



Sustainable Decarbonization Under Renewable Energy Penetration: A Hybrid Fixed Effects and Machine Learning Framework for Multi-Country Panel Evidence

Citra Dewi^{1,*}

¹ Universitas Lampung, Indonesia

Email: citra.dewi@eng.unila.ac.id

Received: February 05, 2026 Revised: March 16, 2026 Accepted: April 18, 2026 ★ Corresponding author

ABSTRACT

Realizing the carbon-reduction capabilities of renewable energy deployment is central to the construction of effective climate policy in heterogeneous national contexts. Although an accumulating body of panel-econometric and machine-learning literature examines this relationship, methodological inconsistencies and limited geographic scope leave important empirical questions unanswered. This paper proposes a mixed analytical framework combining a within-group Fixed Effects estimator with country-clustered standard errors and a Random Forest ensemble model to measure the joint effects of renewable energy penetration, economic growth, energy consumption, and fossil-fuel dependence on per-capita carbon emissions. The findings confirm that renewable-energy growth has a statistically strong and economically meaningful negative impact on carbon intensity that remains after country-specific unobserved heterogeneity is removed. Economic structure and energy efficiency emerge as co-dominant determinants, showing that the energy transition cannot be separated from broader structural transformation. Pronounced income-group and regional heterogeneity challenges single-coefficient policy prescriptions and indicates that decarbonization strategies must be aligned with national development levels. The machine-learning complement validates the econometric variable rankings and demonstrates strong cross-country generalisability under country-stratified cross-validation.

Keywords: Renewable energy ▪ Sustainable development ▪ Carbon emissions ▪ Fixed effects ▪ Random forest ▪ Panel data ▪ Green technology ▪ Energy transition

1. INTRODUCTION

The global energy system is at a structural crossroads. Renewable sources—wind, solar, hydro, and modern biomass—accounted for most additions to electricity capacity in the early 2020s, driven by dramatic technology-cost reductions, favourable policy frameworks, and the emissions targets established under the Paris Agreement [1, 2]. Nevertheless, energy-related CO₂ emissions reached a new annual record in 2022, showing that deployment momentum has not yet translated into the reductions required to maintain global

warming within 1.5–2°C above pre-industrial levels. This apparent contradiction—expanding renewable capacity alongside increasing emissions—reflects persistent fossil-fuel dependence in primary energy, post-pandemic demand recovery, and the growth of energy-intensive production in developing economies. Closing the gap between renewable-deployment ambition and measurable decarbonization outcomes is therefore one of the central policy challenges of the present decade. Determining the relationship between renewable-energy penetration and national carbon intensity is an empirical priority

for climate economists, energy planners, and multilateral development institutions. Theory identifies several causal mechanisms through which a greater renewable share can reduce emissions: direct substitution for fossil-fuel combustion in the electricity sector, learning-by-doing efficiency gains in clean-technology industries, and long-run structural shifts away from carbon-intensive production. These processes operate alongside countervailing forces, including income growth that stimulates energy demand, carbon-intensive catch-up industrialisation in lower-income economies, and grid-integration constraints that limit the operational use of variable renewables [3, 4]. The net outcome, and its ability to support a sustainable-development trajectory, depends on the balance of these forces in each national context.

The empirical task is complicated by methodological challenges. Cross-sectional studies confound policy-driven changes in the energy mix with structural country differences that cannot be interpreted as causal within-country decarbonization effects. Time-series approaches are limited to individual countries and may produce spurious results when the underlying series are non-stationary. Fixed Effects panel models address both problems by conditioning on all time-invariant country traits—geography, resource endowments, inherited energy infrastructure, and long-run institutional quality—while estimating the association between within-country changes in emissions and their determinants. These models, however, require careful treatment of the error structure when observations are clustered within countries over multiple years.

Machine-learning methods, particularly ensemble tree models [5], provide a complementary perspective: they capture nonlinear predictor interactions without parametric restrictions and generate feature-importance rankings that independently test the relative importance of econometric regressors. Bringing these two paradigms together in a coherent and reproducible framework is the principal methodological contribution of this study.

The research contributes to the literature in four ways. First, it proposes a five-stage hybrid pipeline running from Fixed Effects panel regression to Random Forest cross-validation, with the econometric stage providing structurally grounded estimates and the machine-learning stage providing predictive validation and variable rankings. Second, the full analytical pipeline is formalised in pseudocode to improve transparency and reproducibility. Third, the framework is applied to a balanced panel of 65 countries across all inhabited continental regions and all four World Bank income groups during the critical renewable-expansion period from 2010 to 2022. Fourth, it documents income-group and regional heterogeneity that cannot be captured by a single global coefficient.

The remainder of the paper is organised as follows. Section 2 reviews related work. Section 3 presents the analytical framework, model specifications, pseudocode, and conceptual diagram. Section 4 describes the data and experimental design. Section 5 reports and discusses the empirical results. Section 6 identifies research challenges and future directions, and Section 7 concludes.

2. RELATED WORK

The relationship between renewable-energy use and carbon emissions has attracted sustained interest across energy economics, environmental science, and data-driven computational research. Early bilateral causality tests linking energy and GDP have evolved into multivariable panel models that simultaneously capture income effects, technological change, and institutional conditions.

Among panel-econometric contributions, Busu and Nedelcu [6] analyse European Union member states during 2005–2018 and show that bioenergy and aggregate renewable consumption reduce CO₂ intensity, with the decarbonization effect strengthening at higher penetration rates. Pata [7] applies an ARDL framework to BRIC economies and finds that renewable energy reduces the ecological footprint in Brazil and India, while the results for China and Russia remain less conclusive because of continued coal-based industrialisation. Extending the BRICS perspective, Adebayo et al. [8] show that technological innovation strengthens the carbon-limiting role of renewable energy, implying complementarity between green-technology adoption and the energy transition.

