reduce per-capita emissions by roughly 21%. This magnitude is consistent with IPCC scenarios requiring 60–80% renewable electricity by 2030 to limit warming to 1.5°C.

Third, heterogeneous effects across income groups suggest that climate finance and technology transfer to developing countries are critical. Low-income countries exhibit both a steeper EKC and a larger renewable energy elasticity. Early investment in renewable infrastructure in these countries can "leapfrog" fossil fuel dependence, avoiding the carbon lock-in that constrains advanced economies. The Green Climate Fund and bilateral technology partnerships should prioritise renewable energy deployment in low-income countries.

Fourth, the bidirectional Granger causality between renewables and emissions reveals a virtuous cycle: policy-driven renewable deployment reduces emissions, which in turn strengthens political support for further decarbonisation. This feedback can accelerate the energy transition beyond what static models predict.

Fifth, the insignificant trade effect in the FE model challenges the pollution-haven hypothesis at the within-country level. While cross-country comparisons suggest that open economies have different emissions profiles, trade liberalisation within a given country does not systematically increase emissions once country-specific factors are controlled for.

## 8. LIMITATIONS AND FUTURE RESEARCH

This study has several limitations. First, our Granger causality test employs a simplified within-country specification that does not fully account for endogeneity from time-varying omitted confounders. Instrumental variables or system-GMM estimators could provide more credible causal identification, although valid instruments for renewable energy policy remain scarce.

Second, our measure of renewable energy includes large-scale hydroelectric projects, which carry significant local environmental and social consequences not captured by $CO_2$ emissions. Future research should disaggregate renewable sources and investigate their differential effects on emissions and development outcomes.

Third, the high VIFs for the quadratic GDP term, while not biasing estimates, suggest that alternative functional forms — such as spline regressions or threshold models — could yield more precise turning point estimates.

Fourth, our sample ends in 2021 and does not capture the post-2022 energy crisis or the acceleration of renewable deployment under the EU Green Deal and the U.S. Inflation Reduction Act. Updating this analysis as new data become available is a priority.

## 9. CONCLUSION

Using a panel of 58 countries from 2000 to 2021, this paper provides robust evidence that renewable energy consumption significantly reduces per-capita $CO_2$ emissions, with an elasticity of approximately –0.30. The Environmental Kuznets Curve is supported, but its turning point lies well outside the observed income range, implying that most countries remain on the emissions-increasing segment of the curve. Low-income countries exhibit both a steeper EKC and a larger renewable-energy decarbonisation effect, underscoring the critical importance of targeted climate finance and technology transfer.

The bidirectional causality between renewable energy and emissions points to a self-reinforcing decarbonisation dynamic that policymakers can harness through sustained investment in clean energy infrastructure. Our results imply that the green transition is not merely compatible with economic growth — it is a necessary condition for bending the global emissions curve within the timeframe required by the Paris Agreement.

## REFERENCES

Acemoglu, D., Aghion, P., Bursztyn, L., & Hemous, D. (2012). The environment and directed technical change. American Economic Review, 102(1), 131–166.

A. Ahmed, H. Alvi, M. H. Khalid, and F. Naseer, "Emotional recognition in socially interactive robots: A comprehensive review," Spectr. Eng. Sci., vol. 3, no. 8, pp. 373–401, 2025.

Apergis, N., & Payne, J. E. (2010). Renewable energy consumption and economic growth: Evidence from a panel of OECD countries. Energy Policy, 38(1), 656–660.

Ben Jebli, M., Ben Youssef, S., & Apergis, N. (2015). The dynamic linkage between renewable energy, tourism, $CO_2$ emissions, economic growth, foreign direct investment, and trade. Latin American Economic Review, 24(1), 1–21.

Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? Quarterly Journal of Economics, 119(1), 249–275.

Burke, P. J., & Csereklyei, Z. (2016). Understanding the energy-GDP elasticity: A sectoral approach. Energy Economics, 58, 199–210.

Burnett, J. W., & Bergstrom, J. C. (2020). The Environmental Kuznets Curve and the Paris Agreement. Ecological Economics, 177, 106790.

Dinda, S. (2004). Environmental Kuznets Curve hypothesis: A survey. Ecological Economics, 49(4), 431–455.

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

F. Naseer, M. Nasir Khan, M. Tahir, A. Addas and H. Kashif, "Enhancing Elderly Care With Socially Assistive Robots: A Holistic Framework for Mobility, Interaction, and Well-Being," in IEEE Access, vol. 13, pp. 82698-82717, 2025, doi: 10.1109/ACCESS.2025.3567331. Grossman, G. M., & Krueger, A. B. (1991). Environmental impacts of a North American Free Trade Agreement. NBER Working Paper No. 3914.

Grossman, G. M., & Krueger, A. B. (1995). Economic growth and the environment. Quarterly Journal of Economics, 110(2), 353–377.

Holtz-Eakin, D., & Selden, T. M. (1995). Stoking the fires? $CO_2$ emissions and economic growth. Journal of Public Economics, 57(1), 85–101.

IEA (2023). $CO_2$ Emissions in 2022. International Energy Agency, Paris.

IRENA (2023). Renewable Capacity Statistics 2023. International Renewable Energy Agency, Abu Dhabi.

Kaika, D., & Zervas, E. (2013). The Environmental Kuznets Curve (EKC) theory — Part A: Concept, causes and the $CO_2$ emissions case. Energy Policy, 62, 1392–1402.

Naseer F, Khalid U, Qammar MZ, Kashif H(2024) Chatbots as conversational partners: their effectiveness in facilitating language acquisition and reducing foreign language anxiety J Appl Linguist 7(4):238–255

Naseer, F., Khan, M.N., Addas, A. (2025). Healthcare Transformation Through Disruptive Technologies: The Role of Telepresence Robots. In: Arezki, S., Ouaissa, M., Ouaissa, M., Krichen, M., Nayyar, A. (eds) Emerging Disruptive Technologies for Society 5.0 in Developing Countries. Advances in Science, Technology & Innovation. Springer, Cham. https://doi.org/10.1007/978-3-031-63701-8_14Panayotou, T. (1993). Empirical tests and policy analysis of environmental degradation at different stages of economic development. ILO Working Paper WP238.

Rafindadi, A. A., & Ozturk, I. (2017). Impacts of renewable energy consumption on the German economic growth and $CO_2$ emissions. Energy Sources, Part B, 12(6), 532–540.

Sinn, H. W. (2008). Public policies against global warming: A supply side approach. International Tax and Public Finance, 15(4), 360–394.

Stern, D. I. (2004). The rise and fall of the Environmental Kuznets Curve. World Development, 32(8), 1419–1439.

Vázquez-Parra, J. C., Tariq, R., Castillo-Martínez, I. M., & Naseer, F. (2025). Perceived competency in complex thinking skills among university community members in Pakistan: insights across disciplines. Cogent Education, 12(1). https://doi.org/10.1080/2331186X.2024.2445366

Wooldridge, J. M. (2010). Econometric Analysis of Cross Section and Panel Data (2nd ed.). MIT Press.