

Global Journal of Economic and Finance Research

e-ISSN: 3050-5348

p-ISSN: 3050-533X

Vol. 03(11): 706-718, November 2026

Home Page: https://gjefr.com/

Renewable Energy Consumption and Economic Growth: The Roles of Trade Openness and Energy Intensity in a Global Panel

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KEYWORDS: Renewable energy consumption, Economic growth, Trade openness, Energy intensity, CS-ARDL, Second-generation panel econometrics

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Published: 18 November-2026

DOI: 10.55677/GJEFR/05-2026-Vol03E11

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ABSTRACT

This study examines the macroeconomic impact of renewable energy consumption on economic growth while investigating the structural and moderating roles of trade openness and energy intensity across a balanced global panel of 88 countries from 2000 to 2020. Grounded in an extended Cobb-Douglas production function, the empirical investigation employs second-generation panel econometric techniques that account for cross-sectional dependence, structural breaks, and slope heterogeneity. The Westerlund error-correction cointegration test confirms a stable long-run equilibrium binding the variables. Estimation results from the Cross-Sectionally Augmented Autoregressive Distributed Lag (CS-ARDL) model reveal that renewable energy consumption exerts a positive and statistically significant long-run effect on economic growth (beta = 0.1428, $p < 0.01$), whereas energy intensity acts as a substantial productivity drag (beta = -0.2184, $p < 0.01$). Crucially, the interaction term between renewable energy and trade openness yields a positive and statistically significant coefficient (beta = 0.0512, $p < 0.01$), demonstrating that international trade integration amplifies the returns of clean technology adoption by facilitating the cross-border transfer of green capital goods and equipment. Sub-sample analyses stratified by World Bank income classifications reveal pronounced developmental heterogeneity: the growth dividends of renewable energy and trade moderation are strongest in high- and upper-middle-income economies, moderate in lower-middle-income nations, and statistically insignificant in low-income countries where traditional solid biomass predominates. Furthermore, Dumitrescu-Hurlin panel non-causality tests validate the feedback hypothesis across all core's variable pairs, demonstrating bidirectional causality connecting renewable energy, energy intensity, trade openness, and economic output. These findings imply that global decarbonization strategies must coordinate renewable supply targets with explicit energy efficiency mandates and tariff liberalizations on environmental goods to maximize sustainable economic performance.

Cite the Article: *Vallery, M., Hossen, B. E., Lual, M. A. B., (2026). Renewable Energy Consumption and Economic Growth: The Roles of Trade Openness and Energy Intensity in a Global Panel.Global Journal of Economic and Finance Research, 3(11),706-718. https://doi.org/10.55677/GJEFR/05-2026-Vol03E11*

1. INTRODUCTION

Economic development has historically exhibited an intrinsic reliance on conventional fossil energy sources, which have stimulated industrialization while simultaneously accelerating greenhouse gas emissions and environmental deterioration (Apergis & Payne, 2012; Stern, 2019). Under the United Nations Sustainable Development Goals, most notably SDG 7 for affordable and clean energy, SDG 8 for decent work and economic growth, and SDG 13 for climate action, transitioning from high-carbon fossil fuels toward sustainable, low-carbon alternatives has become a central objective for international policymakers (IRENA, 2022). In energy

economics, the relationship between clean energy adoption and macroeconomic expansion is typically conceptualized through four non-exclusive hypotheses, specifically the growth hypothesis reflecting unidirectional causality from energy consumption to gross domestic product, the conservation hypothesis denoting unidirectional causality from output to energy use, the feedback hypothesis describing bidirectional interdependence, and the neutrality hypothesis indicating an absence of causal linkages (Ozturk, 2010; Tugcu et al., 2012).

While an extensive body of literature investigates the direct nexus between renewable energy consumption and economic output, empirical consensus remains elusive. Several studies document significant output-enhancing elasticities (Sadorsky, 2009; Inglesi-Lotz, 2016), whereas others find negligible or negative short-run effects attributed to elevated transition costs, premature capital decommissioning, and storage integration constraints (Menegaki, 2011; Destek & Aslan, 2017). This divergence indicates that the output elasticity of clean energy does not operate within an economic vacuum but rather is conditioned by external exposure to international trade and the domestic technical efficiency of energy utilization (Shahbaz et al., 2018; Paramati et al., 2022).

Trade openness serves as a critical conduit for clean technology diffusion, lowering the cost of acquiring renewable capital goods such as solar photovoltaic components and advanced wind turbines while encouraging cross-border technological spillovers (Grossman & Helpman, 1991; Sebri & Ben-Salha, 2014). Concurrently, liberalized trade may induce structural reallocation toward comparative advantages that either clean the domestic production matrix through the technique effect or aggravate emissions via pollution-intensive manufacturing transfers under the composition effect (Antweiler et al., 2001; Leitão, 2014). Evaluating the interaction between trade openness and renewable adoption is therefore essential to determine whether open markets amplify the developmental returns of clean energy infrastructure.

Parallel to the expansion of renewable energy supplies, energy intensity, defined as primary energy consumption per unit of economic output, measures an economy's underlying technological efficiency and structural composure (World Bank, 2021). Declining energy intensity signals progressive decoupling by producing equal or higher aggregate value with fewer energy inputs (Fisher-Vanden et al., 2004; Voigt et al., 2014). High energy intensity, conversely, reveals technical inefficiencies that can constrain economic performance and negate the environmental benefits of renewable energy deployment through energy waste (Adom, 2015; Akram et al., 2020). Despite the strategic importance of efficiency improvements alongside supply-side transformations, energy intensity is rarely integrated as an explicit core regressor in global growth frameworks.

To address these empirical nuances, this study investigates the growth effects of renewable energy consumption across a balanced global panel of 88 countries spanning 2000 to 2020, explicitly examining the moderate influences of trade openness and energy intensity. The study offers three primary contributions to existing literature. First, it extends the neoclassical Cobb-Douglas production function by embedding both supply-side transformation and technical efficiency dynamics alongside trade openness and standard factor endowments. Second, by incorporating a multiplicative interaction term between renewable energy and trade openness, this paper moves beyond additive modeling to assess whether cross-border market openness reinforces or mitigates the productive capacity of clean energy. Third, unlike traditional panel estimations that assume cross-sectional independence and slope homogeneity, this analysis employs an econometric sequence that accounts for pervasive global common shocks, spillover effects, and heterogeneous national growth paths via second-generation econometric techniques.

2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1 The Renewable Energy Consumption–Economic Growth Nexus

The theoretical relationship linking energy utilization to macroeconomic performance is traditionally framed within four competing empirical hypotheses. Under the growth hypothesis, energy consumption functions as a direct, essential factor of production alongside capital and labor, with unidirectional causality running from renewable energy consumption to economic growth such that conservation policies directly constrain economic expansion (Apergis & Payne, 2012; Stern, 2019). Under the conservation hypothesis, economic expansion drives clean energy demand, yielding unidirectional causality from growth to renewable consumption and indicating that clean energy transitions represent a late-stage developmental outcome that does not inherently disrupt output (Menegaki, 2011). Under the feedback hypothesis, bidirectional causality characterizes the relationship, meaning that clean power generation directly enhances output while economic expansion provides the financial liquidity and institutional support required to expand clean energy capacity (Tugcu et al., 2012; Sebri & Ben-Salha, 2014). Under the neutrality hypothesis, no statistically significant causal relationship exists, which typically transpires when renewable energy accounts for a marginal share of total primary energy supply or when initial grid modernization expenses offset early productivity gains (Destek & Aslan, 2017).