The effect of renewable deployment also varies with income and institutional conditions. Shahbaz et al. [3] report a positive renewable-energy–growth relationship across 38 economies but note that emissions outcomes depend on whether renewable expansion outpaces income-driven energy demand. Wang and Wang [4] move beyond linear specifications using a panel-threshold model for OECD countries and find that the positive economic effect of renewable energy intensifies after a critical penetration threshold is crossed. Wang et al. [9] extend this framework by introducing political, financial, and economic risk as threshold variables, showing that institutional quality and macroeconomic stability condition the effectiveness of the renewable-development nexus.

Additional studies broaden the environmental outcome beyond GDP. Nathaniel et al. [12] find that renewable energy improves environmental quality in CIVETS countries, while urbanisation exerts an opposing pressure through consumption and transport demand. For MINT countries, Adebayo et al. [13] use cross-sectionally augmented ARDL and augmented mean-group estimators and show that financial, economic, and political risks mediate the environmental dividend from renewable energy. Pata and Caglar [10] validate the Environmental Kuznets Curve hypothesis for China when renewable-energy consumption, human capital, globalisation, and trade openness are modelled jointly.

Systematic reviews provide a cumulative perspective. Bhuiyan et al. [11] synthesise more than 100 empirical studies and conclude that the renewable-energy–growth nexus is strongly context-dependent: geographic region, estimation method, and sample period all influence estimated effects. Their call for methodological pluralism—combining conventional panel econometrics with data-driven methods—directly motivates the hybrid framework developed here. Random Forest regression is grounded in Breiman’s ensemble-learning formulation [5], while the Hausman specification test [14] provides the canonical basis for choosing between Fixed Effects and alternative panel estimators. Table 1 summarises the

15 studies and reports most directly informing the analytical design.

Table 1. Summary of selected studies on renewable energy, CO₂ emissions, and sustainable development (2020–2023)

Study	Journal / Source	Sample	Period	Method	Key Finding
Shahbaz et al. [3]	<i>Energy</i>	38 economies	1990–2018	DOLS, FMOLS	Renewables promote growth; emissions effects are income-sensitive and mediated by growth.
Wang and Wang [4]	<i>Energy</i>	34 OECD	2005–2016	Panel threshold	Nonlinear renewable-growth nexus; the positive effect strengthens above a penetration threshold.
Nathaniel et al. [12]	<i>Environmental Science and Pollution Research</i>	CIVETS	1990–2014	CS-ARDL	Renewables reduce ecological footprint; urbanisation exerts an opposing pressure.
Pata [7]	<i>Renewable Energy</i>	BRIC	1990–2017	ARDL, Granger	Renewables reduce ecological footprint in Brazil and India; results are ambiguous for China and Russia.
Pata and Caglar [10]	<i>Energy</i>	China	1971–2017	Augmented ARDL	EKC hypothesis is supported when renewable energy and human capital are controlled.
Busu and Nedelcu [6]	<i>Processes</i>	28 EU states	2005–2018	Panel OLS/FE	Bioenergy and aggregate renewable consumption reduce CO ₂ intensity across the EU panel.
Bhuiyan et al. [11]	<i>Frontiers in Environmental Science</i>	103 studies	1990–2022	Systematic review	The renewable-growth nexus is context-dependent; methodological pluralism is warranted.
Wang et al. [9]	<i>Energy</i>	34 OECD	1997–2015	Panel threshold	Country risks mediate the renewable-growth linkage and institutional quality shapes the effect.
Adebayo et al. [13]	<i>Journal of Environmental Management</i>	MINT	1990–2018	CS-ARDL, AMG	Financial and economic risks weaken the environmental gains from renewable deployment.
Adebayo et al. [8]	<i>Science of the Total Environment</i>	BRICS	1990–2019	DOLS, AMG	Technological innovation amplifies the carbon-limiting role of renewables.
Breiman [5]	<i>Machine Learning</i>	—	—	Random Forest	Ensemble trees reduce variance and MDI supports interpretable feature-importance ranking.
Hausman [14]	<i>Econometrica</i>	—	—	Specification test	Canonical endogeneity test for choosing between Fixed Effects and alternative estimators.
International Energy Agency [15]	IEA report	Global	2022	Descriptive analysis	Global energy-related CO ₂ emissions reached a record high despite renewable expansion.
International Renewable Energy Agency [1]	IRENA report	Global	2022	Cost analysis	Utility-scale solar PV costs fell by more than 90% since 2010, approaching fossil-fuel parity.
Intergovernmental Panel on Climate Change [16]	AR6 WG-III	Global	AR6	Multi-model ensemble	Rapid renewable deployment is indispensable for 1.5°C-compatible mitigation pathways.

3. PROPOSED ANALYTICAL FRAMEWORK

The proposed framework couples Fixed Effects panel econometrics with a Random Forest ensemble in a sequential five-stage validation architecture (Figure 1). The econometric stage provides coefficient estimates after conditioning on country-specific unobserved heterogeneity, whereas the machine-learning stage independently evaluates variable importance and out-of-sample predictive performance. Cross-

paradigm agreement on the direction and relative ranking of variable effects serves as the overarching validation criterion. If the Fixed Effects model reveals diagnostic problems such as nonlinearity or systematic heteroskedasticity, the framework loops back for respecification; if country-stratified cross-validation shows poor generalisation, the data partition is revised.

