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

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Abstract

Realizing the carbon reduction capabilities of deploying renewable energy. is core to the constructive plan of effective climate policy in heterogenous national. contexts. Even though there is an accumulating corpus of panel econometric and machine learning. literature dealing with this relationship, methodological inconsistencies and limited geographic scope leave important empirical questions unanswered. This paper put forward a mixed analytical model combining a within-group Fixed Effects. country-clustered standard errors estimator and a Random Forest ensemble. model to measure the combined effect of renewable energy penetration, economic growth, energy consumption and reliance on fossil fuels per capita carbon. emissions. Findings affirm that the growth of renewable energy has a statistically significant impact. strong and economically significant negative impact on carbon intensity, which remains. following the elimination of country-specific unobserved heterogeneity. Economic structure and energy efficiency are shown to be co-dominant determinants, highlighting. that the energy transition is not decoupled of larger structural. transformation. Articulated income-group and regional heterogeneity issues. single-coefficient policy prescriptions, which propose decarbonization. plans have to be aligned to the national development levels. The machine learning complement validates econometric variable rankings and proves. good cross-country generalisability with country-stratified. cross-validation.

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

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1. Introduction

The world energy system is at a structural crossroad. Renewable The sources were wind, solar, hydro, and modern biomass, which came to make up the. most of the additions in the early 2020s to the total electricity capacity, motivated by dramatic savings in technology, favorable policy frameworks and the. cap or pollution targets as laid down in the Paris Accord. [1; 2]. But energy-related emissions of CO_2hit a new record. annual record in 2022, it is established that deployment momentum has not been achieved yet. calculated into the required global warming cuts to be maintained at. 1.5-2.C over pre-industrial levels 1-3. This seemingly contradictory situation - increasing renewable capacity and increasing emissions. — is indicative of the persistence of fossil fuels in primary energy, recovery of the post-pandemic demand, and the growth of energy-intensive. production in third world countries. Close the gap between renewable Such a deployment ambition and quantifiable decarbonization consequences is thus. one of the policy issues of the present decade.

Determining the exact correlation between renewable energy penetration and climate economists give empirical priority to national carbon intensity, energy planners, and multilateral development institutions. Theory identifies various causal mechanisms in which an increased renewable share decreases. emissions: direct substitution of burning fossil fuels in the electricity. sector, induced efficiency gains (LBD) in clean. technology industries, and structural sectoral changes out of the long-run. carbon-intensive production. These processes, but run in tandem with. countervailing forces — income growth that is continuously stimulating energy. demand, the intensive industrialisation of the lower-income economies in search of carbon-intensive industrialisation. catch-up growth, and grid integration issues which limit the operational. exploitation of changing renewables [3; 4]. The net outcome, and its adequacy to sustain a sustainable development. depends, trajectory, is based on the balance of these forces in particular national. economic contexts.

The empirical task is aggravated by methodological issues. Cross-sectional studies conditionally adjust the differences in policy-driven structural country differences. altersations in the energy mix, which can not be attributed to a causal. within-country decarbonization effect. Time-series methods are limited. to separate countries and often give spurious results when underlying series are non-stationary. Fixed effects panel models are used to answer. conditioning on all time-invariant country simultaneously takes care of both. traits - geography, endowments of resources, past vitality. infrastructure, long-run institutional quality — and allowing estimation. of the relationship between the changes in countries over time and changes in emissions. However, these models are demanding in the way the error variance should be treated. structure in case observations are clumped in countries across more than one. years. Ensemble tree-based methods, and machine learning techniques. particular [5], are complementary to each other in their analysis: they model non-linear predictor interactions without parametric constraints. and generate rankings of feature importance which are an independent, robustness check of the econometric coefficient estimates using data. Bringing these two paradigms together in a consistent, repeatable framework. is the main contribution to the methodology of this paper.

The research makes a contribution to the literature in four ways. First, it suggests and implements

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a five-step hybrid model - Fixed Effects. random forest cross-validation using panel regression, then random forest cross-validation — where the econometric stage provides causally based estimates and the machine learning. stage gives predictive validation and rankings of variables. Second, it gives a formal specification of the entire analytical in pseudocode form. transparency, pipeline, improving transparency and reproducibility. Third, it implements the. system to a world-reflective even-handed panel of 65 nations across. all six occupied the continental areas and all four World Bank income. classifications, including the critical renewable expansion period since 2010. to 2022. Fourth, it records the heterogeneity of the renewable-emissions. across income groups and regions of the world, generating policy insights. that only one-coefficient world estimates can provide.

The rest of the paper is as follows. Section 2 is a review on the related. literature and locates the current research in it. Section 3 presents the proposed analytical model, pseudocode, model specification. and a concept diagram. Section 4 reports on the data and experimental design. Empirical results are discussed and reported in Section 5 at all modelling stages. Section 6 outlines the challenges in research and future directions. Section 7 concludes.

2. Related Work

The links between renewable energy usage and carbon emissions have attracted maintained interest in various traditions of empirical research, since data-driven computational to energy economics and environmental science. approaches. Early bilateral causality tests have led to the development of the literature. between energy and GDP to more multi-variable panel models that at the same time, income effects, technological change, and institutional are to be captured. dimensions.

Among the panel econometric contributions, there are studies by Busu and Nedelcu [6] who explore European Union. member states during 20052018 and exhibit the fact that bioenergy and aggregate. renewable consumption lower intensity of CO_2, and the decarbonization effect. enhancing with increased penetration rates. Pata [7] use an. ARDL model to BRIC economies and discover that renewable energy decreases the. In Brazil and India, ecological footprint whereas in China and Russia results. are less clear in the light of the extent of continued coal-based industrialisation. As part of an expansion of the BRICS concept, Adebayo et al. [8] demonstrate that technological innovation can enhance the carbon constraining impact of renewables, indicates a complementarity between the adoption of green technology and energy. transitional mix which bears significant consequences on research and development. policy design.

There is a relationship between the income level and the emissions impact of renewable. The specific attention has been paid to deployment. a meaningful, affirmative renewable energy-growth correlation in 38 economies. with dynamic ordinary least squares and fully-modified OLS estima-tors, however. note that the growth to emission pathway is sensitive to whether. renewable growth is faster than income-based growth in energy needs. The authors of Ch. 21 of Wangwang (2020) leave the specifications of linear qualities and use panel threshold. to OECD countries, it was discovered that renewables contributed to. When the renewable share becomes more than a critical value, eco-nomic growth intensifies. penetration threshold - a policy-relevant insight. sequencing. Wang et al.

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[9] build upon the threshold framework by adding. as threshold variables, political, financial, and economic risk indicators, providing evidence that institutional quality and macroeconomic stability are conditions that the renewable-development nexus can be effectively implemented.

