

Renewable Energy and Economic Growth Across Growth Regimes in Sub-Saharan Africa

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Article

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Abstract

This study tests whether renewable energy exerts different growth effects across endogenously identified growth regimes in Sub-Saharan Africa. The data covers 1990 to 2023, but the renewable energy consumption series ends in 2022; the complete-case estimation sample therefore contains 959 country-year observations for 37 economies over 1993 to 2022. Real GDP per capita growth serves as the outcome. Renewable energy consumption as a share of total final energy use provides the principal energy measure, while gross capital formation, trade openness, inflation, and population growth enter as controls. The transition variable equals the lagged three-year mean of real GDP per capita growth, which avoids assigning regimes with the contemporaneous dependent variable. The empirical sequence combines two-way fixed effects with Driscoll-Kraay inference, Pesaran cross-sectional dependence and CIPS tests, a Hansen-type fixed-effects panel threshold estimator with 999 country-clustered wild-bootstrap replications, two-step difference GMM with a restricted instrument set, and dynamic common correlated effects mean group estimation. The linear fixed-effects coefficient on renewable energy equals 0.014 ($p = .530$). The estimated growth threshold equals 1.716%, but the bootstrap linearity test does not reject a constant coefficient ($p = .384$). Low- and high-regime renewable coefficients equal 0.006 and 0.017, respectively, and neither differs from zero. Difference GMM and DCCEMG estimates also remain statistically insignificant. The evidence does not support a stable aggregate growth dividend from a higher broad renewable share, nor does it support regime dependence. Measurement composition, particularly the mixture of modern renewable supply and traditional biomass, constrains interpretation. Policy evaluation should therefore use delivered modern energy services, reliability, and technology-specific output rather than the aggregate renewable share alone.

1. Introduction

Renewable energy can affect output through several distinct mechanisms. New electricity supply may reduce outages, lower firms' reliance on diesel generation, protect importers from fuel-price shocks, and support capital utilisation. Investment in generation and networks can also raise construction demand and create technical capabilities. These channels do not imply a uniform coefficient. A rising renewable share may reflect modern solar, wind, hydro, or geothermal supply, but it may also reflect persistent dependence on traditional biomass. The same percentage-point change can therefore represent different quantities and qualities of usable energy services.

Growth conditions may alter the marginal effect. During weak growth, spare capacity, constrained finance, and depressed demand can limit the short-run return to new infrastructure. The same investment may become more productive when credit, transmission, and final demand recover. The opposite argument also has force: renewable projects may matter most during weak growth when fuel imports and unreliable grids impose binding constraints. These competing mechanisms make the regime boundary an empirical parameter rather than a zero-growth convention.

The Sub-Saharan African evidence remains unsettled. Maji et al. (2019) reported a negative growth association for renewable energy in West Africa and linked the result to the composition of energy use. Vural (2020) obtained positive long-run effects for selected countries after separating renewable and nonrenewable energy. Kouton (2021) found a positive effect on inclusive growth, particularly at lower inclusive-growth levels. Tenaw (2022) used dynamic common correlated effects and threshold methods for 20 economies and showed that traditional energy dependence and development conditions shape the clean-energy transition. Muazu et al. (2023) also estimated threshold effects across African countries, while Diallo and Ouoba (2024) placed institutional quality at the centre of the renewable-growth relationship. Differences in outcome definitions, samples, estimators, and renewable measures prevent a single regional conclusion.

Three econometric problems complicate inference. First, growth and renewable energy can respond jointly to investment, fiscal capacity, and policy. Second, commodity cycles, climate shocks, technology costs, and global financial conditions create cross-sectional dependence. Third, national energy structures imply slope heterogeneity. A conventional pooled model can report a precise average coefficient while obscuring these features. A credible design must treat nonlinear identification, common factors, dynamics, and instrument proliferation as connected problems.

This study makes four contributions. It defines the growth regime with information dated before the outcome year. It estimates the threshold rather than imposing a recession cutoff. It subjects the threshold result to nonstandard bootstrap inference, dynamic GMM, and common-factor correction. It also supplies the exact data and code that generated every numerical claim. The resulting evidence is deliberately conservative: an estimated threshold has substantive meaning only when the bootstrap rejects linearity and the regime coefficients remain stable under alternative specifications.

The executed sample covers 37 economies and 959 observations. The World Bank renewable-consumption indicator fixes the effective terminal year at 2022 even though the data ends in 2023. This distinction matters because describing unavailable observations as part of the estimation window would overstate coverage. Section 2 develops the analytical framework and reviews the empirical literature. Section 3 presents the data and estimators. Section 4 reports the results, Section 5 discusses their meaning and limitations, and Section 6 concludes.