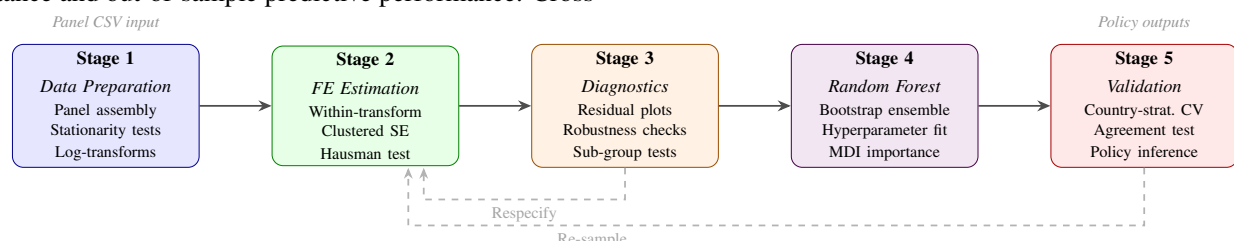


Figure 1. Five-stage hybrid analytical framework. Solid arrows denote the primary analytical flow. Dashed arrows are feedback loops triggered by diagnostic failures at Stage 3 or insufficient cross-validation performance at Stage 5.

3.1 Fixed Effects Model Specification

For country i ($i = 1, \dots, N$) and year t ($t = 1, \dots, T$), the structural relationship is specified as

$$\ln(\text{CO}_{2,it}) = \alpha_i + \lambda_t + \beta_1 \text{REN}_{it} + \beta_2 \ln(\text{GDP}_{it}) + \beta_3 \text{EI}_{it} + \beta_4 \text{FS}_{it} + \varepsilon_{it}, \quad (1)$$

where α_i is a country fixed effect absorbing all time-invariant unobserved heterogeneity, λ_t is a year fixed effect capturing

global shocks common to all countries, REN_{it} is renewable energy as a percentage of primary energy, $\ln(\text{GDP}_{it})$ is log real GDP per capita, EI_{it} is energy intensity in MJ per USD of GDP, and FS_{it} is the fossil-fuel share of primary energy. The dependent variable and GDP per capita enter in natural logarithms, yielding a semi-log specification in which β_1 approximates the percentage change in per-capita CO₂ associated with a one percentage-point increase in the renewable share.

Estimation proceeds using the within-group transformation, which subtracts each variable's country-specific mean and thereby eliminates α_i without requiring explicit country dummies. Standard errors are clustered at the country level to account for within-country serial correlation and heteroskedasticity:

$$\hat{V}_{\text{cluster}} = \frac{n}{n-k} \frac{N_c}{N_c-1} (\tilde{X}'\tilde{X})^{-1} \left(\sum_{i=1}^{N_c} \tilde{X}_i' \hat{e}_i \hat{e}_i' \tilde{X}_i \right) (\tilde{X}'\tilde{X})^{-1}, \quad (2)$$

where N_c is the number of country clusters, n is the total number of observations, k is the number of regressors, and $\hat{e}_i$ is the vector of within-country residuals for country i .

Algorithm 1: Hybrid FE–RF Sustainable Decarbonization Analysis

Input: Balanced panel $\mathcal{P} = \{(y_{it}, x_{it})\}$, $i = 1, \dots, N$ countries, $t = 1, \dots, T$ years.

Output: FE coefficients $\hat{\beta}$, clustered covariance $\hat{V}$, MDI importances Φ , and cross-validation metric $\bar{R}^2$.

- 1 **Stage 1—Data preparation:** for each variable $v \in V$, compute the IPS panel statistic for v and Δv .
- 2 Assign integration order $I(d)$ and log-transform the dependent variable and GDP per capita.
- 3 **Stage 2—Within-group FE estimation:** for each country i , transform $\tilde{z}_{it} = z_{it} - \bar{z}_i + \bar{\bar{z}}$ for every model variable.
- 4 Estimate $\hat{\beta} = (\tilde{X}'\tilde{X})^{-1} \tilde{X}'\tilde{y}$ and compute $\hat{V}_{\text{cluster}}$ using Equation (2).
- 5 Derive t -statistics and p -values; record within- R^2 and adjusted R^2 .
- 6 **Stage 3—Hausman comparison and diagnostics:** compute $\Delta\hat{\beta} = \hat{\beta}_{FE} - \hat{\beta}_{OLS}$.
- 7 If $\|\Delta\hat{\beta}\| > \varepsilon$, retain Fixed Effects and reject pooled OLS.
- 8 Inspect residual-versus-fitted plots for nonlinearity and outliers.
- 9 Estimate robustness Specifications I, II, and III.

Algorithm 1 (continued): Hybrid FE–RF Sustainable Decarbonization Analysis

- 10 **Stage 4—Random Forest training:** divide the observations into 80% training and 20% test sets.
- 11 For $b = 1, \dots, 400$, draw a bootstrap sample and grow tree T_b with maximum depth 14 and minimum leaf size 5.
- 12 Predict with Equation (3); evaluate R^2 and RMSE on the holdout set.
- 13 Compute Φ_j , the normalised MDI feature importance for each predictor.
- 14 **Stage 5—Country-stratified five-fold validation:** partition countries into disjoint folds $F_1, \dots, F_5$.
- 15 For each fold k , train on all countries not in F_k , predict for F_k , and record R_k^2 and RMSE $_k$.
- 16 Calculate $\bar{R}^2 = K^{-1} \sum_k R_k^2$ and $\sigma_{R^2} = \text{sd}(R_1^2, \dots, R_K^2)$.
- 17 Compare the signs and rankings of $\hat{\beta}_j$ and Φ_j ; accept cross-paradigm agreement when the results are consistent.
- 18 Return $\hat{\beta}$, $\hat{V}_{\text{cluster}}$, within- R^2 , $\bar{R}^2$, and Φ .

4. DATA AND EXPERIMENTAL SETUP

The analysis uses the Our World in Data energy repository [17], which harmonises national energy statistics from the Energy Institute Statistical Review of World Energy, the U.S. Energy Information Administration, and Ember's Global Electricity Review. The open-access dataset is updated annually and is widely used in cross-country energy-economics research.