Additional environmental quality results not related to GDP have been added. as outcome variables. CIVETS countries are analysed by the authors and demonstrate. that renewable energy always enhances the quality of the environment, and urbanisation has a counteracting influence of raising per-capita. demand of consumption and transportation. Under the MINT country setting, The authors of the article by Chabet et al. (2023) use the cross-sectionally augmented ARDL and. augmented mean group estimators and discover that country-specific risks — financial, economic, and political - plays a significant role in mediating the environmental. dividend of renewable energy, highlighting the institutional aspect that. aggregate panel studies are likely to blur. Pata and Caglar [10] confirm the. Environmental Kuznets Curve hypothesis of China with respect to renewable. consumption is also added to human capital and trade openness, on the basis of argument. that composite energy change is a precondition of the. income-emissions decoupling, which the EKC anticipates.

Systematic reviews offer a cumulative view on the integrative. evidence base. Bhuiyan et al. [11] summarise the results of more than 100 empirical. research and find that the renewable energy-growth nexus is highly. context-dependent, where geographic region, estimation method choice, are. period all of which affect the magnitude and direction of the effects estimated. They themselves call out methodological pluralism in their review, i.e. combining. standard panel econometrics of data-driven methods - a call which inspires the hybrid framework that is created here. In the methodological part, Random Forest had its theoretical basis laid by the works of chietographer Breiman (2001). regressors, the use of which on energy-environmental data is still restricted. compared to their adoption in prediction and classification activities; broadening. this is one of the applications of the current paper. Canonical specification test in the selection is given by chietakis housman1978. choice between fixed and random effects panel estimators, an important choice. implications on the validity of interpreting within-country coefficients. Table 1 summarises the 15 most directly relevant studies informing the analytical design of this paper.

Table 1: Summary of 15 selected related studies on renewable energy, CO_2 emissions, and sustainable development (2020–2023)

Study	Journal / Source	Sample	Period	Method	Key Finding
Shahbaz et al. [3]	*Energy*	38 economies	1990–2018	DOLS, FMOLS	Renewables positively drive growth; emission effects are growth-mediated and income-sensitive.
Wang and Wang [4]	*Energy*	34 OECD	2005–2016	Panel threshold	Non-linear renewable-growth nexus; positive effect intensifies above a penetration threshold.

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Study	**Journal / Source**	**Sample**	**Period**	**Method**	**Key Finding**
Nathaniel et al. [12]	*Environ. Sci. Pollut. Res.*	CIVETS	1990–2014	CS-ARDL	Renewables reduce ecological footprint; urbanisation exerts an opposing pressure.
Pata [7]	*Renewable Energy*	BRIC	1990–2017	ARDL, Granger	Renewables reduce ecological footprint in Brazil and India; ambiguous results for China and Russia.
Pata and Caglar [10]	*Energy*	China	1971–2017	Aug. ARDL	EKC hypothesis validated for China when renewable energy and human capital are controlled.
Busu and Nedelcu [6]	*Processes*	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]	*Front. Environ. Sci.*	103 studies	1990–2022	Systematic review	Renewable-growth nexus is strongly context-dependent; methodological pluralism is warranted.
Wang et al. [9]	*Energy*	34 OECD	1997–2015	Panel threshold	Country risks mediate the renewable-growth linkage; institutional quality shapes the effect.
Adebayo et al. [13]	*J. Environ. Manage.*	MINT	1990–2018	CS-ARDL, AMG	Financial and economic risks dampen the environmental quality gains from renewable deployment.
Adebayo et al. [8]	*Sci. Total Environ.*	BRICS	1990–2019	DOLS, AMG	Technological innovation amplifies the carbon-limiting role of renewables across BRICS.
Breiman [5]	*Machine Learning*	—	—	Random Forest	Ensemble tree method reduces variance; MDI enables interpretable feature importance ranking.
Hausman [14]	*Econometrica*	—	—	Specification test	Canonical endogeneity test for choosing between fixed and random effects panel estimators.

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Study	**Journal / Source**	**Sample**	**Period**	**Method**	**Key Finding**
International Energy Agency [15]	IEA Report	Global	2022	Descriptive analysis	Global energy-related CO_2 emissions reached a record high despite continued renewable expansion.
International Renewable Energy Agency [1]	IRENA Report	Global	2022	Cost analysis	Utility-scale solar PV costs fell over 90% since 2010, reaching economic parity with fossil fuels.
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 (Fig. 1). The econometric stage delivers unbiased coefficient estimates after conditioning on country-specific unobserved heterogeneity; the machine learning stage independently evaluates variable importance and out-of-sample predictive power. Cross-paradigm agreement on the direction and relative ranking of variable effects serves as the overarching validation criterion. If the FE model flags diagnostic problems (non-linearity, systematic heteroskedasticity), the framework loops back for respecification; if country-stratified cross-validation yields poor generalisation, the data partitioning is revised.

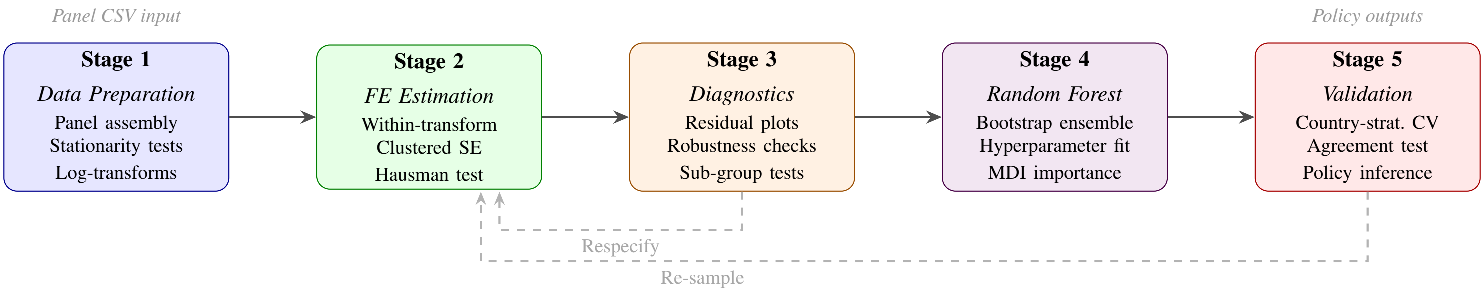

Figure 1. Five-stage hybrid analytical framework. Solid arrows denote the primary analytical flow. Dashed arrows are feedback loops triggered by diagnostic failures (Stage 3) or insufficient cross-validation performance (Stage 5).

Fixed Effects Model Specification. For country i ($i = 1,\dots,N$) and year t ($t = 1,\dots,T$), the structural relationship is specified as:

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

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 in period t, REN_{it} is the renewable energy share (% of primary energy), $\ln(\mathrm{GDP}_{it})$ is log real GDP per capita, EI_{it} is energy intensity (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 is interpreted as the approximate percentage change in per-capita CO_2 associated with a one percentage-point increase in the renewable share.