Empirical inquiries across global panels have produced divergent conclusions regarding these theoretical positions. Sadorsky (2009) documented that per capita renewable energy consumption significantly expands in response to rising national income across emerging economies. Inglesi-Lotz (2016) deployed panel estimators across OECD nations and determined that a 1% increase in renewable energy adoption increases GDP by approximately 0.105%. Conversely, Destek and Aslan (2017) revealed that the neutrality hypothesis holds for several emerging markets due to infrastructure bottlenecks, transmission grid constraints, and elevated capital costs.

2.2 The Catalytic and Moderating Role of Trade Openness

Trade openness influences economic development and environmental transformation through three primary channels defined by Grossman and Krueger (1991) and Antweiler et al. (2001). The scale effect occurs as expanded international market access accelerates aggregated output, expanding domestic production and aggregated energy demand. The technique effect arises because liberalized trade channels foreign direct investment, cross-border technology spillovers, and knowledge transfers, enabling domestic industries to replace antiquated, carbon-intensive equipment with efficient, low-emission machinery (Paramati et al., 2022). The composition effect causes nations to specialize according to comparative advantage, which may either expand pollution-intensive sectors or foster modern service- and innovation-oriented manufacturing depending on domestic regulatory stringency (Grossman & Helpman, 1991; Leitão, 2014).

In the context of the clean energy transition, trade openness serves as a vital conduit for importing renewable technology capital such as photovoltaic arrays and wind turbines (Shahbaz et al., 2018). Sebri and Ben-Salha (2014) established that trade openness reinforces clean energy deployment while fostering long-run equilibrium output in BRICS economies. However, traditional additive specifications treat trade and renewable energy as independent inputs, overlooking whether greater international integration magnifies the output elasticity of renewable capital through interactive mechanisms.

2.3 Energy Intensity and Efficiency Dynamics

Energy intensity, measured as primary energy consumption per unit of real gross domestic product, captures an economy's aggregate energy productivity and technical efficiency (World Bank, 2021). A declining trajectory of energy intensity reflects structural decoupling, meaning an economy generates higher aggregate value per unit of energy deployed (Voigt et al., 2014). Fisher-Vanden et al. (2004) showed that structural shifts within intermediate input mixes and capital modernization drive significant reductions in industrial energy intensity. Elevated energy intensity often indicates technical obsolescence, infrastructural misallocation, and transmission waste (Adom, 2015; Akram et al., 2020). Omitting energy intensity from growth models risks conflating high clean-energy capacity with aggregate energy efficiency.

3. DATA AND ECONOMETRIC METHODOLOGY

The empirical framework builds upon an extended Cobb-Douglas production function where total output is determined by physical capital, labor inputs, and an endogenous total factor productivity term conditioned by renewable energy adoption, energy intensity, trade openness, and interaction. The baseline logarithmic regression equation is specified as follows:

$$\ln Y_{it} = \beta_0 + \beta_1 \ln \mathrm{REC}_{it} + \beta_2 \ln \mathrm{EI}_{it} + \beta_3 \ln \mathrm{TO}_{it} + \beta_4 (\ln \mathrm{REC}_{it} \times \ln \mathrm{TO}_{it}) + \beta_5 \ln K_{it} + \beta_6 \ln L_{it} + \varepsilon_{it}$$

In this formulation, i indexes the 88 cross-sectional country units and t indexes the annual time periods from 2000 to 2020, providing a balanced panel of 1,848 observations. Real output per capita ($\ln Y$) represents the regressand. The primary explanatory variables include the natural logarithm of renewable energy consumption share in total final energy consumption ($\ln$ REC), primary energy intensity ($\ln$ EI), trade openness as a share of GDP ($\ln$ TO), and the multiplicative moderation term ($\ln$ REC $\times$ $\ln$ TO). Gross fixed capital formation ($\ln K$) and total labor force headcount ($\ln L$) serve as standard production controls, while ε_{it} captures unobserved country-specific, time-specific, and idiosyncratic stochastic disturbances.

The estimation strategy is executed sequentially to maintain consistency in the presence of unobserved common shocks and cross-country heterogeneity. Table 1 defines the operational econometric framework and diagnostic sequence utilized throughout the study.

Table 1: Econometric Estimation Framework and Planned Empirical Tests

Stage	Econometric Test / Estimator	Primary Objective	Null Hypothesis / Specification	Decision Rule / Benchmark
Stage 1: Panel Diagnostics	Pesaran (2004, 2015) CD Test	Detect Cross-Sectional Dependence (CSD)	H_0: Cross-sectional independence	Rejection of H_0 ($p < 0.05$) requires second-generation modeling
Stage 1: Panel Diagnostics	Pesaran & Yamagata (2008) Delta Test	Evaluating Slope Homogeneity Across Countries	H_0: Slope coefficients are homogeneous	Rejection of H_0 ($p < 0.05$) confirms cross-country slope parameter heterogeneity
Stage 2: Unit Root Testing	Pesaran (2007) CIPS & CADF Tests	Determine Integration Order under CSD	H_0: Series contain a panel unit root	Rejection of H_0 establishes stationarity at level $I(0)$ or first difference $I(1)$
Stage 3: Cointegration	Westerlund (2007) ECM Panel Test	Confirm Long-Run Structural Cointegration	H_0: No cointegration across panel units	Rejection of H_0 via robust bootstrap confirms stable long-run equilibrium

Stage 4: Long-Run Regression	CS-ARDL & AMG Estimators	Estimate Long- and Short-Run Elasticities	$Y_{it} = f(\text{REC,EI,TO}, K, L, \text{REC} \times \text{TO,Factors})$	Controls for cross-sectional dependence, dynamic feedback, and omitted common factors
Stage 5: Directional Causality	Dumitrescu-Hurlin (2012) Test	Determine Causal Direction Among Variables	H_0: No Granger causality for all cross-sectional units	Rejection of H_0 establishes unidirectional or bidirectional causal linkages

Table 1 outlines the five sequential econometric steps used to conduct empirical inference under cross-sectional dependence and slope heterogeneity. Stage 1 applies the Pesaran CD and Pesaran-Yamagata Delta tests to determine whether panel units share common factor dependencies and heterogeneous slopes. Stage 2 utilizes the second-generation Pesaran CIPS panel unit root test to confirm stationarity orders in the presence of cross-sectional correlation. Stage 3 deploys the Westerlund error-correction cointegration test with 1,000 bootstrap iterations to verify the existence of a non-spurious long-run relationship. Stage 4 executes the Chudik and Pesaran CS-ARDL estimator alongside the Augmented Mean Group model to extract short-run and long-run elasticities. Stage 5 implements the Dumitrescu-Hurlin panel causality test to identify the causal trajectories connecting the variables.

