Renewable Energy Transition and GDP Growth: Does Green Energy Pay Off?

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1. Introduction

The global energy system is undergoing its most profound structural transformation since the Industrial Revolution. Global renewable power capacity additions reached a record 295 GW in 2022, with cumulative installed capacity exceeding 3,400 GW more than tripling since 2010 (IRENA, 2023). Governments worldwide are committing trillions of dollars to renewable transition through landmark legislation: the US Inflation Reduction Act, EU REPowerEU, and China's 14th Five-Year Plan collectively mobilise over $3 trillion through 2030. Yet a fundamental macroeconomic question persists:

Under what conditions does investing in green energy make economies richer?

The empirical literature on the energy-growth nexus spans three decades but produces inconsistent findings positive, negative, neutral, and bidirectional relationships coexist (Apergis & Payne, 2015; Bilan et al., 2019) attributable to methodological heterogeneity, endogeneity mishandling, and homogeneous treatment of distinct renewable technologies. This paper addresses four interrelated gaps: (i) source-level disaggregation of renewables (solar, wind, hydro, bioenergy); (ii) robust causal identification via sequential multi-estimator strategy; (iii) income-group heterogeneity analysis; and (iv) distributional analysis via quantile regression. Our 60-country panel (2000–2022) provides the most comprehensive evidence to date that green energy pays off but the magnitude, mechanism, and beneficiaries depend critically on source type, income level, and complementary policy architecture.

2. Literature Review and Theoretical Framework

The theoretical case for a renewable energy-growth nexus draws on three pillars. Neoclassical growth theory (Solow, 1956) treats energy as a productivity-augmenting intermediate input: lower long-run energy costs shift the production possibilities frontier outward. Endogenous growth theory (Romer, 1990) provides a richer mechanism through knowledge spillovers from green technology R&D that compound TFP gains over time. The Natural Resource-Based View (Hart, 1995) and Porter Hypothesis (Porter & van der Linde, 1995) further predict that proactive environmental investment builds dynamic competitive capabilities and generates innovation rents that offset compliance costs.

Empirically, Apergis and Payne (2010) identified bidirectional causality between renewables and output across 20 OECD economies. Adams et al. (2020) documented heterogeneous effects across 47 African countries: positive in resource-scarce economies, null in oil-dependent states. Source-level evidence shows solar positively affecting manufacturing output in South Asia (Khatun et al., 2021) and wind capacity linked to industrial value-added in Europe (Okafor et al., 2022). Koengkan et al. (2022) identified a 22% renewable share threshold for robust GDP effects via threshold panel modelling. Critically, Asongu & Nwachukwu (2018) demonstrate that institutional quality moderates the renewable-growth nexus in Africa, and Dogan & Seker (2016) show that financial development amplifies the effect in the EU findings that motivate our income-stratified and conditionality analysis. **Table 1**: contains synthesis of Key empirical studies on renewable energy and GDP Growth.

Table 1: Synthesis of Key Empirical Studies on Renewable Energy and GDP Growth

Authors (Year)	Sample	Period	Method	Key Finding	Gap Addressed
Apergis & Payne (2010)	20 OECD	1985–2005	PVECM	Bidirectional causality; renewable energy and growth mutually reinforcing	Causality
Sadorsky (2009)	18 Emerging	1994–2003	DOLS, FMOLS	Income is primary driver of renewable demand; supply-side effects smaller	Demand-side
Adams et al. (2020)	47 Africa	2000–2016	ARDL, PMG	Heterogeneous: positive in resource-scarce; null in oil-dependent states	Africa context
Khatun et al. (2021)	S/SE Asia	2005–2019	FE, GMM	Solar positively affects manufacturing output with 2-year lag	Source-level
Koengkan et al. (2022)	35 countries	2000–2018	Threshold Panel	22% renewable share threshold for significant GDP effect	Non-linearity
Dogan & Seker (2016)	EU (32)	1990–2012	Pedroni, VECM	Finance & trade openness amplify renewable-growth nexus	Conditionality
This Study	**60 countries**	**2000–2022**	**TWFE, S-GMM, PVAR, QR, AMG**	**Source-disaggregated, income-stratified, distributional analysis with full robustness suite**	**All gaps**

Source: Author's compilation from reviewed literature.

Our four formal hypotheses are: H1: Renewable energy share positively and significantly predicts GDP growth (main effect); H2: The growth dividend differs significantly across sources, with wind and solar exceeding hydro and bio; H3: The premium is larger in high-income economies but statistically significant across all income groups; H4: Quantile regression reveals concentration of the premium in the upper growth distribution.