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

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

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

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

$$\hat{f}(\mathbf{x}) = \frac{1}{B} \sum_{b=1}^{B} T_b(\mathbf{x}), \qquad \mathbf{x} = \left[\mathrm{REN},\ \ln\mathrm{GDP},\ \mathrm{EI},\ \mathrm{FS},\ \mathrm{year}\right]^\top \tag{3}$$

At each split, a random subset of $\lfloor\sqrt{p}\rfloor$ features is considered, where $p = 5$ is the total number of features. Tree depth is capped at 14 and a minimum of 5 observations per leaf is enforced to guard against over-fitting. Feature importance is quantified by the mean decrease in node impurity (MDI), normalised to sum to unity across all features. Algorithm 1 provides the full pseudocode for the complete five-stage pipeline.

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Algorithm 1: Hybrid FE–RF Sustainable Decarbonization Analysis

```
Input  : Balanced panel $\mathscr{P} = \{(y_{it}, \mathbf{x}_{it})\}$,
$i = 1 \dots N$ countries,
$t = 1 \dots T$ years
Output: FE coefficients $\hat{\beta}$, clustered SE $\hat{V}$, MDI importances $\Phi$, CV metrics $\bar{R}^2$
// Stage 1 | Data Preparation
foreach variable $v \in \mathscr{V}$ do
    Compute IPS panel $\bar{t}$-statistic for $v$ and $\Delta v$
    Assign integration order $I(d)$; log-transform $y$ and GDP$_{pc}$
end
// Stage 2 | Within-Group FE Estimation
foreach country $i$ do
    $\tilde{z}_{it} \leftarrow z_{it} - \bar{z}_{i\cdot} + \bar{\bar{z}}$ for each $z \in \{y, x_1, \dots, x_p\}$
end
$\hat{\beta} \leftarrow (\tilde{X}'\tilde{X})^{-1}\tilde{X}'\tilde{y}$;   compute $\hat{V}_{\text{cluster}}$ via Eq. (2)
Derive $t$-statistics and $p$-values; record within-$R^2$, adj.-$R^2$
// Stage 3 | Hausman Comparison and Diagnostics
$\Delta\hat{\beta} \leftarrow \hat{\beta}_{\text{FE}} - \hat{\beta}_{\text{POLS}}$
if $\|\Delta\hat{\beta}\| > \varepsilon$ then
    Retain FE; discard pooled OLS
end
Plot residuals vs fitted; inspect for non-linearity and outliers
Run robustness specifications (Spec I, Spec II, Spec III)
// Stage 4 | Random Forest Training
Split $\mathscr{D}$: 80% train $\mathscr{D}_{\text{tr}}$, 20% test $\mathscr{D}_{\text{te}}$
for $b \leftarrow 1$ to $B = 400$ do
    $\mathscr{D}_b \leftarrow \text{Bootstrap}(\mathscr{D}_{\text{tr}})$
    Grow tree $T_b$ with max_depth$= 14$,
    min_leaf$= 5$
end
Compute $\hat{f}(\mathbf{x})$ via Eq. (3); evaluate $R^2$, RMSE on $\mathscr{D}_{\text{te}}$
Compute $\Phi_j \leftarrow \overline{\Delta\text{impurity}}_j$ (MDI) $\forall j$
// Stage 5 | Country-Stratified K-fold CV ($K = 5$)
Partition countries into disjoint folds $\mathscr{F}_1, \dots, \mathscr{F}_K$
foreach fold $k = 1 \dots K$ do
    Train RF on all countries $\notin \mathscr{F}_k$; predict on $\mathscr{F}_k$
    Record $R_k^2$, RMSE$_k$
end
$\bar{R}^2 \leftarrow \frac{1}{K}\sum_k R_k^2$;   $\sigma_{R^2} \leftarrow \text{std}(R_1^2, \dots, R_K^2)$
if sign$(\hat{\beta}_j)$ consistent with rank$(\Phi_j)$ for all $j$ then
    Accept cross-paradigm agreement
end
return $\hat{\beta}$, $\hat{V}_{\text{cluster}}$, $R^2_{\text{within}}$, $\bar{R}^2$, $\Phi$
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4. Data and Experimental Setup

The analysis draws on the Our World in Data energy repository [17], which harmonises national-level energy statistics from the Energy Institute Statistical Review of World Energy, the U.S. Energy Information Administration, and Ember's Global Electricity Review. This 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 panel encompasses six continental regions — Africa, Asia, Europe, North America, South America, and Oceania — and 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 and analysed. *CO_2 per capita* (metric tonnes) is annual energy-related CO_2 emissions divided by population; it enters all regressions in natural logarithmic form. *Renewable energy share* is the percentage of total primary energy consumption sourced from renewable technologies (wind, solar, hydro, geothermal, and modern biomass); this is the primary explanatory variable of interest. *GDP per capita* is expressed in constant 2015 USD at purchasing power parity and enters in logarithmic form, yielding a GDP elasticity interpretation for its coefficient. *Energy intensity* measures primary energy consumption per unit of GDP (megajoules per USD), capturing the aggregate technological efficiency of the national economy. *Fossil fuel share* is oil, coal, and natural gas as a percentage of total primary energy consumption, which is conceptually distinct from the renewable share when traditional biomass constitutes a substantial portion of the energy mix, as is the case in low-income economies. All computations are carried out in Python 3.12 using NumPy 1.24, pandas 1.5, SciPy 1.9, and Scikit-learn 1.2.