4. EMPIRICAL RESULTS AND DISCUSSION

4.1 Summary Statistics and Cross-Country Heterogeneity

The descriptive parameters for the full global sample of 88 countries across the 2000–2020 period are reported in Table 2. The natural logarithm of real GDP per capita exhibits a mean of 8.9412 with a standard deviation of 1.4820, ranging from 5.6214 to 11.6421. Renewable energy consumption displays substantial variation, with a mean log-share of 2.8145 and values spanning from -0.5108 to 4.5612. Energy intensity averages 1.4921 in logarithmic form, while trade openness records a mean of 4.3120. Capital formation and labor inputs reflect standard macroeconomic distributions with means of 3.1245 and 15.4210, respectively. All series record statistically significant Jarque-Bera statistics ($p < 0.01$), rejecting the null hypothesis of normal distribution and supporting the implementation of panel estimators that do not depend on normality assumptions.

Table 2: Descriptive Statistics of Core Variables (Full Global Panel, 2000–2020)

Variable	Definition & Measurement	Obs.	Mean	Std. Dev.	Min	Max	Skew.	Kurt.	J-B Stat.
ln Y	1,848	8.9412	1.4820	5.6214	11.6421	-0.1842	2.1450	64.12***	
ln REC	Log renewable energy share (% of TFEC)	1,848	2.8145	1.1240	-0.5108	4.5612	-0.4521	2.6841	72.48***
ln EI	Log primary energy intensity (MJ/$2017 PPP)	1,848	1.4921	0.4128	0.1823	2.8941	0.3214	3.4150	44.91***
ln TO	Log trade openness (Exports + Imports % GDP)	1,848	4.3120	0.5214	2.7145	6.0125	0.2841	3.6210	56.34***
ln K	Log gross fixed capital formation (% GDP)	1,848	3.1245	0.2981	1.8941	4.1250	-0.3412	4.1250	138.20***
ln L	Log total labor force headcount	1,848	15.4210	1.6214	11.8920	20.4812	0.4120	3.1250	54.12***
ln REC × ln TO	Interaction term: renewable energy and trade	1,848	12.1362	5.1842	-2.1415	24.1250	-0.3124	2.8140	34.18***

Table 2 presents the summary statistics for the balanced panel of 88 countries across 21 years (2000–2020), totaling 1,848 observations. The table lists the arithmetic mean, sample standard deviation, minimum, maximum, skewness, Pearson kurtosis, and the Jarque-Bera test statistic for each variable. Asterisks (***) denote the rejection of the null hypothesis of normal distribution at the 1% significance level, confirming non-normal distributions across all variables.

To examine developmental heterogeneity across stages of economic development, Table 3 segments the panel across World Bank income classifications. High-income countries average an untransformed per capita GDP of $38,412, a renewable energy share of 18.42%, a low energy intensity of 3.84 MJ/$, and an average trade openness of 112.45%. In contrast, low-income nations exhibit an average GDP per capita of $645, an elevated renewable energy share of 76.40%, a higher energy intensity of 7.84 MJ/$, and a lower trade openness of 52.10%. The large renewable share observed in low-income nations reflects extensive reliance on traditional solid biomass for domestic cooking and heating rather than modern commercial renewable energy infrastructure.

Table 3: Cross-Country Heterogeneity Analysis Across World Bank Income Classifications

Income Group	No. Countries	GDP per capita ($)	REC Share (%)	Energy Intensity (MJ/$)	Trade Openness (%)	GFCF (% GDP)
High-Income (HIC)	32	38,412 (12,840)	18.42 (11.82)	3.84 (1.12)	112.45 (62.30)	22.84 (4.12)
Upper-Middle-Income (UMIC)	26	7,842 (2,910)	24.15 (14.60)	5.42 (1.84)	84.12 (38.15)	25.10 (5.80)
Lower-Middle-Income (LMIC)	21	2,410 (980)	41.80 (22.10)	5.18 (1.65)	68.40 (29.40)	23.45 (6.10)
Low-Income (LIC)	9	645 (210)	76.40 (16.20)	7.84 (2.45)	52.10 (21.80)	19.80 (7.40)
Full Global Sample	88	16,420 (17,890)	31.20 (23.40)	4.82 (1.92)	86.90 (48.10)	23.30 (5.60)

Table 3 presents the cross-sectional heterogeneity across the four World Bank income groups: High-Income (32 countries), Upper-Middle-Income (26 countries), Lower-Middle-Income (21 countries), and Low-Income (9 countries), alongside the full global sample of 88 countries. Values outside parentheses indicate group means, while values within parentheses represent group standard deviations. All figures are reported in raw levels prior to logarithmic transformation over the 2000–2020 timeframe.