2. Literature Review and Analytical Framework

2.1 Productive energy services and regime dependence

A growth model that omits usable energy services assigns their contribution to capital, labour, or productivity. Energy permits installed capital to operate, extends working time, supports communications, and allows firms to reorganise production. Stern (1993, 2000) showed that multivariate specifications can change the direction and significance of the energy-growth relationship. The

implication for renewable energy is direct: capacity affects output when it delivers reliable services at a cost that does not displace more productive investment.

The broad renewable share contains two opposing signals in many low-income economies. Modern renewable electricity may represent technological upgrading, while a high traditional-biomass share may track low industrial energy use and limited access to clean fuels. Maji et al. (2019) treated this composition as a central explanation for a negative aggregate coefficient in West Africa. Tenaw (2022) reached a related conclusion by distinguishing the clean-energy transition from traditional energy dependence. A regression coefficient on the broad share therefore cannot be interpreted as the return to a solar or wind project without additional measurement evidence.

Regime dependence can arise through both constraints and complementarities. If electricity shortages bind most severely after weak growth, additional renewable supply may yield a larger low-regime effect. If renewable projects require strong demand, finance, transmission, and institutional execution, the coefficient may instead rise in the high-growth regime. Capital adjustment costs may also delay output effects beyond the year of installation. The sign and ranking of the two coefficients remain open empirical questions.

2.2 Evidence from Africa and comparable panels

The energy-growth literature has long examined competing causal directions and measurement issues (Kraft & Kraft, 1978; Ozturk, 2010; Payne, 2010). Early African studies rejected a uniform causal pattern. Wolde-Rufael (2006), Akinlo (2008), Ezzo (2010), and Ouedraogo (2013) obtained results that varied across countries, energy measures, and time-series methods. Multi-country renewable studies likewise produced positive, negative, and neutral estimates (Apergis & Payne, 2010; Bhattacharya et al., 2016; Inglesi-Lotz, 2016). Those findings establish heterogeneity, but average linear models do not identify whether recent growth conditions organise that heterogeneity.

Recent African work uses richer designs. Kouton (2021) applied system GMM to 44 African economies for 1991 to 2015 and reported that renewable energy supported inclusive growth, with larger effects at low inclusive-growth levels. Tenaw (2022) studied 20 Sub-Saharan African countries from 2000 to 2017 with DCCMG and a dynamic threshold model. The study linked the renewable-growth relationship to traditional energy dependence, income, and education. Muazu et al. (2023) applied panel threshold regression to 54 African countries and used nonrenewable energy, urbanisation, and per capita income as transition variables. These studies demonstrate that nonlinear effects depend strongly on the chosen threshold variable.

Institutional and distributional work adds further qualifications. Diallo and Ouoba (2024) examined 25 Sub-Saharan African countries from 2002 to 2018 and found that institutional quality conditioned the growth effect of renewable energy. Mazorodze (2025) found an insignificant preferred estimate for green growth after addressing cross-sectional dependence and slope heterogeneity. The relevant empirical

question has shifted from whether one average coefficient exists to which energy measure, state variable, and institutional setting produce a defensible coefficient.

Common shocks remain a separate concern. Year effects remove a common intercept, but they do not allow countries to load differently on oil prices, drought, external finance, or renewable technology costs. Pesaran (2004, 2006) proposed diagnostic and estimation approaches for cross-sectional dependence and unobserved common factors. Pesaran (2006) proposed cross-sectional averages as proxies for unobserved factors, and Chudik and Pesaran (2015) extended the method to dynamic heterogeneous panels. Tenaw's (2022) use of DCCEMG in this literature makes a common-factor robustness test necessary for any new regional estimate.

Dynamic GMM addresses reverse causality and persistence, but instrument count and serial-correlation tests determine whether its estimates deserve causal language. Arellano and Bond (1991), Blundell and Bond (1998), Windmeijer (2005), and Roodman (2009) show why unrestricted lag sets can overfit endogenous variables and weaken specification tests. The present study therefore collapses the conceptual instrument set into 15 columns, fewer than the 37 countries, and publishes Hansen and AR test outcomes with the coefficient.

2.3 Research gap and propositions

Existing threshold studies generally classify regimes with income, energy structure, urbanisation, or institutions. They do not directly ask whether the renewable coefficient changes with the economy's recent growth state while separating the state variable from current growth. This study fills that narrower gap. The transition variable uses the mean of the three preceding growth rates, so the outcome in year t cannot mechanically determine its own regime.