3. Data and Methodology

3.1 Sample and Coverage

Our dataset comprises a balanced panel of 60 countries spanning 2000–2022 (23 annual observations per country; N = 1,380 country-year observations). Countries were selected to ensure representation across all four World Bank income groups (15 high-income, 15 upper-middle-income, 15 lower-middle-income, 15 low-income) and six geographic regions (Europe & Central Asia, East Asia & Pacific, South Asia, Sub-Saharan Africa, Latin America & Caribbean, Middle East & North Africa). Countries with more than 10% missing observations in any core variable were excluded, yielding a balanced panel that avoids attrition bias.

3.2 Variable Definitions and Sources

Table 2: Variable Definitions, Measurement, and Sources

Variable	Measurement	Role	Expected Sign	Source
GDP_pc_growth	Real GDP per capita, annual % growth (constant 2015 USD)	Dependent	—	World Bank WDI
REN_share	Renewable energy as % of total final energy consumption	Main IV	+	IEA / WDI
SOLAR_cap	Solar PV installed capacity per 1000 persons (MW)	Source IV	+	IRENA (2023)
WIND_cap	Wind energy installed capacity per 1000 persons (MW)	Source IV	+	IRENA (2023)
HYDRO_share	Hydropower as % of electricity generation	Source IV	+/−	IEA Statistics
BIO_share	Bioenergy as % of total energy consumption	Source IV	+	IEA Statistics
GFCF	Gross fixed capital formation as % of GDP	Control	+	WDI
TRADE	Trade openness: (Exports + Imports)/GDP × 100	Control	+	WDI
FINDEV	Domestic credit to private sector as % of GDP	Control	+	WDI
INST	World Governance Indicators composite (average of 6 dimensions)	Control	+	World Bank WGI
INFL	CPI-based annual inflation rate (%)	Control	−	IMF IFS
HUMAN_CAP	Mean years of schooling, population 25+ (Penn World Table)	Control	+	Penn World Table 10.0
CO2_intens	CO2 emissions per unit of energy use (kg per kg of oil equivalent)	Moderator	−	IEA Statistics

Note: WDI = World Development Indicators; IEA = International Energy Agency; IRENA = International Renewable Energy Agency; IMF IFS = International Monetary Fund International Financial Statistics; WGI = Worldwide Governance Indicators.

3.3 Descriptive Statistics

Our balanced panel covers 60 countries across four World Bank income groups (15 each: HIC, UMIC, LMIC, LIC) and six geographic regions over 2000–2022 (N = 1,380 obs.). The dependent variable is real GDP per capita growth (WDI: NY.GDP.PCAP.KD.ZG). Core independent variable is renewable energy share of total final energy consumption (EG.FEC.RNEW.ZS). Source-specific variables include IRENA solar and wind installed capacity per 1,000 persons, and IEA hydropower and bioenergy shares. Controls comprise gross fixed capital formation (% GDP), trade openness, domestic credit to private sector (financial development), a World Governance Indicators composite (mean of 6 dimensions), CPI inflation, and Penn World Table 10.0 human capital index. All variables are sourced from publicly available databases (WDI, IRENA, IEA, IMF IFS, PWT 10.0, WGI).

Table 3: Selected Descriptive Statistics (N = 1,380)

Variable	N	Mean	SD	Min	P25	Median	P75	Max
GDP pc Growth (%)	1,380	2.84	4.12	-14.72	0.96	2.65	5.11	24.38
Renewable Share (%)	1,380	27.4	21.8	1.2	9.4	22.6	41.3	98.7
Solar Cap (MW/1000)	1,380	0.083	0.198	0.000	0.002	0.017	0.079	1.812
Wind Cap (MW/1000)	1,380	0.064	0.142	0.000	0.000	0.009	0.067	1.204
GFCF (% GDP)	1,380	24.1	7.4	5.8	19.2	23.6	28.4	58.7
Institutions (WGI)	1,380	0.014	0.782	-1.84	-0.51	-0.08	0.62	1.98

Note: All monetary variables in constant 2015 USD. P25/P75 = 25th/75th percentile. Capacity in MW per 1,000 persons.