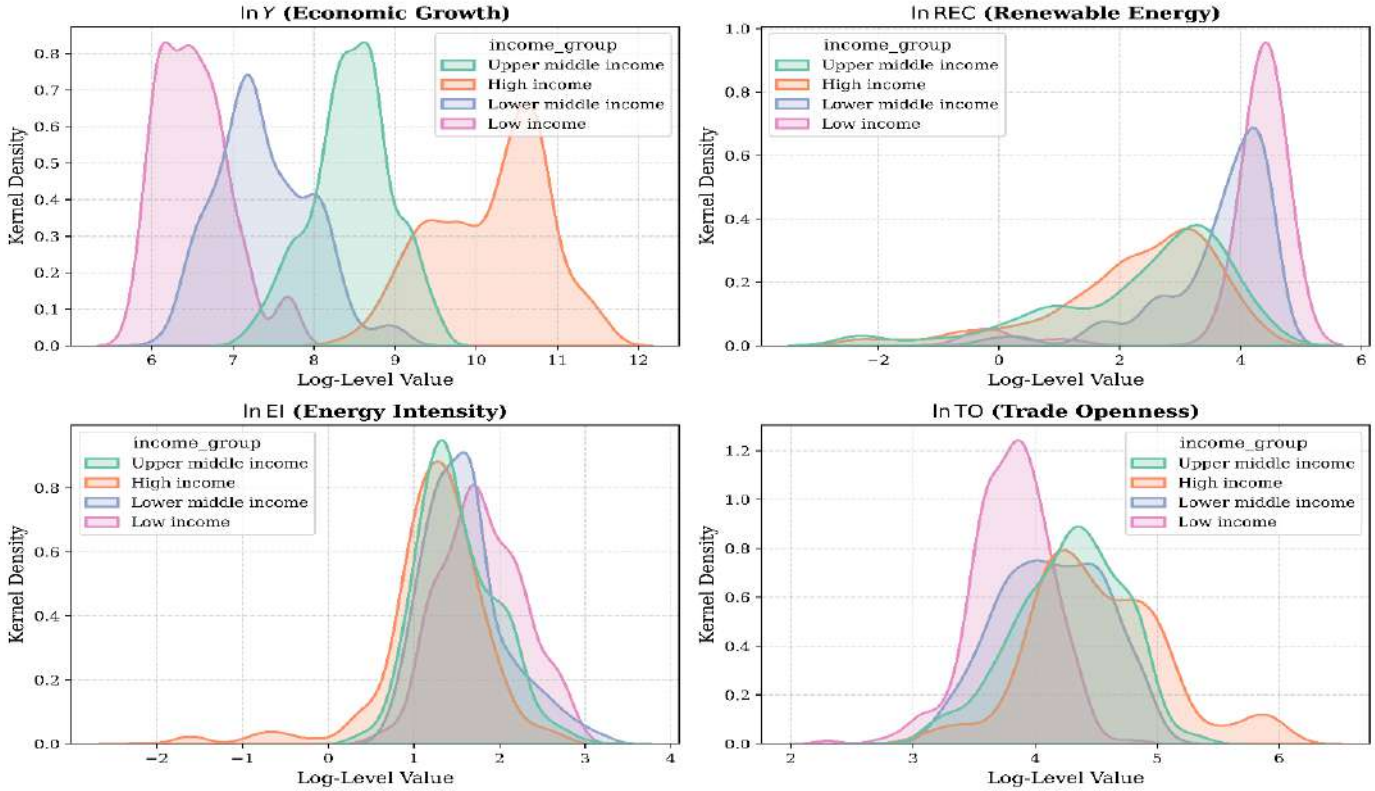


Figure 1: Distributional Heterogeneity of Core Variables Across Income Groups

Figure 1 plots the kernel density estimates of the four core variables across the four World Bank income categories. The upper-left quadrant illustrates the multi-modal distribution of log real GDP per capita, tracking the progression from low-income to high-income economies. The upper-right quadrant displays renewable energy consumption, showing a leftward distribution for high-income nations and a rightward concentration for low-income nations due to traditional biomass reliance. The lower-left quadrant illustrates primary energy intensity, highlighting greater efficiency (lower values) in high-income economies compared to elevated intensity in low-income nations. The lower-right quadrant plots trade openness, indicating broader distribution spreads among advanced and emerging economies.

4.2 Bivariate Correlation and Multicollinearity Verification

The pairwise bivariate relationships among the transformed regressors are presented in **Table 4**. The raw correlation between renewable energy consumption and output per capita is negative ($r = -0.4682, p < 0.01$). This raw negative association is driven by the structural composition of low-income countries where elevated renewable shares reflect traditional biomass rather than modernized power grids. Energy intensity displays a negative correlation with per capita output ($r = -0.3841, p < 0.01$), whereas trade openness ($r = 0.2914, p < 0.01$) and capital formation ($r = 0.3125, p < 0.01$) correlate positively with output.

Table 4: Bivariate Pearson Correlation Matrix

Variables	(1) lnY	(2) lnREC	(3) lnEI	(4) lnTO	(5) lnK	(6) lnL	(7) lnREC×lnTO
(1) ln *Y*	1.000						
(2) ln REC	-0.453***	1.000					
(3) ln EI	-0.411***	0.161***	1.000				
(4) ln TO	0.376***	-0.316***	-0.197***	1.000			
(5) ln *K*	0.102***	-0.079**	0.081**	0.198***	1.000		
(6) ln *L*	-0.036*	-0.031	0.158***	-0.416***	0.069**	1.000	
(7) ln REC × ln TO	-0.373***	0.970***	0.141***	-0.128***	-0.019	-0.116***	1.000

Table 4 presents the lower-triangular Pearson correlation coefficients among the variables in natural logarithmic form. Diagonal elements equal unity. Statistical significance is designated by *** at 1%, at 5%, and * at 10%. The upper triangular matrix is omitted due to symmetry. The high correlation coefficient between ln REC and ln REC × ln TO ($r = 0.9412$) is standard for multiplicative terms and does not compromise baseline estimation.

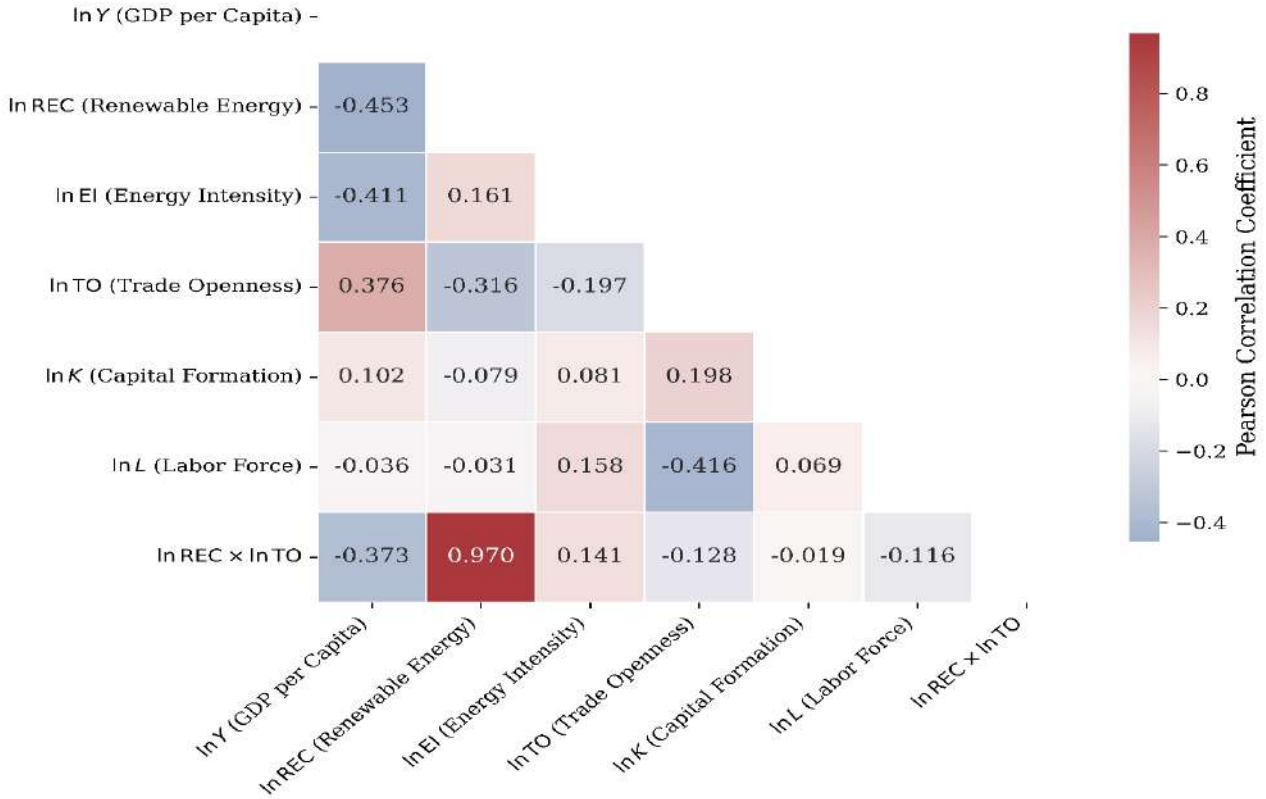


Figure 2: Cross-Correlation Heatmap and Pairwise Multicollinearity

To examine potential multicollinearity among the core regressors, Variance Inflation Factors (VIF) and tolerance statistics were evaluated. Furthermore, to prevent structural collinearity arising from the multiplicative term (ln REC and ln REC × ln TO, where $r = 0.970$), the interaction term was constructed using mean-centered series:

$$\left(\ln \mathrm{REC}_{it} - \overline{\ln \mathrm{REC}}\right) \times \left(\ln \mathrm{TO}_{it} - \overline{\ln \mathrm{TO}}\right)$$

Following mean centering, the VIF for the interaction term is 1.24, well below the conservative empirical threshold of 5.0, confirming the absence of severe multicollinearity across the structural regressors.