The first proposition states that renewable energy has a nonzero conditional average association with real GDP per capita growth. The second states that the renewable coefficient differs below and above an unknown threshold in lagged growth. The third requires the result to survive controls for endogeneity, cross-sectional dependence, and slope heterogeneity. Failure at any stage narrows the permissible conclusion even when a coefficient carries a conventional significance marker.

3. Data and Econometric Methodology

3.1 Data, variables, and sample construction

The analysis uses World Development Indicators through the World Bank API. The panel-data structure follows standard econometric treatments of longitudinal datasets in line with (Baltagi, 2021). The observation window spans 1990 to 2023. GDP per capita growth has observations beyond 2023 in the current database, but renewable energy consumption as a share of total final energy consumption has published coverage through 2022. Joint availability and the three-year lag construction produce an effective sample from 1993 to 2022.

The country metadata endpoint identifies 48 economies in the Sub-Saharan Africa region. The estimation rule retains a country when at least 15 observations jointly report growth, renewable energy, gross capital formation, trade, inflation, population growth, and the lagged regime measure. This rule retains 37 countries and 959 country-year observations. It excludes Burundi, Eritrea, Eswatini, Ethiopia, Liberia, Malawi, Nigeria, Somalia, South Sudan, Zambia, and Zimbabwe because one or more core series fail the minimum joint-coverage rule. No interpolation or extrapolation fills missing observations.

Real GDP per capita growth serves as the dependent variable. The main regressor equals renewable energy consumption as a percentage of total final energy consumption. Gross capital formation and trade enter as shares of GDP. The inverse hyperbolic sine of consumer-price inflation retains zero and negative values while limiting extreme scale. Population growth controls for demographic pressure. Renewable electricity output as a share of total electricity output provides a measurement robustness check.

Table 1
Variable definitions and econometric roles

Variable	Measurement	WDI code/construction	Role
g	Real GDP per capita growth, annual %	NY.GDP.PCAP.KD.ZG	Outcome
R	Renewable energy consumption, % of total final energy use	EG.FEC.RNEW.ZS	Main regressor
K	Gross capital formation, % of GDP	NE.GDI.TOTL.ZS	Control
T	Exports plus imports, % of GDP	NE.TRD.GNFS.ZS	Control
π	Consumer-price inflation, annual %; asinh transformation	FP.CPI.TOTL.ZG	Control
n	Population growth, annual %	SP.POP.GROW	Control
q	Mean of g at t - 1, t - 2, and t - 3	Constructed	Transition

Source: World Bank, World Development Indicators. Data preparation and sample audit: Python 3.12 companion code.

Table 1 explains the variables used in the econometric model and their specific roles in examining the relationship between renewable energy and economic growth. Real GDP per capita growth (g) is the dependent variable representing economic performance, while renewable energy consumption (R) is the main explanatory variable. Gross capital formation, trade openness, inflation, and population growth are included as control variables to account for other factors that may influence economic growth. The transition variable (q), constructed from the average of previous three years' growth rates, is used to identify possible differences in renewable energy effects across growth regimes.

3.2 Baseline model and predetermined growth state

The baseline model estimates a within-country association following standard panel-data econometric approaches in accordance with (Wooldridge, 2010). After country and year effects remove persistent national differences and common year shocks. Driscoll and Kraay (1998) proposed covariance estimators that address heteroskedasticity, serial dependence, and general cross-sectional dependence in panel settings. Driscoll-Kraay standard errors allow heteroskedasticity, serial dependence, and general cross-sectional dependence over a three-year bandwidth.

$$g_{it} = \alpha_i + \lambda_t + \beta R_{it} + \gamma' X_{it} + \varepsilon_{it}. \quad (1)$$

Here, X contains gross capital formation, trade openness, transformed inflation, and population growth. A one-unit change in R is one percentage point of total final energy consumption. The regime variable uses only lagged outcomes:

$$q_{it} = (g_{it-1} + g_{it-2} + g_{it-3}) / 3. \quad (2)$$

The three-year mean reduces classification sensitivity to one exceptional growth observation. It also prevents current growth from appearing on both sides of the threshold assignment. A five-year lagged mean supplies a longer-memory robustness check.