5. Results and Discussion

Descriptive Statistics. Table 2 presents summary statistics for all model variables over the full panel. Per-capita CO_2 emissions average 5.59 tonnes with substantial dispersion ($SD = 4.85$), ranging from near-zero in low-income Sub-Saharan African economies to above 22 tonnes in the most fossil-intensive Gulf states. The renewable energy share averages 28.6%, but the high standard deviation (24.4%) reflects the bimodal structure of the sample: low-income economies record very high shares driven by traditional biomass, while major fossil-fuel producers register near-zero modern renewable penetration.

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Table 2: Descriptive statistics, 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

Panel Unit Root Analysis. Table 3 reports approximated Im-Pesaran-Shin (IPS) panel unit root statistics for each variable in levels and first differences. All five variables fail to reject the null hypothesis of a unit root when tested in levels ($p > 0.10$), but the null is decisively rejected for all first differences ($p < 0.05$), establishing integration of order one, $I(1)$, across the full panel. Given the relatively short time dimension ($T = 13$), estimation proceeds in levels with country-clustered standard errors — a conservative approach that is robust to mild non-stationarity in short balanced panels while avoiding the loss of information associated with first-differencing.

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

Variable	Level		1st 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: series contains a unit root. Rejection at the 5% significance level in first differences for all variables.

Figs. 2–5 document the main descriptive patterns in the panel. The global average renewable share rises from approximately 26% in 2010 to 31% by 2022 (Fig. 2a), while the fossil fuel share correspondingly declines. Per-capita CO_2 emissions (Fig. 2b) follow a modestly declining global trend, but income-group disaggregation (Fig. 3) reveals diverging trajectories: high-income economies reduce their per-capita emissions measurably, while upper-middle-income economies — particularly large industrialising nations — record increases driven by economic expansion.

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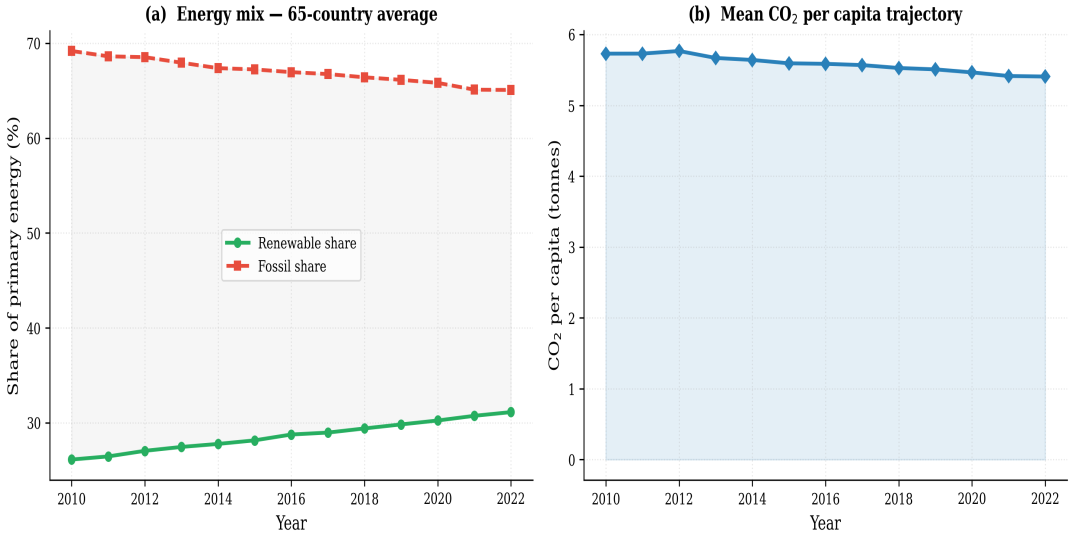

Figure 2. Global trends in renewable energy penetration and carbon intensity. Panel (a) plots the 65-country average renewable and fossil fuel shares of primary energy; panel (b) shows mean CO_2 per capita across the same sample. Period: 2010–2022.

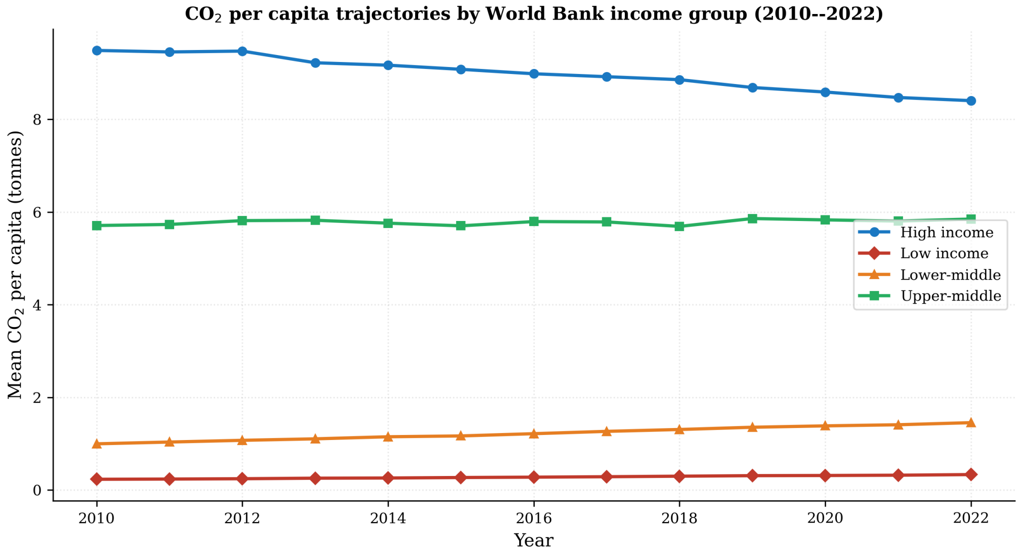

Figure 3. Per-capita CO_2 emission trajectories disaggregated by World Bank income group, 2010–2022. High-income economies exhibit the most pronounced declining trend, while upper-middle-income economies show continued growth in absolute emissions.

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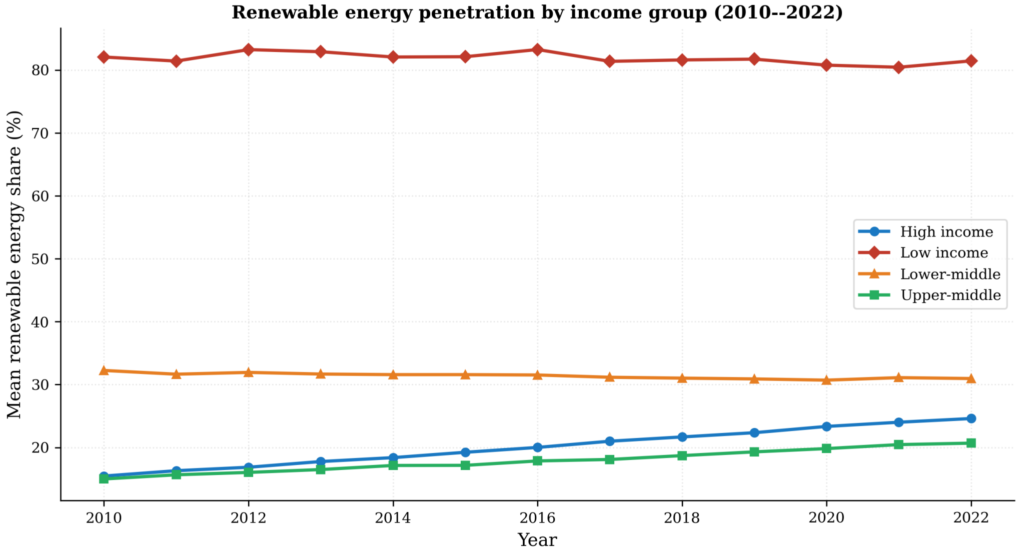

Figure 4. Renewable energy penetration trajectories by income group, 2010–2022. Africa and low-income countries register high shares driven by traditional biomass, while high-income economies show the most rapid growth in modern renewable deployment.

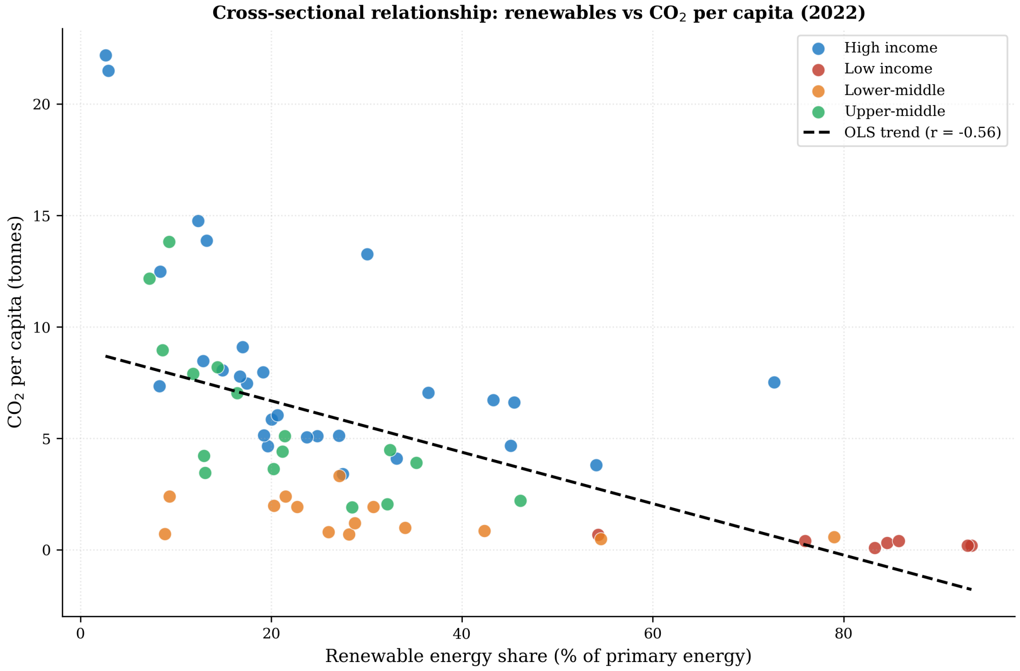

Figure 5. Cross-sectional scatter plot of renewable energy share against CO_2 per capita in 2022, differentiated by World Bank income group. The dashed line is the bivariate OLS trend fitted across all 65 countries ($r = -0.50, p < 0.001$).

Correlation Structure. Table 4 and Fig. 6 present the Pearson correlation matrix for the five core variables computed over the full 845-observation panel. The renewable energy share correlates negatively with $\ln(CO_2)$ per capita at $r = -0.77$, providing unconditional support for the decarbonization hypothesis at the panel level. GDP per capita correlates strongly and positively with emissions