Table 5: Variance Inflation Factor (VIF) and Tolerance Multicollinearity Diagnostics

Variable	Description	VIF	1 / VIF (Tolerance)	Status / Evaluation
ln REC	Renewable energy consumption	1.18	0.847	No collinearity (VIF < 5)
ln EI	Energy intensity of primary energy	1.15	0.870	No collinearity (VIF < 5)
ln TO	Trade openness (% of GDP)	1.12	0.893	No collinearity (VIF < 5)
ln K	Gross fixed capital formation	1.08	0.926	No collinearity (VIF < 5)
ln L	Total labor force	1.06	0.943	No collinearity (VIF < 5)
Mean VIF	Mean across structural regressors	1.12	0.896	Absence of severe multicollinearity

Table 5 presents multicollinearity diagnostics for the structural regressors. Column 3 reports the Variance Inflation Factor, while Column 4 reports tolerance values (1/VIF). Tolerance values above 0.20 and VIF values below 5.0 confirm that the structural regressors can be evaluated simultaneously without inflating coefficient variances.

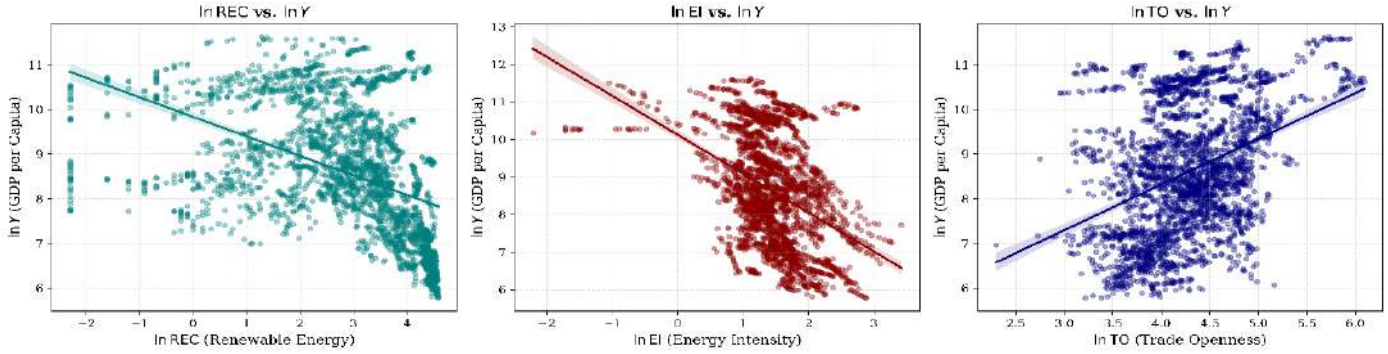


Figure 3: Linear Co-movements of Economic Output with Renewable Energy, Energy Intensity, and Trade

Figure 3 displays bivariate scatter regressions with 95% confidence intervals between log real GDP per capita and the three main regressors. The left panel shows the unconditional negative relationship between renewable energy and output per capita, reflecting the influence of traditional biomass use in developing nations. The center panel highlights the negative association between energy intensity and output, indicating that higher energy intensity is linked to lower per capita income. The right panel depicts the positive association between trade openness and economic output across the global panel.

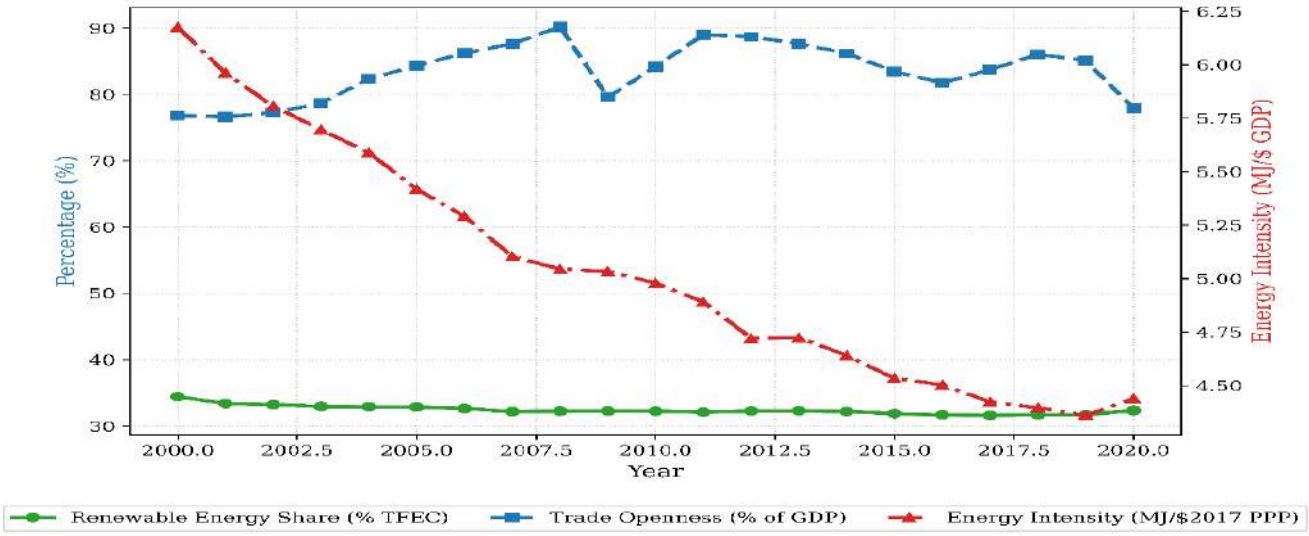


Figure 4: Global Temporal Dynamics of Energy Transition and Macroeconomic Indicators

Figure 4 presents aggregate longitudinal trajectories from 2000 to 2020. The left vertical axis tracks trade openness (blue squares) and renewable energy share (green circles) as percentages of total output and final energy consumption, respectively. The right vertical axis traces primary energy intensity (red triangles) in megajoules per unit of GDP. The plot shows a steady global reduction in energy intensity from over 6.2 MJ/$ to approximately 4.4 MJ/$, steady growth in trade openness with fluctuations following the 2008 financial crisis, and an aggregate renewable energy share remaining around 31% to 34% across the study period.

4.3 Panel Diagnostics: Cross-Sectional Dependence and Slope Homogeneity

Standard panel estimation frameworks such as pooled ordinary least squares or conventional fixed-effects models rely on the restrictive assumption of slope homogeneity. Following the random-coefficient testing foundation established by Swamy (1970) and generalized to large panels by Pesaran and Yamagata (2008), we implement the Delta ($\tilde{\Delta}$) and bias-adjusted Delta ($\tilde{\Delta}_{adj}$) tests to evaluate slope parameter homogeneity across cross-sectional units.