3.3 Fixed-effects threshold estimator and inference

The principal specification allows the renewable slope to change at an unknown threshold c while retaining common control coefficients. The candidate set excludes the lowest and highest 15% of q to maintain usable regime sizes.

$$g_{it} = \alpha_i + \lambda_t + \beta R_{it}(q_{it} \leq c) + \beta R_{it}1(q_{it} > c) + \gamma' X_{it} + \varepsilon_{it}. \quad (3)$$

$$\hat{c} = \arg \min_c SSR(c), c \in [q_{0.15}, q_{0.85}]. \quad (4)$$

The threshold lacks identification under the linear null. Dynamic threshold panel approaches with endogeneity considerations have also been discussed by Seo and Shin (2016). Conventional Wald inference for a fixed c therefore cannot establish threshold existence. The code computes the sup-F improvement over the linear model and obtains its p value from 999 country-clustered wild-bootstrap replications. Rademacher weights preserve the full time path within each country. The likelihood-ratio profile defines the threshold confidence set using Hansen's (1999) 95% critical value of 7.35.

3.4 Dynamic GMM and common correlated effects

A dynamic first-difference equation addresses growth persistence and potential reverse causality. Lagged growth and renewable energy enter as endogenous variables instrumented by levels dated $t - 2$ through $t - 4$. Differenced controls and five-year time-block indicators enter as their own instruments. The design uses 15 instruments for 37 countries, satisfying the instrument-count rule proposed by Roodman (2009).

$$\Delta g_{it} = \rho \Delta g_{it-1} + \beta \Delta R_{it} + \gamma' \Delta X_{it} + \tau + \Delta \varepsilon_{it}. \quad (5)$$

$$E[z_{it} \Delta \varepsilon_{it}] = 0, s = 2, 3, 4. \quad (6)$$

The two-step estimator reports a country-cluster robust sandwich covariance matrix, the Hansen J test, and Arellano-Bond AR(1) and AR(2) tests. The dynamic estimate remains a robustness result because annual macro panels can provide weak internal instruments even when the formal tests do not reject.

The DCCEMG model permits heterogeneous country slopes and augments each country regression with current cross-sectional averages of growth and regressors plus lagged cross-sectional averages of growth and renewable energy. The reported regional coefficient equals the arithmetic mean of 28 estimable country slopes. The standard error uses their cross-country dispersion.

$$g_{it} = a_i + \rho_i g_{it-1} + \beta_i R_{it} + \gamma_i' X_{it} + \delta_i' Z_{it} + \varphi_i' Z_{it-1} + u_{it}. \quad (7)$$

3.5 Diagnostic and robustness sequence

Pre-estimation checks cover missingness, within-variable collinearity, cross-sectional dependence, slope heterogeneity, and second-generation unit roots. Post-estimation checks cover residual dependence, serial correlation, groupwise heteroskedasticity, threshold stability, instrument validity, and GMM residual serial correlation. Robustness exercises change the renewable measure, sample, period, transformation, lag window, and regime memory. The conclusion requires consistency across this sequence; one isolated p value cannot overturn the bootstrap or measurement evidence.

4. Empirical Results

4.1 Sample behaviour and pre-estimation tests

Table 2
Descriptive statistics

Variable	N	Mean	SD	Min	Median	Max
Real GDP per capita growth (%)	959	1.22	4.51	-36.82	1.70	27.81
Renewable energy consumption (% of TFEC)	959	63.56	26.92	0.70	73.40	98.30
Gross capital formation (% of GDP)	959	22.72	9.23	2.10	21.48	76.78
Trade (% of GDP)	959	66.23	34.08	4.13	55.35	222.18
Inflation, inverse hyperbolic sine	959	2.09	1.41	-3.52	2.27	10.77
Population growth (%)	959	2.52	1.09	-2.63	2.63	16.75

Source: Author’s computation from World Bank WDI. Software: Python 3.12, pandas 2.2.3 and NumPy 2.3.5.

From Table 2, it can be observed that the Mean real GDP per capita growth equals 1.225%, with a standard deviation of 4.512 percentage points and a range from – 36.825% to 27.807%. The renewable share averages 63.558%, but this high mean does not imply a modern electricity system. Traditional biomass contributes substantially to the WDI aggregate in many sample economies. Gross capital formation averages 22.719% of GDP and trade averages 66.225%.

Table 3
Pre-estimation and residual diagnostics

Procedure	Statistic	p value/critical value	Decision
Pesaran residual CD	-3.349	0.001	Cross-sectional dependence remains
Average residual pair correlation	-0.029		Small mean, jointly nonzero
Slope heterogeneity delta	14.702	< .001	Reject common slopes
Maximum within VIF	1.086		No material collinearity
Residual AR(1) coefficient	0.062	0.208	No residual persistence at 5%
Brown-Forsythe/Levene	3.310	< .001	Groupwise heteroskedasticity
CIPS: gdp_pc_growth	-3.190	5% cv = - 2.25	Reject unit root
CIPS: renewable_share	-1.593	5% cv = - 2.25	Do not reject
CIPS: gcf_share	-2.231	5% cv = - 2.25	Do not reject
CIPS: trade_share	-1.996	5% cv = - 2.25	Do not reject
CIPS: inflation_asinh	-3.330	5% cv = - 2.25	Reject unit root
CIPS: population_growth	-3.633	5% cv = - 2.25	Reject unit root

Source: Author's computation from World Bank WDI. Software: Python 3.12, NumPy and SciPy. CIPS decision uses the approximate 5% intercept-case critical value for panels of this size from Pesaran (2007).