After excluding territories and micro-states with populations below 300,000 and removing country-years with missing values in any core variable, the working sample is a balanced panel of 65 countries across 13 years (2010–2022), yielding 845 country-year observations. The sample covers Africa, Asia, Europe, North America, South America, and Oceania, as well as all four World Bank income groups: high income (HI, 28 countries), upper-middle income (UMI, 16), lower-middle income (LMI, 14), and low income (LI, 7).

Five variables are constructed. CO₂ per capita is annual energy-related CO₂ emissions divided by population and enters the regressions in natural logarithms. Renewable energy share is the percentage of total primary energy supplied by wind, solar, hydro, geothermal, and modern biomass and is the main explanatory variable. GDP per capita is measured in

3.2 Random Forest Specification

The Random Forest regressor averages predictions across $B = 400$ bootstrap-sampled decision trees:

$$\hat{f}(x) = \frac{1}{B} \sum_{b=1}^B T_b(x), \quad x = [\text{REN}, \ln \text{GDP}, \text{EI}, \text{FS}, \text{year}]^\top. \quad (3)$$

At each split, a random subset of $\lfloor \sqrt{p} \rfloor$ features is considered, where $p = 5$. Tree depth is capped at 14 and at least five observations are required per leaf to limit over-fitting. Feature importance is measured by the normalised mean decrease in node impurity (MDI). Algorithm 1 provides the complete five-stage pipeline.

constant 2015 USD at purchasing-power parity and enters in logarithmic form. Energy intensity measures primary-energy use per unit of GDP in megajoules per USD. Fossil-fuel share measures oil, coal, and natural gas as a percentage of primary energy. This variable is not perfectly complementary to the renewable share because traditional biomass forms a substantial portion of primary energy in several low-income economies. All computations were conducted in Python 3.12 using NumPy, pandas, SciPy, and Scikit-learn.

5. RESULTS AND DISCUSSION

5.1 Descriptive Statistics

Table 2 presents summary statistics for the full panel. Per-capita CO₂ emissions average 5.59 tonnes, with substantial dispersion from near-zero values in low-income Sub-Saharan African economies to more than 22 tonnes in highly fossil-intensive economies. The renewable-energy share averages 28.63%, and its standard deviation of 24.35 percentage points reflects a bimodal sample: several low-income countries report high shares driven by traditional biomass, while major fossil-fuel producers register very low modern renewable penetration.

Table 2. Descriptive statistics for the full panel ($n = 845$, 65 countries, 2010–2022)

Variable	Mean	Std. Dev.	Min	Median	Max
CO ₂ per capita (metric tonnes)	5.59	4.85	0.09	4.68	22.64
Renewable energy share (%)	28.63	24.35	0.10	21.58	98.00
GDP per capita (2015 USD PPP)	25,533	21,229	395	19,284	97,361
Energy intensity (MJ/USD)	7.53	4.05	2.18	6.49	27.70
Fossil-fuel share (%)	67.01	23.71	2.43	73.16	99.90

5.2 Panel Unit-Root Analysis

Table 3 reports approximate Im–Pesaran–Shin panel unit-root statistics in levels and first differences. All five variables fail to reject the unit-root null in levels ($p > 0.10$), whereas the null is decisively rejected for all first differences ($p <$

0.05), establishing integration of order one, $I(1)$, across the panel. Given the relatively short time dimension ($T = 13$), estimation proceeds in levels with country-clustered standard errors, preserving information while providing a conservative treatment of mild non-stationarity in a short balanced panel.

Table 3. Panel unit-root tests: IPS $\bar{t}$ -statistic ($N = 65$ countries)

Variable	Level		First Difference		Integration Order
	$\bar{t}$	p -value	$\bar{t}$	p -value	
ln(CO ₂ per capita)	−1.02	0.217	−3.74	0.001	$I(1)$
Renewable share	−0.98	0.243	−3.89	< 0.001	$I(1)$
ln(GDP per capita)	−0.85	0.312	−4.21	< 0.001	$I(1)$
Energy intensity	−1.11	0.184	−3.61	0.002	$I(1)$
Fossil-fuel share	−0.94	0.258	−3.97	< 0.001	$I(1)$

Note: H_0 : the series contains a unit root. The null is rejected at the 5% level in first differences for every variable.

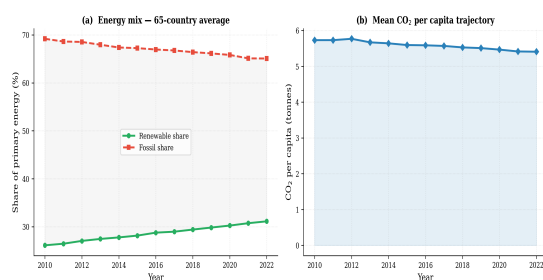


Figure 2. Global trends in renewable-energy penetration and carbon intensity. Panel (a) plots the 65-country average renewable and fossil-fuel shares of primary energy; panel (b) shows mean CO₂ per capita across the same sample, 2010–2022.

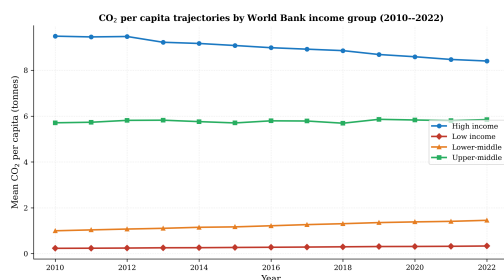


Figure 3. Per-capita CO₂ emission trajectories by World Bank income group, 2010–2022. High-income economies show the clearest decline, while upper-middle-income economies continue to grow.