3.4 Econometric Methodology

We deploy a four-stage identification strategy. First, baseline Two-Way Fixed Effects (TWFE) with Driscoll-Kraay (1998) standard errors (bandwidth = 3) addresses cross-sectional dependence, confirmed by the Pesaran (2004) CD test ($p < 0.001$ for all variables):

$$GDP\_pc\_growth_{it} = \alpha + \beta_1 REN\_share_{it} + \beta_2 GFCF_{it} + \beta_3 TRADE_{it} + \beta_4 FINDEV_{it} + \beta_5 INST_{it} + \beta_6 INFL_{it} + \beta_7 HUMAN\_CAP_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad \ldots (1)$$

Second, System-GMM (Blundell & Bond, 1998) controls for endogeneity and dynamic persistence, instrumenting REN_share, GFCF, and FINDEV with their own lags (collapsed per Roodman, 2009). Third, a Panel VAR (PVAR) traces dynamic Granger-causal relationships and computes impulse response functions (500 Monte Carlo draws, 95% CI). Fourth, quantile regression at Q10–Q90 with bootstrapped standard errors (1,000 replications) examines distributional heterogeneity, formally tested via a Wald slope-equality test. Robustness uses the Augmented Mean Group (AMG) estimator (Bond & Eberhardt, 2013) allowing country-specific slopes and joint treatment of cross-sectional dependence. Im-Pesaran-Shin unit root tests confirm variables are I(0) or I(1); Westerlund (2007) panel cointegration tests validate long-run relationships among I(1) variables.

3.5 Dynamic Panel: System-GMM

Given the endogeneity concerns inherent in the energy-growth nexus — wealthier countries can afford more renewables, creating reverse causality — and the dynamic persistence in GDP growth, we employ System-GMM (Blundell & Bond, 1998) as our primary causal identification strategy:

$$GDP\_pc\_growth_{it} = \alpha_0 + \alpha_1 GDP\_pc\_growth_{i,t-1} + \beta REN\_share_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad ...(2)$$

where $GDP\_pc\_growth_{i,\ t-1}$ captures growth persistence, X_{it} is the vector of control variables, and endogenous regressors (REN_share, FINDEV, GFCF) are instrumented using their own lags in the difference equation and lagged levels in the levels equation. We follow Roodman's (2009) instrument collapse procedure to avoid instrument proliferation (instrument count < group count). Validity is confirmed by the Arellano-Bond AR(2) test ($p > 0.10$) and the Hansen J-test of overidentification restrictions ($p > 0.25$).

3.6 Panel Vector Autoregression (PVAR)

To examine the dynamic, simultaneous interactions between renewable energy, GDP, and CO2 intensity, we estimate a first-order Panel VAR (Love & Zicchino, 2006) using forward orthogonal deviations to remove fixed effects while preserving observations:

$$Y_{it} = A_0 + A_1 Y_{i,t-1} + f_i + e_{it} \quad ...(3)$$

where $Y_{it} = \{GDP\_pc\_growth_{it}, REN\_share_{it}, CO2\_intens_{it}\}$ is the endogenous variable vector, A_1 is the coefficient matrix, f_i captures country fixed effects, and $e_{it} \sim N(0,\Sigma)$. Ordering is based on the Cholesky decomposition following theoretical priors (GDP ordered first as slowest-moving). Impulse Response Functions (IRFs) with 95% confidence bands (500 Monte Carlo draws) trace the dynamic response of GDP growth to orthogonalised shocks in renewable energy.

3.7 Quantile Regression

To examine distributional heterogeneity, we extend the baseline to quantile regression (Koenker & Bassett, 1978), estimating effects at the 10th, 25th, 50th, 75th, and 90th percentiles of the conditional GDP growth distribution. This reveals whether the renewable energy dividend is concentrated in fast-growing or slow-growing economies, information critical for targeting policy interventions:

$$Q_\varphi(GDP\_pc\_growth_{it} \mid X_{it}) = \alpha_\varphi + \beta_\varphi REN\_share_{it} + \gamma_\varphi X_{it} \quad ...(4)$$

Bootstrapped standard errors (1,000 replications) are reported. We test slope equality across quantiles using the Wald test to formally confirm distributional heterogeneity.

3.8 Robustness: Augmented Mean Group (AMG)

Our robustness checks employ the Augmented Mean Group (AMG) estimator (Bond & Eberhardt, 2013), which allows for country-specific slopes (parameter heterogeneity) and estimates a 'common dynamic process' to account for unobserved cross-sectional dependence. This estimator is particularly appropriate when the CD test rejects the null, as it jointly addresses cross-sectional dependence and slope heterogeneity, two pervasive features of international macro panels that standard TWFE ignores.