The Unit root tests performed in Table 3 shows that The CD test rejects cross-sectional independence, consistent with the importance of testing cross-sectional dependence in heterogeneous panels (Pesaran, 2004). (CD = - 3.349, $p < .001$), and the heterogeneity statistic rejects a common-slope restriction, consistent with slope heterogeneity testing approaches (Pesaran & Yamagata, 2008). (delta = 14.702, $p < .001$). These results support both Driscoll-Kraay inference and the DCCMG robustness model. The maximum VIF equals 1.086, so multicollinearity does not explain imprecision in the renewable coefficient.

CIPS rejects a unit root for growth, transformed inflation, and population growth. It does not reject for the renewable share, capital formation, or trade. Because the dependent variable is a stationary growth rate,

the study does not estimate a levels cointegrating equation. It instead reports first-difference renewable results and treats level-share coefficients cautiously. This choice avoids attaching long-run equilibrium language to a short-run growth specification.

Figure 1 shows the average yearly movement in GDP per capita growth and renewable energy consumption across the sampled Sub Saharan African countries. Economic growth fluctuated considerably, with a sharp contraction around 2020 followed by recovery. In contrast, the average renewable energy share declined steadily over most of the study period, before a modest rise toward 2022. The contrasting trends suggest that changes in renewable energy use did not move closely with short term economic growth, which supports the need for the formal econometric tests used in the study.

4.2 Linear fixed-effects estimates

Table 4
Two-way fixed effects with Driscoll-Kraay standard errors

Regressor	Coefficient	DK SE	p value	95% CI
Renewable energy consumption (% of TFEC)	0.014	0.023	0.530	[-0.030, 0.059]
Gross capital formation (% of GDP)	0.079	0.019	0.000	[0.042, 0.115]
Trade (% of GDP)	0.030	0.013	0.024	[0.004, 0.056]
Inflation, inverse hyperbolic sine	-0.365	0.222	0.101	[-0.800, 0.071]
Population growth (%)	-0.505	0.194	0.009	[-0.886, -0.125]

Source: Author’s computation from World Bank WDI. Software: Python 3.12. Country and year effects included; Driscoll-Kraay bandwidth = 3; N = 959; countries = 37; within R² = .047.

Results from Table 4 presents that the renewable coefficient equals 0.014 with a standard error of 0.023 (p = .530). A ten-percentage-point increase in the renewable share corresponds to only 0.143 percentage points of growth at the point estimate, while the 95% interval includes effects from – 0.304 to 0.591 percentage points for the same change. The data therefore do not identify a precise average growth response.

Gross capital formation carries a positive coefficient of 0.079 (p < .001), and trade carries a coefficient of 0.030 (p = .024). Population growth enters negatively at – 0.505 (p = .009). Transformed inflation is negative but imprecise (p = .101). These coefficients describe within-country annual covariation after country and year effects; only the dynamic models address stronger endogeneity claims.

4.3 Threshold estimates

Table 5
Fixed-effects panel threshold estimates

Regressor	Coefficient	Cluster SE	p value	95% CI
Renewable share: low-growth regime	0.006	0.028	0.822	[-0.049, 0.061]
Renewable share: high-growth regime	0.017	0.029	0.552	[-0.040, 0.075]
Gross capital formation	0.070	0.033	0.034	[0.005, 0.135]
Trade openness	0.029	0.015	0.049	[0.000, 0.058]
Inflation (asinh)	-0.325	0.213	0.127	[-0.741, 0.092]
Population growth	-0.498	0.220	0.024	[-0.930, -0.067]

Source: Author's computation from World Bank WDI. Software: Python 3.12. Estimated threshold = 1.716%; 95% profile set = [-1.553, 3.831]; wild-bootstrap linearity $p = 0.384$; 999 replications.

Table 5 presents the result of the Fixed-effects panel threshold estimates. The least-squares objective reaches its minimum at a lagged three-year growth rate of 1.716%. The low regime contains 522 observations and the high regime contains 437. The low-regime renewable coefficient equals 0.006 ($p = .822$), while the high-regime coefficient equals 0.017 ($p = .552$). Both confidence intervals include zero.