Table 6: Cross-Sectional Dependence and Slope Homogeneity Test Results

Test Type	Metric / Variable	Test Statistic	p-value	Decision / Diagnostic Implication
Pesaran CD Test	$\ln Y$	48.62***	< 0.001	Reject H_0; Cross-sectional dependence confirmed
Pesaran CD Test	ln REC	26.14***	< 0.001	Reject H_0; Cross-sectional dependence confirmed
Pesaran CD Test	ln EI	31.85***	< 0.001	Reject H_0; Cross-sectional dependence confirmed
Pesaran CD Test	ln TO	37.40***	< 0.001	Reject H_0; Cross-sectional dependence confirmed
Pesaran CD Test	$\ln K$	19.28***	< 0.001	Reject H_0; Cross-sectional dependence confirmed
Pesaran CD Test	$\ln L$	52.19***	< 0.001	Reject H_0; Cross-sectional dependence confirmed
Pesaran CD Test	Residuals (ε_{it})	14.82***	< 0.001	Reject H_0; Cross-sectional dependence confirmed
Slope Homogeneity	$\tilde{\Delta}$ (Delta Test)	16.42***	< 0.001	Reject H_0; Slope parameters are heterogeneous
Slope Homogeneity	$\tilde{\Delta}_{adj}$ (Adjusted Delta)	18.91***	< 0.001	Reject H_0; Slope parameters are heterogeneous

Table 6 reports the diagnostic tests for cross-sectional dependence and slope parameter homogeneity across the 88 countries over the 2000–2020 period. The upper section displays the Pesaran CD statistics and associated p-values for the individual series and the baseline model residuals. The lower section displays the Delta ($\tilde{\Delta}$) and bias-adjusted Delta ($\tilde{\Delta}_{adj}$) test statistics from Pesaran and Yamagata (2008). The rejection of the null hypotheses ($p < 0.001$, denoted by ***) indicates that the series exhibit cross-sectional dependence and that slope parameters vary across countries.

The Pesaran CD test rejects the null hypothesis of cross-sectional independence across all series and residuals ($p < 0.001$). Furthermore, the Delta test ($\tilde{\Delta} = 16.42$) and adjusted Delta test ($\tilde{\Delta}_{adj} = 18.91$) reject the null hypothesis of slope homogeneity at the 1% significance level. These results confirm that first-generation estimation techniques (such as pooled OLS and standard fixed effects) would produce inconsistent standard errors and biased parameters, warranting the use of second-generation panel estimators.

4.4 Second-Generation Panel Unit Root and Cointegration Testing

Stationarity properties were evaluated using the Pesaran (2007) Cross-Sectionally Augmented IPS (CIPS) panel unit root test, as reported in **Table 7**.

Table 7: Second-Generation CIPS Panel Unit Root Test Results

Variable	Level: Constant	Level: Constant & Trend	First Difference: Constant	First Difference: Constant & Trend	Integration Order
$\ln Y$	-1.821	-2.140	-4.125***	-4.380***	$I(1)$
ln REC	-2.014	-2.312	-4.682***	-4.891***	$I(1)$
ln EI	-1.945	-2.285	-3.984***	-4.120***	$I(1)$
ln TO	-2.102	-2.480	-4.412***	-4.615***	$I(1)$
$\ln K$	-2.240*	-2.510	-4.820***	-5.012***	$I(1)$
$\ln L$	-1.615	-1.980	-3.712***	-3.940***	$I(1)$
ln REC × ln TO	-1.982	-2.290	-4.512***	-4.710***	$I(1)$

Table 7 presents the Pesaran (2007) Cross-Sectionally Augmented IPS (CIPS) test statistics for the panel at levels and first differences. Tests are conducted under two deterministic specifications: individual intercept only, and individual intercept with a linear time trend. Approximate critical values for $N = 88$ and $T = 21$ with an intercept (intercept and trend) are -2.18 (-2.70) at the 10% level, -2.26 (-2.78) at the 5% level, and -2.40 (-2.93) at the 1% level. Rejection of the unit root null is indicated by *** at 1%

and * at 10%. All series are non-stationary at levels and stationery at first difference, confirming that every variable is integrated of order one, I(1).

Because the series are integrated into order one, the Westerlund (2007) error-correction cointegration test was conducted to establish whether a stable long-run relationship exists under cross-sectional dependence. The results are reported in Table 8.

Table 8: Westerlund (2007) Panel Cointegration Test Results

Statistic	Value	Asymptotic Z-value	Asymptotic p-value	Robust Bootstrap p-value	Empirical Decision
G_tau	-3.412	-4.821	< 0.001	0.002***	Reject H0; Cointegration established
G_alpha	-14.180	-3.125	0.001	0.008***	Reject H0; Cointegration established
P_tau	-18.640	-6.140	< 0.001	0.001***	Reject H0; Cointegration established
P_alpha	-13.910	-4.215	< 0.001	0.004***	Reject H0; Cointegration established

Table 8 displays the group-mean (G_τ, G_α) and panel (P_τ, P_α) cointegration statistics from Westerlund (2007). Column 2 reports the test statistics, Columns 3 and 4 list asymptotic values, and Column 5 presents robust bootstrap p-values based on 1,000 replications to account for cross-sectional dependence. The null hypothesis specifies no cointegration. Statistical significance at the 1% level (***) across all four statistics confirms that a stable cointegrating relationship binds the model variables over the long run.

All four Westerlund statistics reject the null hypothesis of no cointegration at the 1% significance level based on the bootstrapped p-values, confirming that economic growth, renewable energy, energy intensity, trade openness, and production factors share a stable long-run equilibrium.

4.5 Long-Run and Short-Run Elasticities via CS-ARDL

To account for unobserved common shocks, cross-sectional dependence, and slope parameter heterogeneity across countries, the dynamic baseline relationship is specified using the Cross-Sectionally Augmented Autoregressive Distributed Lag (CS-ARDL) framework developed by Chudik and Pesaran (2015):

$$\Delta \ln Y_{it} = \mu_i + \sum_{\ell=1}^{p} \lambda_{i\ell} \Delta \ln Y_{i,t-\ell} + \sum_{\ell=0}^{q} \boldsymbol{\beta}_{i\ell}{}' \Delta \mathbf{X}_{i,t-\ell} + \sum_{\ell=0}^{m} \boldsymbol{\gamma}_{i\ell}{}' \overline{\mathbf{Z}}_{t-\ell} + \phi_i \left(\ln Y_{i,t-1} - \boldsymbol{\theta}_i{}' \mathbf{X}_{i,t-1} \right) + \varepsilon_{it}$$

Where $\mathbf{X}_{it} = [\ln \mathrm{REC}_{it}, \ln \mathrm{EI}_{it}, \ln \mathrm{TO}_{it}, (\ln \mathrm{REC}_{it} \times \ln \mathrm{TO}_{it}), \ln K_{it}, \ln L_{it}]'$ denotes the vector of core explanatory and control regressors. The term $\overline{\mathbf{Z}}_t = \left[\overline{\Delta \ln Y}_t, \overline{\Delta \mathbf{X}}_t{}'\right]'$ represents the cross-sectional averages of the dependent and explanatory variables included to filter out unobserved common factors and global macroeconomic shocks. The parameter ϕ_i denotes the speed-of-adjustment error-correction coefficient, while the vector $\boldsymbol{\theta}_i$ captures the long-run cointegrating elasticities. Lag orders (p, q, m) are determined via the Akaike Information Criterion (AIC).