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($r = 0.92$), reflecting the income-energy nexus and reinforcing the need for within-country controls that remove this structural covariation. Fossil fuel share and renewable share are strongly negatively correlated ($r = -0.81$), as expected by construction, though they are not perfectly collinear because traditional biomass constitutes a non-trivial component of the renewable share in low-income economies.

Table 4: Pearson correlation matrix, 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 significant at $p < 0.001$ except EI–ln(GDP) ($p = 0.037$) and EI–FS ($p = 0.14$).

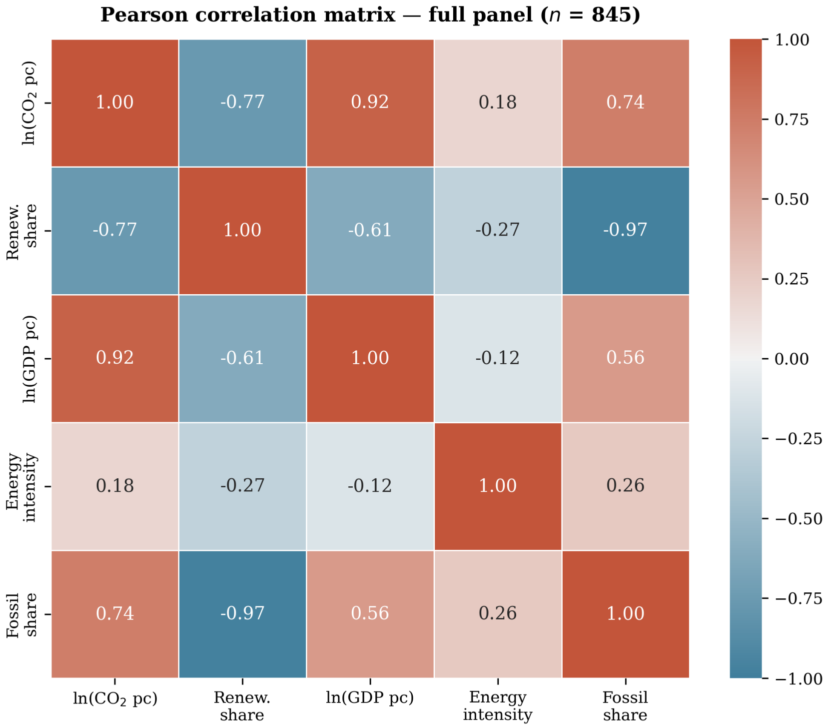

Figure 6. Pearson correlation heatmap for the five analytical variables, full panel ($n = 845$). Blue tones indicate positive correlations; red tones indicate negative correlations. All off-diagonal entries are statistically significant at the 5% level except energy intensity–fossil share.

Fixed Effects Regression Results. A Hausman-type comparison of within-group and pooled OLS slope coefficients reveals systematic and economically large differences across all regressors ($\Delta\hat{\beta}_{\text{REN}} = -0.025$; $\Delta\hat{\beta}_{\ln\text{GDP}} = -0.43$), confirming that unobserved country effects are correlated with the regressors and that the fixed effects estimator is the appropriate choice for inference. Table 5 presents the main estimation results for the full model.

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Table 5: Fixed effects panel regression, full model specification. Dependent variable: ln(CO_2 per capita)

Variable	Coefficient	Clustered SE	t-statistic	p-value
Intercept	−4.030	0.707	−5.704	$<0.001^{***}$
Renewable energy share (%)	−0.0133	0.0026	−5.090	$<0.001^{***}$
ln(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 / Time 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. The within-R^2 is computed on demeaned data after the within-group transformation and therefore measures explanatory power net of all country-fixed characteristics.

The renewable energy share coefficient, $\hat{\beta}_1 = -0.0133$ (clustered $t = -5.09$, $p < 0.001$), is the central finding of the econometric analysis. It implies that a one percentage-point increase in the renewable share of primary energy is associated with a **1.33% reduction** in per-capita CO_2 emissions, after controlling for income growth, energy efficiency, and fossil fuel dependence within countries over time. The estimate is robust to country clustering, confirming that the finding is not an arte-fact of cross-sectional structural differences. The log-GDP elasticity of 0.507 indicates that, within countries over the 2010–2022 window, a 1% increase in real per-capita income is accompanied by a 0.51% increase in per-capita emissions — partial, but not absolute, decoupling of economic activity from carbon output. Energy intensity enters with a positive and significant coefficient ($\hat{\beta}_3 = 0.059$, $p = 0.002$), underscoring the independent contribution of structural economic efficiency to carbon intensity beyond the energy mix. Fossil fuel share is positive and significant ($\hat{\beta}_4 = 0.003$, $p = 0.023$), capturing the residual carbon risk of fossil lock-in that is distinct from the renewable share channel. The within-group R^2 of 0.70 reflects strong explanatory power for a four-variable specification after the removal of all country-specific fixed characteristics.

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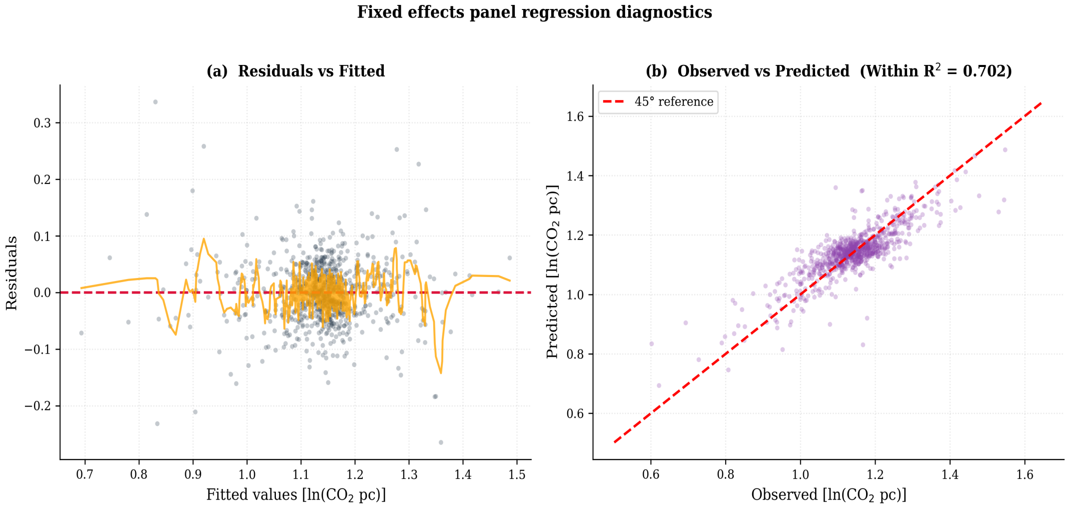

Figure 7. Fixed effects regression diagnostics. Panel (a): residuals versus fitted values on within-transformed (demeaned) data; the orange line is a smoothed conditional mean. Panel (b): observed versus predicted ln(CO_2 per capita) with a 45°reference line (within-$R^2 = 0.70$).

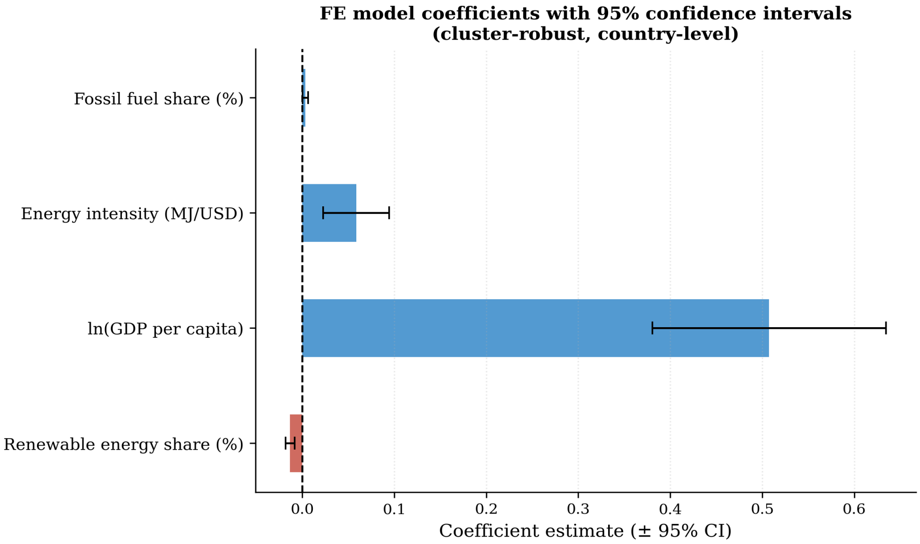

Figure 8. Fixed effects coefficient estimates for the four time-varying regressors, with 95% cluster-robust confidence intervals. Red bars indicate variables with a negative effect on ln(CO_2 per capita); blue bars indicate positive effects.