A fixed-threshold equality test returns $p = .045$, but that statistic conditions on a threshold selected from the same data. The appropriate nonstandard test is the sup-F wild bootstrap. Its p value equals .384, so the analysis does not reject the linear null. The broad profile confidence set, from -1.553% to 3.831% , confirms weak threshold localisation. Reporting only the conditional equality test would overstate evidence for regime dependence.

Figure 2 presents the likelihood-ratio profile used to identify whether a threshold effect exists in the renewable energy and economic growth relationship. The estimated threshold occurs at approximately 1.716% lagged GDP per capita growth, but the profile does not exceed Hansen's 95% critical value, indicating that the threshold is not statistically significant. This suggests that the apparent difference between low-growth and high-growth regimes may be due to sample variation rather than a true structural change in the renewable energy growth relationship.

Figure 3 compares the renewable energy coefficients between the low-growth and high-growth regimes. The estimated effects are positive in both regimes, but the confidence intervals include zero, showing that neither effect is statistically significant. The high-growth regime has a slightly larger coefficient (0.017) compared with the low-growth regime (0.006), but the difference is not strong enough to confirm that economic growth conditions change the impact of renewable energy. Therefore, the figure suggests that renewable energy share alone does not produce a consistent growth effect across different growth states.

4.4 Dynamic GMM and common-factor estimates

Table 6
Dynamic and common-factor robustness estimates

Estimator/test	Estimate	SE	p value	Specification note
Difference GMM, renewable share	0.255	0.279	0.361	Lags 2–4; 15 instruments
Hansen J	8.804		0.066	df = 4
Arellano-Bond AR(1)	-3.753		0.000	Expected rejection
Arellano-Bond AR(2)	-1.662		0.096	No rejection at 5%
DCCEMG, renewable share	0.100	0.466	0.829	28 country slopes
DCCEMG residual CD	-1.861		0.063	Dependence reduced

Source: Author's computation from World Bank WDI. Software: Python 3.12, NumPy and SciPy. Difference GMM uses five-year time blocks and country-cluster robust two-step covariance.

Difference GMM results in Tables 6 estimates a renewable coefficient of 0.255 ($p = .361$). The Hansen test does not reject the instrument set at 5% ($p = .066$), and AR(2) does not reject at 5% ($p = .096$), although both values sit close enough to conventional boundaries to require caution. Lag-window sensitivity gives renewable p values between .361 and .503; specifications that exclude part of the 2-to-4 window fail either Hansen or AR(2) more clearly. The dynamic result therefore supports the null of an imprecise renewable-growth effect rather than a positive causal claim.

DCCEMG produces a mean renewable coefficient of 0.100 with a mean-group standard error of 0.466 ($p = .829$). Residual CD falls to -1.861 ($p = .063$), compared with -3.349 in the baseline residuals. Common-factor augmentation therefore reduces detectable dependence, but it does not reveal a stable renewable slope. Large dispersion in the country estimates explains the wide mean-group interval.

4.5 Robustness checks

Table 7
Measurement, sample, and transformation robustness

Specification	Renewable coefficient	SE	p value	N	Countries
Baseline renewable share	0.014	0.023	0.530	959	37
Exclude major oil exporters	0.022	0.029	0.459	835	32
1990–2004 subsample	0.009	0.031	0.774	327	30
2005 onward subsample	-0.064	0.055	0.240	632	37
Pooled 1/99 winsorisation	0.021	0.023	0.362	959	37
First difference of renewable share	-0.147	0.067	0.028	922	37
Renewable electricity output share	-0.029	0.008	0.000	835	37

Source: Author's computation from World Bank WDI. Software: Python 3.12. Fixed-effects rows use Driscoll-Kraay covariance. Subsamples retain country and year effects.

In Table 7 above, it can be observed that, the baseline coefficient remains insignificant after excluding major oil exporters, splitting the sample, and winsorising at the first and ninety-ninth percentiles. The first difference of the renewable share yields -0.147 ($p = .028$). Renewable electricity output yields -0.029 ($p < .001$). These negative estimates do not establish that renewable projects reduce growth. A share can rise because its denominator falls, and renewable electricity in the sample contains large hydropower systems exposed to rainfall and demand variation. The sign reversal shows that measurement and transformation matter more than the estimated growth threshold.

Leave-one-country-out estimates at the selected threshold range from -0.005 to 0.023 in the low regime and from 0.005 to 0.034 in the high regime. The five-year transition variable produces a threshold of -0.413% , but its 399-replication bootstrap p value equals $.683$. Longer regime memory therefore weakens, rather than strengthens, the evidence for nonlinear growth-state effects.