4. Results

4.1 Main Effect: TWFE and System-GMM

Table 4 presents TWFE estimates across full sample and income-group subsamples, alongside System-GMM. Cross-sectional dependence, confirmed by the Pesaran CD test, is addressed throughout via Driscoll-Kraay SEs.

Table 4: Main Regression Results — TWFE and System-GMM

Variable	(1) Full	(2) HIC	(3) UMIC	(4) LMIC	(5) LIC	(6) S-GMM
REN_share	0.183***	0.227***	0.196***	0.151**	0.118**	0.217***
(SE)	(0.041)	(0.058)	(0.053)	(0.064)	(0.049)	(0.063)
L.GDP_pc_growth	—	—	—	—	—	0.142***
GFCF	0.214***	0.198***	0.231***	0.188**	0.172**	0.189***
INST	0.782***	0.641***	0.819***	0.794***	0.734***	0.712***
INFL	-0.047***	-0.031**	-0.052***	-0.061***	-0.073***	-0.039***
HUMAN_CAP	0.312***	0.274***	0.339***	0.302**	0.218**	0.298***
Country/Year FE	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes
SE Correction	DK	DK	DK	DK	DK	Robust
R^2 (within) / AR(2)	0.484	0.521	0.498	0.461	0.418	p=0.318
N	1,380	345	345	345	345	1,320

*Notes: *** p<0.01; ** p<0.05; * p<0.10. Standard errors in parentheses. HIC = High-Income Countries; UMIC = Upper-Middle-Income; LMIC = Lower-Middle-Income; LIC = Low-Income Countries. S-GMM uses two-step estimator with Windmeijer (2005) finite-sample correction and collapsed instrument matrix. Dependent variable: Real GDP per capita growth (%). All continuous variables are log-transformed where appropriate.*

The TWFE result (Column 1) confirms H1: a one pp increase in renewable energy share raises GDP per capita growth by 0.183 pp ($p < 0.01$), controlling for investment, trade, institutions, inflation, and human capital. The gradient from HIC (0.227) to LIC (0.118) provides preliminary support for H3. System-GMM (Column 6) yields a marginally larger estimate (0.217), reflecting attenuation bias correction. The AR(2) test ($p = 0.318$) and Hansen J test ($p = 0.412$) confirm model validity.

4.2 Source-Disaggregated Results

Table 5 presents source-specific TWFE models, confirming H2. Wind generates the largest growth premium ($\beta = 0.241$, $p < 0.01$), followed by solar (0.198), bioenergy (0.134), and hydropower (0.072). Wind's superior coefficient reflects stronger manufacturing supply-chain multipliers. Solar's effect is amplified by rural energy-access gains. Crucially, hydropower exhibits statistically significant concavity (quadratic term: -0.008, $p < 0.05$), with a turning point at approximately 62% hydro share, beyond which additional hydro investment yields nil or negative GDP returns — a novel finding with direct implications for hydro-dependent Sub-Saharan African and Latin American economies.

Table 5: Source-Specific Effects and Quantile Regression Results

	Panel A: Source-Specific TWFE					Panel B: Quantile Regression — REN_share		
Variable/Quantile	Solar	Wind	Hydro	Bio	|	Q25	Q50	Q90
Energy coefficient	0.198***	0.241***	0.072*	0.134**	|	REN_share β		
(SE)	(0.053)	(0.062)	(0.041)	(0.058)	|	0.114*	0.171**	0.318***
Hydro² (concavity)	—	—	-0.008**	—	|	(0.061)	(0.058)	(0.071)
Controls / FE	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes	|	Yes/Yes	Yes/Yes	Yes/Yes
R^2 (within) / Pseudo-R^2	0.471	0.489	0.438	0.452	|	0.278	0.331	0.412

Notes: *** p<0.01; ** p<0.05; * p<0.10. All TWFE models use Driscoll-Kraay SEs. Solar and wind variables are log-transformed per-capita capacity. Quantile regression uses within-demeaned variables; bootstrapped SEs (1,000 reps). Wald test for QR slope equality: p = 0.012, rejecting equal slopes across quantiles.

4.3 Distributional Effects and Robustness

Quantile regression results (Table 5, Panel B) confirm H4. The REN_share coefficient rises monotonically from 0.114* (Q25) to 0.318*** (Q90), indicating that the green growth dividend is concentrated in already-dynamic economies. The Wald test rejects slope equality (p = 0.012), confirming significant distributional heterogeneity. At the bottom decile (Q10), the coefficient is statistically indistinguishable from zero, suggesting that low-growth economies require complementary infrastructure and institutional prerequisites to realise renewable energy's macroeconomic returns.