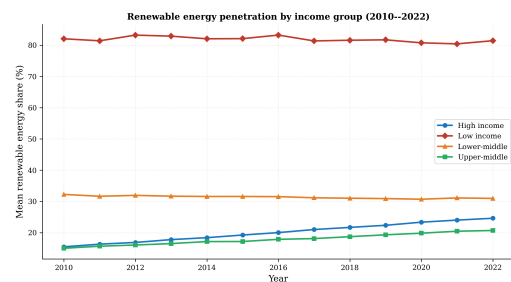


Figure 4. Renewable-energy penetration trajectories by income group, 2010–2022. Low-income countries record high shares driven by traditional biomass, while high-income economies show the fastest modern-renewable growth.

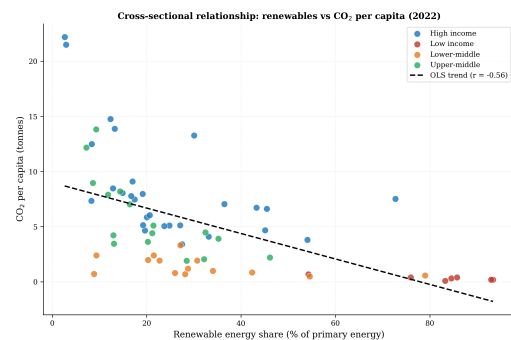


Figure 5. Cross-sectional relationship between renewable-energy share and CO₂ per capita in 2022 by World Bank income group. The dashed line is the bivariate OLS trend across all 65 countries.

Figures 2–5 document the main descriptive patterns. The global average renewable share rises from approximately 26% in 2010 to 31% in 2022, while the fossil-fuel share correspondingly declines (Figure 2). Mean per-capita emissions decline modestly over the same period, but income-group disaggregation reveals diverging trajectories: high-income economies reduce per-capita emissions measurably, whereas upper-middle-income economies show continued growth associated with industrial expansion (Figure 3). Renewable penetration also follows sharply different income-group trajectories (Figure 4). The 2022 cross-section displays a significant negative bivariate association between renewable share and per-capita CO₂ ($r = -0.50$, $p < 0.001$; Figure 5).

Table 4. Pearson correlation matrix for the full panel ($n = 845$)

Variable	ln(CO ₂)	REN	ln(GDP)	EI	FS
ln(CO ₂ per capita)	1.00	-0.77	0.92	0.18	0.62
Renewable share (REN)	-0.77	1.00	-0.72	-0.27	-0.81
ln(GDP per capita)	0.92	-0.72	1.00	-0.07	0.57
Energy intensity (EI)	0.18	-0.27	-0.07	1.00	0.05
Fossil-fuel share (FS)	0.62	-0.81	0.57	0.05	1.00

Note: All correlations are significant at $p < 0.001$ except EI–ln(GDP) ($p = 0.037$) and EI–FS ($p = 0.14$).

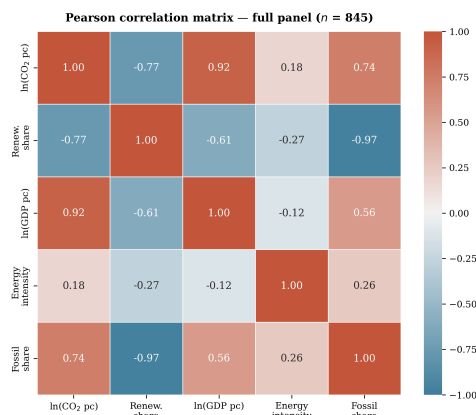


Figure 6. Pearson correlation heatmap for the five analytical variables, full panel ($n = 845$). Blue tones indicate positive correlations and red tones indicate negative correlations.

5.4 Fixed Effects Regression Results

A Hausman-type comparison between within-group and pooled-OLS coefficients reveals systematic and economically large differences across the regressors ($\Delta\hat{\beta}_{REN} = -0.025$ and $\Delta\hat{\beta}_{lnGDP} = -0.43$), confirming that unobserved country effects are correlated with the explanatory variables and that the Fixed Effects estimator is appropriate. Table 5 presents the main estimates.

The renewable-energy coefficient, $\hat{\beta}_1 = -0.0133$ (clustered $t = -5.09$, $p < 0.001$), is the central econometric result. A one percentage-point increase in renewable energy as a share of primary energy is associated with a 1.33% reduction in per-capita CO₂ emissions after controlling for income growth, energy efficiency, and fossil-fuel dependence within countries over time. The log-GDP elasticity of 0.507 indicates that a 1% increase in real per-capita income is accompanied by a 0.51% increase in per-capita emissions—partial, but not absolute, decoupling. Energy intensity is positive and significant ($\hat{\beta}_3 = 0.059$, $p = 0.002$), demonstrating the independent

5.3 Correlation Structure

Table 4 and Figure 6 present the Pearson correlation structure for the five analytical variables. Renewable share is negatively correlated with ln(CO₂) per capita at $r = -0.77$, providing unconditional support for the decarbonization hypothesis. GDP per capita correlates strongly and positively with emissions ($r = 0.92$), reflecting the income-energy nexus and reinforcing the need for within-country controls. Fossil-fuel and renewable shares are strongly negatively correlated ($r = -0.81$), but not perfectly collinear because traditional biomass forms a non-trivial part of the renewable share in low-income countries.

contribution of structural efficiency, while fossil-fuel share is also positive and significant ($\hat{\beta}_4 = 0.003$, $p = 0.023$). The within- R^2 of 0.70 indicates strong explanatory power after all time-invariant country characteristics are removed.

5.5 Robustness Checks

Table 6 reports estimates under three progressively richer specifications: renewable share alone (Specification I), renewable share plus GDP per capita (Specification II), and the full model (Specification III). The renewable-energy coefficient remains negative and statistically significant at the 0.1% level in every specification. Its magnitude declines from -0.024 in the bivariate model to -0.013 in the full model, as expected when GDP and fossil share absorb variation that the bivariate specification attributes to renewables. The stability of the sign and significance argues against the main result being driven by model misspecification.