5. Discussion

The central result is a disciplined null. Across 959 observations, the broad renewable share does not have a statistically distinguishable average effect on real GDP per capita growth. The threshold search identifies a numerical cutoff, but the bootstrap shows that the improvement over a linear model can arise readily under the null. Dynamic GMM and DCCEMG do not alter that conclusion. The finding does not imply that renewable infrastructure lacks economic value. It implies that this aggregate share cannot identify a stable annual macroeconomic return for the sampled countries and years.

The result differs from positive estimates in Kouton (2021) and some multi-country renewable studies, but the outcome and interpretation differ. Kouton models inclusive growth rather than annual GDP per capita growth. Diallo and Ouoba (2024) condition the coefficient on institutional quality. Tenaw (2022) distinguishes modern clean energy from traditional dependence. The present dependent variable is more volatile, and the principal regressor combines technologies and uses. These differences provide testable reasons for divergent coefficients rather than a simple conflict between studies.

The negative first-difference and renewable-electricity estimates require restraint. Both variables are shares. During output contractions, fossil electricity or total final energy use can fall faster than renewable supply, raising the renewable share even when renewable output does not expand. Hydropower-dominant systems can also experience simultaneous generation and agricultural shocks during drought. A quantity measure of delivered solar, wind, hydro, and geothermal electricity per capita would separate numerator expansion from denominator contraction more effectively.

The strong slope-heterogeneity result supports country-specific or technology-specific work. National power pools, fuel import exposure, industrial structure, rainfall risk, and grid capability can change both the sign and timing of the coefficient. DCCEMG absorbs common factors flexibly, yet its wide dispersion

shows that a regional mean masks large uncertainty. A future study should combine national panels with project commissioning dates, transmission additions, outage measures, and night-time lights around project locations.

The empirical design also sets boundaries on policy inference. Governments should not treat a one-percentage-point increase in the broad renewable share as a forecastable increment to annual growth. Project appraisal should measure reliable megawatt-hours delivered, avoided outage costs, import savings, curtailment, financing terms, and local productive use. Where a project meets those conditions, the absence of a regional macro coefficient does not invalidate it. It does prevent the aggregate share from serving as a sufficient growth target.

5.1 Limitations

The complete-case rule excludes 11 regional economies, including Nigeria, because at least one control series lacks sufficient joint coverage. The sample therefore represents countries with stronger statistical continuity. Results may not transfer to fragile states or economies with incomplete national accounts. The workbook reports every inclusion decision so readers can assess this selection.

The threshold model treats the transition variable as predetermined, but it remains an observational design. Lagged growth can correlate with omitted policy expectations and persistent shocks. Difference GMM supplies an endogeneity check, but its Hansen p value of .066 and AR(2) p value of .096 does not provide strong evidence. The DCCEMG model reduces common dependence without identifying the underlying factors. None of these methods creates experimental variation.

The CIPS decision uses an approximate critical value for the observed panel dimensions. Renewable energy, capital formation, and trade remain consistent with unit-root behaviour. First-difference results partly address this issue, but they estimate a short-run response and can magnify measurement noise. A longer technology-specific dataset would permit panel error-correction and distributed-lag models with clearer long-run interpretation.

6. Conclusion and Policy Implications

This paper tested whether renewable energy has different growth effects across recent growth regimes in Sub-Saharan Africa. The design used lagged growth to classify regimes, estimated the threshold from the data, applied country-clustered wild-bootstrap inference, restricted the GMM instrument set, and checked heterogeneous common-factor models. The effective sample contains 37 countries and 959 observations from 1993 to 2022.

The baseline renewable coefficient equals 0.014 ($p = .530$). The estimated threshold equals 1.716%, but the bootstrap fails to reject linearity ($p = .384$). Neither regime coefficient differs from zero. Difference GMM and DCCEMG likewise return imprecise renewable coefficients. A five-year growth state produces

even weaker threshold evidence. The paper therefore finds no robust aggregate renewable-growth effect and no defensible growth-regime discontinuity.

Policy should shift from the broad renewable share to the quality of energy services. Ministries and regulators should report technology-specific generation, delivered electricity, outage reductions, curtailment, storage availability, transmission constraints, and the cost of displaced fuel. These measures connect investment to productive use more directly than the share of total final energy consumption.

Future research should distinguish traditional biomass from modern renewables, match commissioning dates to grid and reliability data, and estimate heterogeneous responses by technology and power-pool membership. Project-level event studies and spatial designs can test mechanisms that annual country shares cannot isolate. The supplied data and code establish an auditable baseline for those extensions.

Declarations

Funding Declaration

No funding was received for this study. The research was conducted without financial support from any funding agency, commercial organisation, or institutional grant.