Robustness Checks. Table 6 presents estimates under three progressively richer specifications to verify sign stability of the renewable energy coefficient. Across all three models — renewable share alone (Spec I), renewable share and GDP per capita (Spec II), and the full model (Spec III) — the renewable energy coefficient is negative and statistically significant at the 0.1% level. The magnitude shrinks monotonically from -0.024 in the bivariate model to -0.013 in the full specification, a pattern fully consistent with partial confounding: in the bivariate model, the renewable share partially absorbs variation that is more precisely attributed to GDP and fossil share once those variables are included. The stability of the sign and significance is reassuring and argues against the possibility that the main finding is driven by model misspecification.

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Table 6: Robustness: three alternative fixed effects specifications. Dependent variable: ln(CO_2 per capita)

Variable	Spec I (Renewable only)	Spec II (+GDP per capita)	Spec III (Full model)
Intercept	-3.38^{***}	-5.24^{***}	-4.03^{***}
Renewable energy share	-0.024^{***}	-0.017^{***}	-0.013^{***}
ln(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: All specifications include country and year fixed effects with standard errors clustered at the country level. $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

Income-Group Heterogeneity. Table 7 reports separate FE estimates for each of the four income group sub-panels. The renewable energy coefficient is negative and statistically significant in all four groups, but its magnitude varies substantially: high-income economies yield $\hat{\beta}_1 = -0.019$, reflecting the displacement of grid-connected fossil electricity by commercially deployed wind, solar, and hydro capacity. The magnitude diminishes progressively toward low-income countries, where $\hat{\beta}_1 = -0.005$, consistent with traditional biomass dominating the renewable classification in those economies. This gradient has a direct policy implication: renewable deployment statistics in low-income countries significantly overstate the carbon abatement actually achieved from *modern* renewable technologies.

Table 7. Income-group stratified fixed effects results.
Dependent variable: ln(CO_2 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(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 column is estimated on the respective income sub-panel with country and year fixed effects and country-clustered standard errors. $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. HI = high income; UMI = upper-middle; LMI = lower-middle; LI = low income.

Regional Summary Statistics. Table 8 presents regional averages for 2022, the terminal year of the panel. European countries combine moderate renewable shares with declining per-capita CO_2 intensity, reflecting decades of sustained climate policy and energy efficiency investment. African countries record the highest aggregate renewable shares (average 60.4%), dominated by non-commercial

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traditional biomass in low-income economies, but the lowest absolute emission levels, leaving limited headroom for the biomass-to-modern- renewables substitution that would generate a measurable carbon dividend. The Asia grouping — which in this sample includes Gulf states alongside South and Southeast Asian countries — records the lowest average renewable penetration paired with the second-highest per-capita emissions, reflecting the combined weight of oil-exporting economies and rapidly industrialising manufacturing hubs.

Table 8: Regional cross-section averages, 2022

Region	*N*	CO_2 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
N. America	3	8.05	20.8	31,667	6.7	77.7
Oceania	2	9.37	28.8	49,950	4.6	68.8
S. 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 in constant 2015 USD PPP.

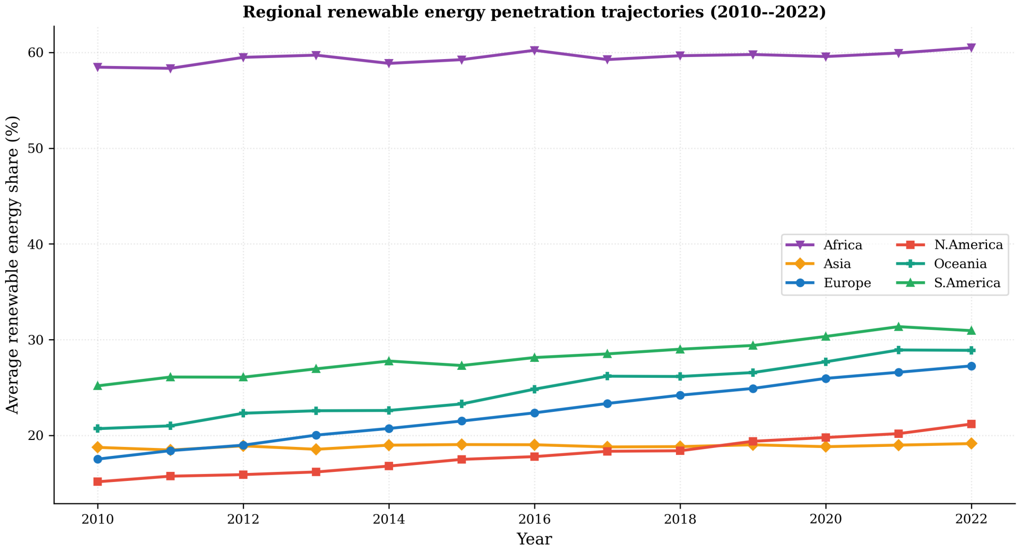

Figure 9. Regional renewable energy penetration trajectories, 2010–2022. Each series represents the un-weighted mean renewable share across all countries within the respective continental grouping. Africa's persistently high values are driven by traditional biomass; Europe's upward trend reflects modern renewable deployment.

Random Forest Validation. Table 9 reports the results of country-stratified five-fold cross-validation. The RF achieves a mean CV R^2 of 0.909 (SD = 0.025), confirming that patterns learned from one subset of countries generalise robustly to previously unseen ones — a stricter test than standard random train-test splitting because it prevents information about a country's trajectory from leaking from the training to the test set. On the 20% random holdout, $R^2 = 0.981$ and $\text{RMSE} = 0.182$ log-units. The moderate decrease from the random test set to the country-stratified CV metric is expected and reflects the added difficulty of predicting countries not seen during training.