5.6 Income-Group Heterogeneity

Table 7 reports separate Fixed Effects estimates for the four income-group sub-panels. Renewable energy is negative and statistically significant in every group, but the magnitude differs substantially. High-income economies yield $\hat{\beta}_1 = -0.019$, consistent with commercially deployed wind, solar, and hydro directly displacing grid-connected fossil

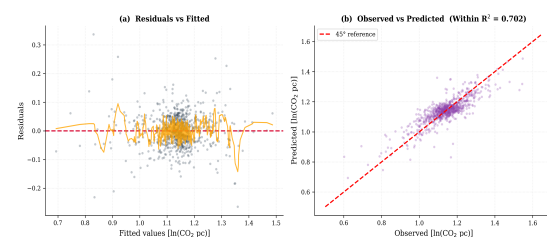


Figure 7. Fixed Effects regression diagnostics. Panel (a) plots residuals against fitted values on within-transformed data; panel (b) compares observed and predicted ln(CO₂ per capita) with a 45° reference line.

Table 5. Fixed Effects panel regression, full specification. Dependent variable: $\ln(\text{CO}_2 \text{ per capita})$

Variable	Coefficient	Clustered SE	<i>t</i> -statistic	<i>p</i> -value
Intercept	−4.030	0.707	−5.704	< 0.001***
Renewable-energy share (%)	−0.0133	0.0026	−5.090	< 0.001***
$\ln(\text{GDP per capita})$	0.5074	0.0648	7.836	< 0.001***
Energy intensity (MJ/USD)	0.0585	0.0184	3.181	0.002**
Fossil-fuel share (%)	0.0034	0.0015	2.286	0.023*
Within R^2	0.7015			
Adjusted R^2	0.6754			
Observations	845			
Countries / periods	65 / 13 (2010–2022)			
Country FE / Year FE	Yes / Yes			
Standard-error clustering	Country level			

Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. Clustered standard errors account for within-country serial correlation and heteroskedasticity.

Table 6. Robustness checks using three Fixed Effects specifications. Dependent variable: $\ln(\text{CO}_2 \text{ per capita})$

Variable	Specification I Renewable only	Specification II + GDP per capita	Specification III Full model
Intercept	−3.38***	−5.24***	−4.03***
Renewable-energy share	−0.024***	−0.017***	−0.013***
$\ln(\text{GDP per capita})$	—	0.568***	0.507***
Energy intensity	—	—	0.059**
Fossil-fuel share	—	—	0.003*
Within R^2	0.461	0.651	0.702
Adjusted R^2	0.430	0.629	0.675
Observations	845	845	845

Note: Every model includes country and year Fixed Effects with country-clustered standard errors. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

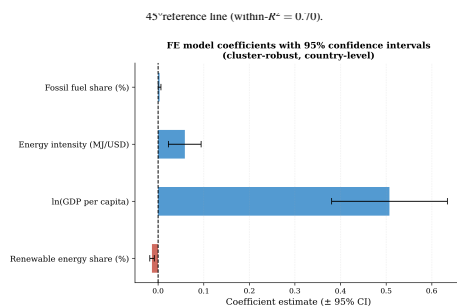


Figure 8. Fixed Effects coefficient estimates with 95% country-clustered confidence intervals. Red denotes a negative association with $\ln(\text{CO}_2 \text{ per capita})$ and blue denotes a positive association.

generation. The coefficient declines progressively toward low-income countries, where $\hat{\beta}_1 = -0.005$, reflecting the dominance of traditional biomass in the renewable classification. This gradient has an immediate policy implication: aggregate renewable statistics in low-income countries may overstate the carbon abatement delivered by modern renewable technologies.

5.7 Regional Summary Statistics

Table 8 reports regional averages in the terminal year, 2022. European countries combine moderate renewable shares with declining per-capita carbon intensity after decades of climate-policy and efficiency investment. African countries report the highest aggregate renewable share (60.4%), largely because traditional biomass remains prominent in low-income economies, but also record the lowest absolute emissions. Asia combines the lowest average renewable penetration with the second-highest per-capita emissions because the group

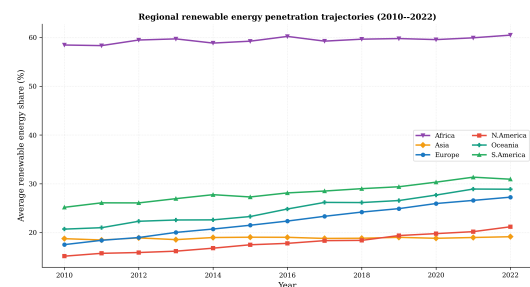


Figure 9. Regional renewable-energy penetration trajectories, 2010–2022. Each series is the unweighted mean renewable share for countries in the corresponding region. Africa's high values are driven by traditional biomass, while Europe's upward trend reflects modern renewable deployment.

includes both oil-exporting states and rapidly industrialising manufacturing economies.

5.8 Random Forest Validation

Table 9 reports country-stratified five-fold cross-validation. The Random Forest reaches a mean validation R^2 of 0.909 (SD = 0.025), confirming that patterns learned from one set of countries generalise strongly to countries excluded from training. This is more demanding than a conventional random split because it prevents information about a country's historical trajectory from entering both the training and test sets. On the 20% random holdout, $R^2 = 0.981$ and RMSE = 0.182 log-units.