Table 6 shows Augmented Mean Group Estimation that Robustness checks confirm the main findings across five alternative specifications: (i) AMG estimation (β = 0.171***, post-estimation CD p = 0.624, confirming cross-sectional independence absorbed); (ii) exclusion of the Global Financial Crisis (2008–09), yielding β = 0.189***; (iii) exclusion of the COVID-19 period (2020–21), β = 0.176***; (iv) alternative DV using per-capita renewable electricity generation, β = 0.162***; and (v) distributed lag specification confirming a cumulative long-run elasticity of 0.287***. The consistency across all specifications provides high confidence in the robustness of the renewable energy-GDP growth relationship.

Table 6: Robustness Check — Augmented Mean Group (AMG) Estimator

Variable	(1) AMG Full	(2) AMG HIC	(3) AMG LMIC+LIC	(4) TWFE (Baseline)
REN_share	**0.171*** **	**0.211*** **	**0.138** **	**0.183*** **
(SE)	(0.048)	(0.062)	(0.055)	(0.041)
Common Dynamic Process	**0.284*** **	**0.312*** **	**0.248*** **	—
Controls	**YES**	**YES**	**YES**	**YES**
CD-test post-estimation	**p = 0.624**	**p = 0.541**	**p = 0.487**	p < 0.001
N	**1,380**	**345**	**690**	**1,380**

*Notes: *** p<0.01; ** p<0.05; * p<0.10. AMG estimator allows country-specific slopes and absorbs cross-sectional dependence via the common dynamic process. Post-estimation CD test confirms that AMG successfully eliminates cross-sectional dependence (p > 0.10). HIC = High-Income Countries; LMIC+LIC combined group.*

5. Discussion and Policy Implications

Our results provide a clear answer: green energy pays off in GDP growth terms, with elasticities ranging from 0.138 to 0.241 across estimators and specifications. For a country at the mean renewable share (27.4%), a policy-driven 10 pp increase — achievable within a decade under aggressive deployment — implies approximately 1.4–2.4 pp additional annual GDP growth, compounding substantially over time. Three critical nuances qualify this finding.

First, source heterogeneity is policy-decisive. Wind's superior premium (0.241) reflects 2.5 times larger supply-chain multipliers relative to solar (IRENA, 2023). Policymakers should weight wind and solar investment over further hydro expansion where hydro penetration already exceeds 60%, given the empirically confirmed concavity finding. Second, income conditionality implies that lower-income economies face a 'green growth trap': they most need clean energy for both climate and development reasons, but the Q10 near-zero coefficient indicates that renewable installation alone is insufficient without grid extension, human capital, and regulatory capacity. This mandates bundled financing architectures not standalone asset finance from multilateral institutions. Third, the distributional concentration of returns at Q90 argues against one-size-fits-all carbon pricing and renewable mandates; developing economies may require sequenced reforms that first build absorptive capacity before regulatory stringency is imposed.

For conference delegates and policymakers: the green energy transition is not merely an environmental imperative, it is a statistically robust driver of economic growth, particularly for wind and solar investment in economies with adequate institutional infrastructure. The evidence strongly supports public co-investment in renewable energy as a simultaneous growth and climate policy for middle- and high-income economies, while recommending complementary capacity-building packages for lower-income contexts.

6. Conclusion

This study provides the most methodologically comprehensive analysis to date of renewable energy transition and GDP growth, using a 60-country balanced panel (2000–2022) with sequential deployment of TWFE, System-GMM, PVAR, quantile regression, and AMG estimation. The core finding is unambiguous: renewable energy transition yields a positive, statistically robust, and economically meaningful GDP growth premium (0.183–0.217 pp per pp of renewable share). Wind (0.241) and solar (0.198) deliver the largest source-specific dividends; hydropower exhibits diminishing returns above 60% penetration; and the growth premium is concentrated in the upper growth distribution, reflecting a complementarity mechanism. These findings have direct implications for national energy policy, multilateral climate finance architecture, and the SDG7-SDG8 nexus. Future research should exploit policy quasi-experiments (feed-in tariff reforms, carbon pricing introductions) via heterogeneity-robust difference-in-differences methods, and examine within-country distributional labour market effects of the renewable transition to inform just transition policy design.

Supplementary Materials: *The complete R replication script (data extraction, panel construction, TWFE, System-GMM, PVAR, quantile regression, and AMG estimation) and the full panel dataset (60 countries, 2000–2022, N = 1,380) are available upon reasonable request from the corresponding author.*

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