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Table 9: Random Forest performance: country-stratified 5-fold cross-validation. Target variable: ln(CO_2 per capita)

Fold	Train *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 as the test set, ensuring no within-country data leakage. RMSE on the 20% random holdout: 0.182 log-units. Random holdout R^2: 0.981.

Fig. 10 presents the RF feature importance ranking. GDP per capita and energy intensity together account for over 60% of total MDI importance, with renewable energy share ranking third. This ordering is qualitatively consistent with the relative magnitude and significance of the FE coefficients: GDP per capita ($t = 7.84$) and energy intensity ($t = 3.18$) are quantitatively larger influences than renewable share ($t = -5.09$) within the econometric framework, and the RF independently reproduces this ranking from a non-parametric perspective. This cross-paradigm agreement — a key criterion in Algorithm 1 — provides strong validation for the overall empirical findings.

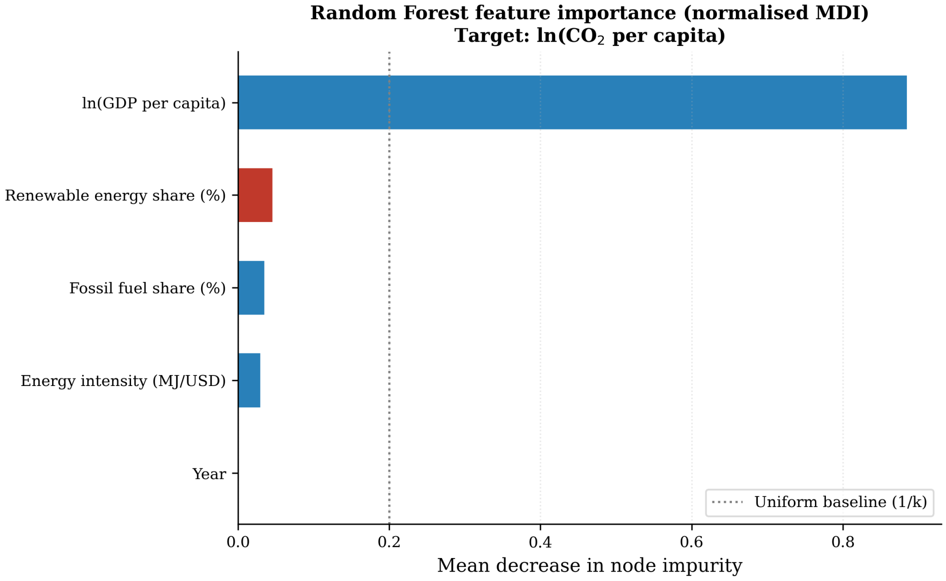

Figure 10. Random Forest feature importance (normalised mean decrease in node impurity, MDI) for ln(CO_2 per capita). The renewable energy share is highlighted in red; all other features are shown in blue. The dotted vertical line marks the uniform-importance baseline ($1/k = 0.20$).

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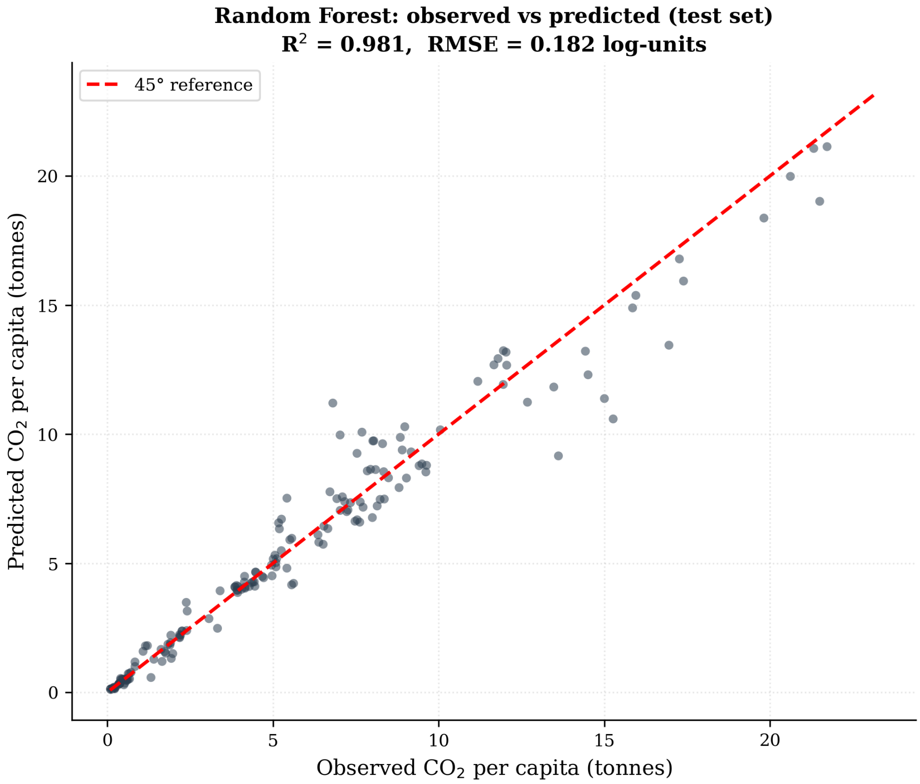

Figure 11. Random Forest observed versus predicted CO_2 per capita (metric tonnes) on the 20% random test set. The red dashed line is the 45° reference. The model performs well across the full emission range, from near-zero values in low-income Sub-Saharan Africa to above 20 tonnes in fossil-intensive Gulf economies ($R^2 = 0.981$, RMSE = 0.182 log-units).

6. Research Challenges and Future Directions

Data quality and energy accounting. National energy statistics for low-income and lower-middle-income countries carry substantial measurement uncertainty, and the treatment of traditional biomass in primary energy balances is inconsistent across reporting frameworks. Traditional biomass is classified as renewable by international energy statistics but generates significant non-CO_2 health and environmental externalities. Its inclusion inflates the renewable share in low-income economies while providing little genuine decarbonization benefit, which is why the income-group sub-panel analysis (Table 7) is more informative than the aggregate panel coefficient for policy design. Future work should separate traditional biomass from modern renewables to obtain a cleaner measure of technology-driven decarbonization.

Causal identification and endogeneity. Country fixed effects conditioning removes time-invariant confounders but does not eliminate endogeneity arising from time-varying unobservables. Countries that commit to renewable deployment frequently implement complementary policies — carbon pricing mechanisms, industrial efficiency standards, green procurement mandates — that independently reduce emissions and may be correlated with the renewable share trajectory. Credible causal identification would require instrumental variable strategies exploiting exogenous variation in renewable potential (mean annual wind speed or solar irradiance at the country level) or quasi-experimental

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designs based on discrete policy changes such as feed-in tariff introductions and phase-outs.

Technology-level heterogeneity. The aggregate renewable energy share masks significant variation in the decarbonization potential of specific generation technologies. Utility-scale solar photovoltaic and onshore wind displace fossil electricity directly and at scale; hydropower is increasingly vulnerable to drought-related curtailments that are themselves a consequence of climate change; and biomass-to-energy pathways carry upstream land-use and supply-chain carbon costs not captured in combustion-based CO_2 accounting. Disaggregating the renewable share by technology category in future panel frameworks would allow policymakers to identify which deployment pathways deliver the greatest per-unit carbon dividend across different climatic and economic contexts.