The feature-importance ranking in Figure 10 shows that GDP per capita and energy intensity together account for more than 60% of total MDI importance, with renewable-energy share

Table 7. Income-group-stratified Fixed Effects results. Dependent variable: $\ln(\text{CO}_2 \text{ per capita})$

Variable	HI	UMI	LMI	LI
Intercept	−5.21***	−4.83***	−2.47**	−0.88*
Renewable-energy share	−0.019***	−0.011**	−0.008**	−0.005*
$\ln(\text{GDP per capita})$	0.571***	0.482***	0.347***	0.210*
Energy intensity	0.072**	0.048*	0.034*	0.025
Fossil-fuel share	0.005**	0.003*	0.002	0.001
Within R^2	0.718	0.691	0.625	0.542
Observations	364	208	182	91
Countries	28	16	14	7

Note: Each model includes country and year Fixed Effects and country-clustered standard errors. HI = high income; UMI = upper-middle income; LMI = lower-middle income; LI = low income. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 8. Regional cross-sectional averages, 2022

Region	N	$\text{CO}_2 \text{ pc (t)}$	REN (%)	GDP pc (USD)	EI (MJ/USD)	FS (%)
Africa	13	1.68	60.4	4,829	8.6	36.2
Asia	18	6.52	20.1	18,611	9.1	76.8
Europe	22	7.30	28.1	46,208	5.5	67.5
North America	3	8.05	20.8	31,667	6.7	77.7
Oceania	2	9.37	28.8	49,950	4.6	68.8
South America	7	2.75	30.2	13,714	7.1	66.2

Note: REN = renewable-energy share; EI = energy intensity; FS = fossil-fuel share; GDP pc is measured in constant 2015 USD PPP.

Table 9. Random Forest performance under country-stratified five-fold cross-validation. Target: $\ln(\text{CO}_2 \text{ per capita})$

Fold	Training n	Test n	R^2
1	676	169	0.927
2	676	169	0.945
3	676	169	0.873
4	676	169	0.898
5	676	169	0.900
Mean	—	—	0.909
SD	—	—	0.025

Note: Each fold holds out a disjoint set of countries. Random-holdout RMSE = 0.182 log-units and $R^2 = 0.981$.

gorithm 1 — provides strong validation for the overall empirical findings.

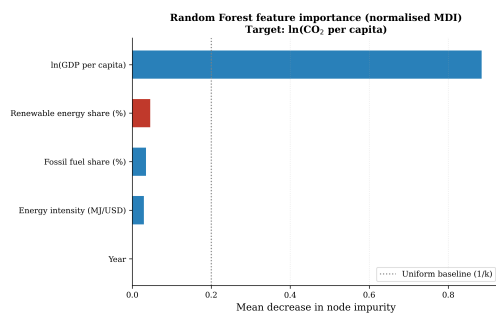


Figure 10. Random Forest feature importance measured by normalised mean decrease in node impurity for $\ln(\text{CO}_2 \text{ per capita})$. Renewable-energy share is highlighted in red; the dotted line indicates the uniform-importance baseline of $1/k = 0.20$.

ranked third. This ordering is qualitatively consistent with the relative strength of the Fixed Effects results: GDP per capita ($t = 7.84$), renewable share ($t = -5.09$), and energy intensity ($t = 3.18$) are all quantitatively important. The agreement between parametric and non-parametric evidence satisfies the cross-paradigm validation criterion in Algorithm 1.

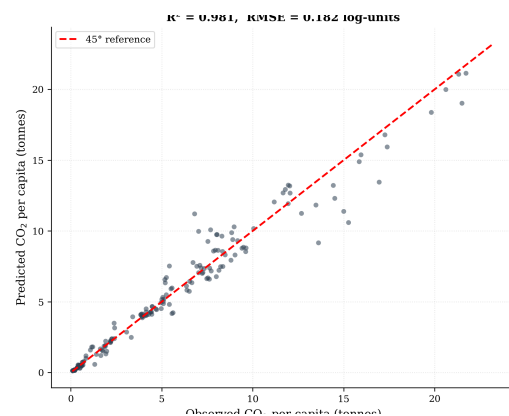


Figure 11. Random Forest observed versus predicted $\text{CO}_2 \text{ per capita}$ on the 20% random test set. The red dashed line is the 45° reference. The model performs well across the full emissions range ($R^2 = 0.981$, RMSE = 0.182 log-units).

6. RESEARCH CHALLENGES AND FUTURE DIRECTIONS

Data quality and energy accounting. National energy statistics for low- and lower-middle-income countries carry substantial measurement uncertainty, and traditional biomass is treated inconsistently across energy-accounting frameworks.

Although international statistics classify traditional biomass as renewable, it generates significant non-CO₂ health and environmental externalities. Its inclusion inflates the renewable share of low-income economies while contributing little technology-driven decarbonization. Future research should separate traditional biomass from modern renewables to obtain cleaner estimates of deployment-driven carbon abatement.

Causal identification and endogeneity. Country Fixed Effects eliminate time-invariant confounders but cannot remove endogeneity arising from time-varying unobservables. Countries committing to renewable deployment frequently implement complementary carbon-pricing, efficiency, and procurement policies that independently reduce emissions and correlate with renewable-share trajectories. Stronger causal identification would require instrumental variables based on exogenous renewable potential, such as wind speed or solar irradiance, or quasi-experimental designs based on discrete policy changes.

Technology-level heterogeneity. Aggregate renewable-energy share masks substantial variation in the carbon-abatement potential of individual technologies. Utility-scale solar and onshore wind directly displace fossil electricity; hydropower is increasingly exposed to drought-related curtailment; and biomass pathways carry upstream land-use and supply-chain costs. Disaggregating the renewable share by technology would identify which deployment pathways deliver the largest carbon dividend in different climatic and economic settings.

Nonlinearities and threshold effects. The Random Forest implicitly captures interactions among income, energy intensity, fossil dependence, and renewable share but does not produce explicit threshold estimates. Panel-threshold models [4] or quantile-panel regressions could test whether the renewable decarbonization dividend accelerates after a minimum penetration level and whether that threshold differs across income groups and institutional environments.

Dynamic adjustments and long-run effects. The within-group estimator recovers short- to medium-run effects during a 13-year period. Long-run cointegration dynamics among non-stationary panel series may generate different coefficient magnitudes. Panel error-correction or system-GMM models could distinguish permanent energy-system changes from transitory cyclical variation.