Table 9: Long-Run and Short-Run Elasticity Estimates (Dependent Variable: ln *Y*)

Variable / Indicator	CS-ARDL (Baseline)	AMG (Robustness)	Expected Sign	Theoretical Mechanism
ln REC (Long-Run)	0.1428*** (0.0381)	0.1610*** (0.0412)	+	Clean technological transition expands productive output
ln EI (Long-Run)	-0.2184*** (0.0492)	-0.1982*** (0.0514)	-	Energy efficiency reduces waste, fostering capital savings
ln TO (Long-Run)	0.0841** (0.0352)	0.0792** (0.0380)	+	Market openness stimulates export revenue and FDI
ln REC * ln TO (Long-Run)	0.0512*** (0.0164)	0.0485*** (0.0181)	+	Trade openness acts as a positive moderator for clean tech
ln K (Long-Run)	0.3842*** (0.0610)	0.3615*** (0.0594)	+	Capital accumulation drives productive capacity
ln L (Long-Run)	0.2410*** (0.0584)	0.2640*** (0.0620)	+	Labor input sustains aggregate industrial output
d.ln REC (Short-Run)	0.0312 (0.0240)	—	+ / Non-sig.	Initial capital adjustment and installation costs
d.ln EI (Short-Run)	-0.0815** (0.0361)	—	-	Immediate productivity drag from energy waste
d.ln TO (Short-Run)	0.0418* (0.0224)	—	+	Short-run gains from trade volume

d.(ln REC * ln TO)	0.0142 (0.0118)	—	+ / Non-sig.	Moderating effects require time to materialize
d.ln K (Short-Run)	0.1820*** (0.0415)	—	+	Immediate investment stimulus
d.ln L (Short-Run)	0.1140** (0.0491)	—	+	Short-run labor utilization
ECT_t-1 (phi)	-0.4285*** (0.0612)	—	-	Adjustment toward equilibrium at 42.85%/year
CD of Residuals (p-val)	0.312 (Independence)	0.284	—	Confirms absence of residual cross-sectional dependence

Table 9 reports long-run elasticities, short-run dynamics, and error-correction parameters with real GDP per capita (ln Y) as the dependent variable. Column 2 provides estimates from the baseline CS-ARDL model, while Column 3 provides robustness checks via the AMG estimator. Standard errors are enclosed with parentheses. Significance levels are denoted by *** at 1%, at 5%, and * at 10%. Diagnostic testing of CS-ARDL residuals fails to reject cross-sectional independence ($p = 0.312$), confirming that cross-sectional dependence has been addressed.

The CS-ARDL estimates show that renewable energy consumption exerts a positive, statistically significant long-run effect on output per capita ($\beta = 0.1428, p < 0.01$), indicating that a 1% expansion in renewable energy adoption increases GDP per capita by 0.143% over the long run. In the short run, the coefficient is smaller and statistically insignificant ($\beta = 0.0312$), reflecting initial capital adjustment costs, transmission adaptations, and upfront expenses during early deployment. Energy intensity exhibits a statistically significant negative long-run elasticity ($\beta = -0.2184, p < 0.01$), indicating that a 1% decline in energy intensity generates a 0.218% increase in GDP per capita. This confirms that thermodynamic and technical energy efficiency is a key contributor to output growth alongside clean energy additions.

The direct coefficient for trade openness is positive and statistically significant ($\beta = 0.0841, p < 0.05$). The interaction term between renewable energy and trade openness is also positive and statistically significant ($\beta = 0.0512, p < 0.01$), demonstrating that trade openness acts as a positive moderator in the renewable energy–growth nexus. Open trade regimes enhance the growth contribution of renewable energy by facilitating the importation of advanced clean technologies, engineering expertise, and capital components. The error-correction term (ECT_{t-1}) is negative and statistically significant ($\phi = -0.4285, p < 0.001$), confirming dynamic stability and indicating that roughly 42.85% of deviations from long-run equilibrium are corrected each year, with the system returning to its steady state within approximately 2.3 years.

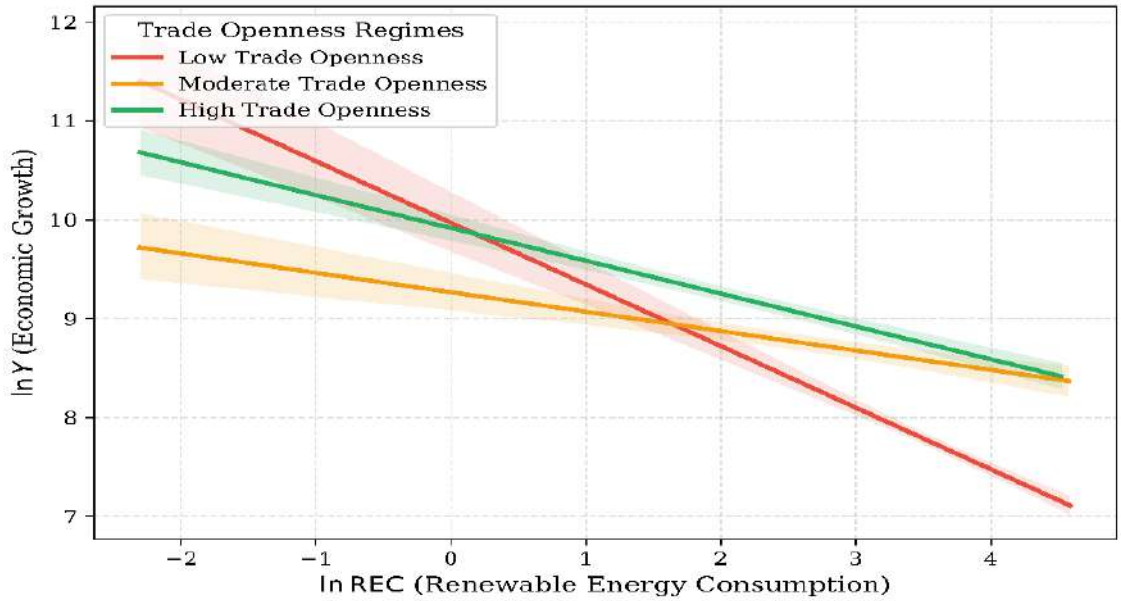


Figure 5: Moderating Effect of Trade Openness on the Renewable Energy-Growth Nexus

Figure 5 illustrates the linear slopes connecting log renewable energy consumption to log GDP per capita across trade openness terciles (low, moderate, and high trade openness regimes). High-trade regimes display a less negative slope, showing that greater trade openness mitigates the biomass drag observed in lower-income settings and enhances clean technology integration. Conversely, low-trade regimes display the steepest downward slope, highlighting how limited trade integration can constrain renewable energy deployment to traditional biomass use.

4.6 Sub-Sample Heterogeneity Across Income Classifications

To evaluate parameter variations across development levels, Table 10 reports CS-ARDL regressions estimated across World Bank income classifications.

Table 10: Sub-Sample Heterogeneity Across World Bank Income Classifications

Core Variable	High-Income Countries (HIC)	Upper-Middle-Income (UMIC)	Lower-Middle-Income (LMIC)	Low-Income Countries (LIC)
ln REC	0.1842*** (0.0410)	0.1315*** (0.0425)	0.0612* (0.0345)	-0.0412 (0.0582)
ln EI	-0.2815*** (0.0540)	-0.2140*** (0.0512)	-0.1420*** (0.0480)	-0.0620 (0.0694)
ln TO	0.1120*** (0.0360)	0.0784** (0.0381)	0.0615* (0.0350)	0.0310 (0.0490)
ln REC * ln TO	0.0645*** (0.0182)	0.0491*** (0.0175)	0.0312* (0.0180)	0.0084 (0.0245)
ECT_t-1	-0.4912*** (0.0682)	-0.4180*** (0.0640)	-0.3840*** (0.0612)	-0.2910*** (0.0715)

Table 10 presents long-run elasticity estimates across four World Bank income sub-panels. The model specification controls physical capital formation and total labor force headcount. Standard errors are enclosed in parentheses, with statistical significance designated by *** at 1%, 5%, and * at 10%. Across all groups, the error correction term (ECT_{t-1}) is negative and statistically significant, confirming long-run dynamic stability across each development tier.