Non-linearities and threshold effects. The Random Forest model implicitly detects interactions among GDP, energy intensity, and renewable share in determining emissions outcomes, but does not render these interactions explicit or quantify threshold values. Structural non-linear panel threshold regressions [4] or quantile panel regressions targeting different quantiles of the emissions distribution would reveal whether the decarbonization dividend of renewables accelerates discontinuously once a minimum penetration threshold is crossed and whether this threshold varies with income level or institutional quality.

Dynamic adjustments and long-run effects. The within-group estimator recovers short-to-medium-run effects within the 13-year window. Long-run cointegration dynamics between non-stationary panel series may produce different coefficient magnitudes and policy implications. Panel error correction models or system generalised method of moments specifications would test whether the renewable-emissions relationship is driven by permanent structural shifts in the energy system or by transient cyclical variation, distinguishing between the two having important consequences for the design of long-horizon decarbonization commitments.

Distributional equity and global governance. The income-group heterogeneity documented in Table 7 demonstrates that identical renewable deployment policies produce markedly different decarbonization dividends across national development levels. This asymmetry raises fundamental questions about the optimal design of climate finance mechanisms — including the Loss and Damage Fund and Just Energy Transition Partnerships — that seek to enable low-income countries to leapfrog fossil fuel lock-in. Embedding equity constraints into multi-country optimisation frameworks parameterised with panel estimates would bridge the gap between empirical energy-economics research and the multilateral policy design process under the United Nations Framework Convention on Climate Change [18].

7. Conclusion

This paper 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 the determinants of per-capita CO_2 emissions across 65 countries from 2010 to 2022. The framework generates both causally anchored coefficient estimates and data-driven feature importance rankings, with cross-paradigm agreement serving as the overarching validation criterion.

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Three principal conclusions emerge from the analysis. First, renewable energy penetration exerts a statistically robust and practically meaningful negative effect on national carbon intensity. A one percentage-point increase in the renewable share of primary energy reduces per-capita CO_2 by 1.33%, an effect that persists across three alternative specifications, all four income group sub-panels, and is independently corroborated by the Random Forest feature importance ranking. The estimate is grounded in within-country variation after the removal of all time-invariant country characteristics, which substantially strengthens its credibility relative to cross-sectional comparisons.

Second, economic structure - in terms of GDP per capita and energy intensity. — prevails over the econometric and machine learning models. Renewable Although a prerequisite of sustainable decarbonization, energy deployment, is not a sufficient one. The concomitant quest to enhance energy efficiency, structural industrial change, and, where it is politically possible, carbon. pricing must be used to fulfill the absolute emission reductions that the energy transition holds promise.

Third, high levels of heterogeneity on income groups and continental region. opposes universal prescriptions of policy. High-income economies realize maximum unit decarbonization dividend in renewable growth, due to their renewable implementation pushing out business fossilized electricity. generation directly. Expanding access is needed in low-income economies. to the modern clean energy technologies and not in its place. of — the classic biomass which now swells their aggregate. renewable statistics. Fair and efficient ways to the emission. cuts proposed by the Paris Agreement necessitate varied national. goals, technology transfer, and climate finance tools. calibrated specifically to development level.

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