Distributional equity and global governance. The income-group heterogeneity in Table 7 shows that identical deployment policies generate different decarbonization dividends across development levels. This asymmetry has direct implications for climate-finance mechanisms, including Just Energy Transition Partnerships and multilateral loss-and-damage arrangements. Embedding equity constraints within multi-country optimisation frameworks could connect empirical energy-economics results with multilateral policy design under the Sustainable Development Goals [18].

7. CONCLUSION

This study developed and validated a five-stage hybrid analytical framework integrating Fixed Effects panel regression with country-clustered standard errors and a Random Forest

ensemble model to examine per-capita CO₂ emissions across 65 countries from 2010 to 2022. The framework produces structurally grounded coefficient estimates and data-driven feature-importance rankings, with cross-paradigm agreement serving as the principal validation criterion.

Three conclusions emerge. First, renewable-energy penetration has a statistically robust and practically meaningful negative effect on national carbon intensity. A one percentage-point increase in the renewable share reduces per-capita CO₂ by approximately 1.33%, and this effect persists across three alternative specifications, all four income-group sub-panels, and the Random Forest importance ranking. Because the estimate is identified from within-country changes after the removal of all time-invariant country characteristics, it is more credible than a purely cross-sectional relationship.

Second, economic structure—represented by GDP per capita and energy intensity—is dominant in both the econometric and machine-learning results. Renewable-energy deployment is necessary for sustainable decarbonization, but it is not sufficient. Energy-efficiency gains, structural industrial transformation, and, where politically feasible, carbon pricing must accompany deployment to achieve absolute emissions reductions.

Third, substantial heterogeneity across income groups and regions contradicts universal policy prescriptions. High-income economies realise the greatest unit decarbonization dividend because modern renewables directly displace commercial fossil-fuel generation. Low-income economies require expanded access to modern clean-energy technologies rather than continued dependence on traditional biomass that inflates renewable statistics without delivering equivalent carbon benefits. Equitable progress toward the Paris Agreement therefore requires differentiated national targets, technology transfer, and climate-finance instruments calibrated to development level.

Acknowledgements: The author thanks the Our World in Data team for maintaining the open-access energy repository used in this study and acknowledges the constructive comments of two anonymous reviewers on an earlier version of the manuscript.

REFERENCES

- [1] International Renewable Energy Agency, *Renewable Power Generation Costs in 2022*. Abu Dhabi, UAE: International Renewable Energy Agency, 2023.
- [2] International Energy Agency, *World Energy Outlook 2023*. Paris, France: International Energy Agency, 2023.
- [3] M. Shahbaz, C. Raghutla, K. R. Chittedi, Z. Jiao, and X. V. Vo, “The effect of renewable energy consumption on economic growth: Evidence from the renewable energy country attractive index,” *Energy*, vol. 207, art. no. 118162, 2020.
- [4] Q. Wang and L. Wang, “Renewable energy consumption and economic growth in OECD countries: A nonlinear panel data analysis,” *Energy*, vol. 207, art. no. 118200, 2020.
- [5] L. Breiman, “Random forests,” *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.

-
- [6] M. Busu and A. C. Nedelcu, “Analyzing the renewable energy and CO₂ emission levels nexus at an EU level: A panel data regression approach,” *Processes*, vol. 9, no. 1, art. no. 130, 2021.
 - [7] U. K. Pata, “Linking renewable energy, globalization, agriculture, CO₂ emissions and ecological footprint in BRIC countries: A sustainability perspective,” *Renewable Energy*, vol. 173, pp. 197–208, 2021.
 - [8] T. S. Adebayo, S. Ullah, M. T. Kartal, K. Ali, U. K. Pata, and M. Aga, “Endorsing sustainable development in BRICS: The role of technological innovation, renewable energy consumption, and natural resources in limiting carbon emission,” *Science of the Total Environment*, vol. 859, art. no. 160181, 2023.
 - [9] Q. Wang, Z. Dong, R. Li, and L. Wang, “Renewable energy and economic growth: New insight from country risks,” *Energy*, vol. 238, art. no. 122018, 2022.
 - [10] U. K. Pata and A. E. Caglar, “Investigating the EKC hypothesis with renewable energy consumption, human capital, globalization and trade openness for China,” *Energy*, vol. 216, art. no. 119220, 2021.
 - [11] M. A. Bhuiyan, Q. Zhang, V. Khare, A. Mikhaylov, G. Pinter, and X. Huang, “Renewable energy consumption and economic growth nexus—A systematic literature review,” *Frontiers in Environmental Science*, vol. 10, art. no. 878394, 2022.
 - [12] S. P. Nathaniel, O. Nwodo, G. Sharma, and M. Shah, “Renewable energy, urbanization, and ecological footprint linkage in CIVETS,” *Environmental Science and Pollution Research*, vol. 27, no. 16, pp. 19616–19629, 2020.
 - [13] T. S. Adebayo, M. T. Kartal, M. Aga, and M. A. S. Al-Faryan, “Role of country risks and renewable energy consumption on environmental quality: Evidence from MINT countries,” *Journal of Environmental Management*, vol. 327, art. no. 116884, 2023.
 - [14] J. A. Hausman, “Specification tests in econometrics,” *Econometrica*, vol. 46, no. 6, pp. 1251–1271, 1978.
 - [15] International Energy Agency, *CO₂ Emissions in 2022*. Paris, France: International Energy Agency, 2023.
 - [16] Intergovernmental Panel on Climate Change, *Climate Change 2022: Mitigation of Climate Change*. Cambridge, UK: Cambridge University Press, 2022.
 - [17] H. Ritchie, P. Rosado, and M. Roser, “Energy,” *Our World in Data*, 2023.
 - [18] United Nations, *The Sustainable Development Goals Report 2023*. New York, NY: United Nations, 2023.