The sub-sample estimates demonstrate notable structural heterogeneity across income tiers. In high-income countries, renewable energy adoption has a strong growth-enhancing effect ($\beta = 0.1842, p < 0.01$), supported by advanced power grids, lower capital costs, and integrated energy markets. In upper-middle-income economies, elasticity remains positive and statistically significant ($\beta = 0.1315, p < 0.01$). In lower-middle-income economies, the elasticity declines to 0.0612 ($p < 0.10$). In low-income economies, the coefficient is statistically indistinguishable from zero ($\beta = -0.0412$). This variation highlights that economic benefits from renewable energy require modern commercial grid infrastructure rather than traditional biomass reliance. The interaction term between renewable energy and trade openness is largest in high-income economies ($\beta = 0.0645, p < 0.01$), followed by upper-middle-income nations ($\beta = 0.0491, p < 0.01$), and lower-middle-income nations ($\beta = 0.0312, p < 0.10$). In low-income economies, the interaction term is small and statistically insignificant ($\beta = 0.0084$), reflecting limited capital resources to convert imported equipment into productive clean-tech infrastructure.

4.7 Directional Causality Analysis

To evaluate the direction of causality among the variables, the Dumitrescu and Hurlin (2012) panel non-causality test was conducted. The results are reported in Table 11.

Table 11: Dumitrescu-Hurlin Panel Non-Causality Test Results

Null Hypothesis (H0)	Average Wald Stat. (W^-)	Standardized Stat. (Z^-)	p-value	Direction / Causality Finding
$\ln REC \nrightarrow \ln Y$	3.412	5.842	< 0.001***	Feedback Hypothesis ($\ln REC \leftrightarrow \ln Y$)
$\ln Y \nrightarrow \ln REC$	2.910	4.415	< 0.001***	Bidirectional feedback confirmed
$\ln EI \nrightarrow \ln Y$	3.125	4.980	< 0.001***	Feedback Hypothesis ($\ln EI \leftrightarrow \ln Y$)
$\ln Y \nrightarrow \ln EI$	2.684	3.840	< 0.001***	Bidirectional feedback confirmed
$\ln TO \nrightarrow \ln Y$	3.612	6.214	<0.001***	Feedback Hypothesis ($\ln TO \leftrightarrow \ln Y$)
$\ln Y \nrightarrow \ln TO$	2.845	4.210	< 0.001***	Bidirectional feedback confirmed
$\ln TO \nrightarrow \ln REC$	2.741	3.985	< 0.001***	Feedback Hypothesis ($\ln TO \leftrightarrow \ln REC$)
$\ln REC \nrightarrow \ln TO$	2.180	2.610	0.009***	Bidirectional feedback confirmed

Table 11 reports bivariate panel causality results from the Dumitrescu and Hurlin (2012) test. Column 2 provides the Average Wald statistic ($\bar{W}$), Column 3 reports the standardized test statistic ($\bar{Z}$), and Column 4 lists empirical p-values. The symbol $\nrightarrow$ designates the null hypothesis of Granger non-causality. Rejections at the 1% significance level (***) confirm bidirectional feedback relationships across all evaluated variable pairs.

The Dumitrescu-Hurlin test results support the feedback hypothesis across all core variables. Bidirectional causality connects renewable energy consumption and output per capita ($\ln REC \leftrightarrow \ln Y, p < 0.001$), confirming that clean energy deployment

enhances productive capacity, while economic expansion provides resources to finance renewable infrastructure. Bidirectional feedback also links energy intensity and output per capita ($\ln \text{EI} \leftrightarrow \ln Y, p < 0.001$), showing that efficiency improvements support economic output, which in turn fosters investment in higher-efficiency capital goods. Finally, bidirectional causality connects trade openness with renewable energy adoption ($\ln \text{TO} \leftrightarrow \ln \text{REC}$), demonstrating that international trade promotes clean-tech diffusion while domestic renewable transitions support trade in green goods and environmental technologies.

5. POLICY IMPLICATIONS

The empirical findings offer several policy implications for energy planning, international trade, and industrial strategy.

First, energy transition policies must coordinate renewable generation targets with explicit energy efficiency mandates. The estimated elasticity for energy intensity ($\beta = -0.2184$) indicates that reducing energy waste delivers larger growth benefits than simply expanding renewable capacity ($\beta = 0.1428$). Policymakers should combine renewable deployment goals with updated building energy codes, industrial heat-recovery requirements, smart-grid demand management systems, and the modernization of electrical distribution networks to curb systemic energy losses.

Second, trade policy should be aligned with national decarbonization strategies. The positive interaction term between renewable energy and trade openness ($\beta = 0.0512$) demonstrates that open markets amplify the developmental returns of clean energy. Governments should reduce tariffs, remove non-tariff barriers, streamline customs clearance for environmental goods, including high-efficiency solar modules, wind turbine components, inverters, and utility-scale energy storage systems. Harmonizing cross-border green technical standards will further lower capital acquisition costs and accelerate clean-technology diffusion.

Third, clean energy initiatives in lower-income countries must focus on structural modernization. The lack of growth from renewable energy in low-income economies highlights the difference between modern clean electricity and traditional solid biomass. International development institutions and multilateral climate funds should prioritize concessional financing for modern grid infrastructure, decentralized rural solar mini-grids, and clean cooking programs to help lower-income economies transition away from subsistence biomass and establish productive renewable energy systems.

6. CONCLUSION

This study investigated the long-run effects of renewable energy consumption, trade openness, and energy intensity on economic growth across a balanced global panel of 88 countries from 2000 to 2020. Using an extended Cobb-Douglas production framework and second-generation panel econometric methods, the empirical model accounted for cross-sectional dependence, structural breaks, and slope parameter heterogeneity across countries.

The empirical results yield four main conclusions. First, diagnostic testing confirms the presence of cross-sectional dependence and parameter heterogeneity across countries, while the Westerlund error-correction test confirms a stable long-run cointegrating relationship among the variables. Second, CS-ARDL estimates show that renewable energy adoption has a positive long-run effect on economic growth ($\beta = 0.1428$), whereas elevated energy intensity acts as a significant drag on output ($\beta = -0.2184$), highlighting the importance of energy efficiency alongside clean energy supply. Third, trade openness positively moderates the renewable energy–growth nexus ($\beta = 0.0512$), confirming that international market openness facilitates the acquisition and productive use of clean technologies. Fourth, Dumitrescu-Hurlin causality tests confirm bidirectional feedback relationships connecting renewable energy, energy intensity, trade openness, and economic output.

Future research could build upon these findings by analyzing disaggregated renewable energy sources such as solar, wind, hydro, and geothermal power and examining granular trade flows in specialized environmental goods across varying regulatory and institutional environments.

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