Ethical Approval

This article does not contain any studies with human participants performed by the author.

Informed Consent

Not applicable. This article does not contain any studies with human participants performed by the author.

Author Contribution

A. A.H. wrote the whole manuscript; Conceptualization; methodology; data curation; software; formal analysis; validation; investigation; visualization; writing the original draft preparation; review and editing; interpretation of results; supervision; and final approval of the manuscript. The author has read and approved the final version of the manuscript.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Figures

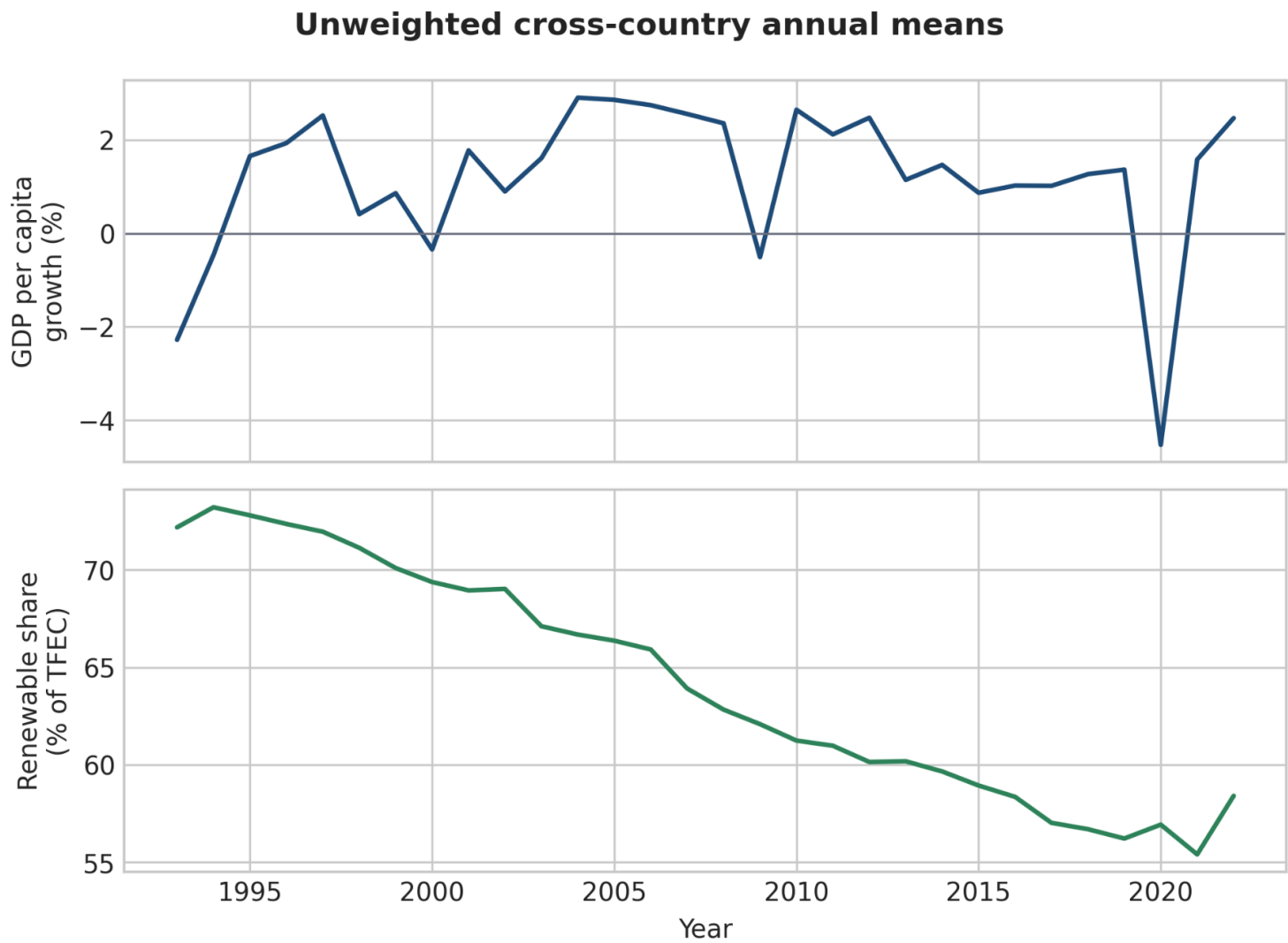


Figure 1

Unweighted annual means of growth and renewable energy

Source: Author’s computation from World Bank WDI. Software: Python 3.12 and Matplotlib 3.10.8. The renewable series ends in 2022.

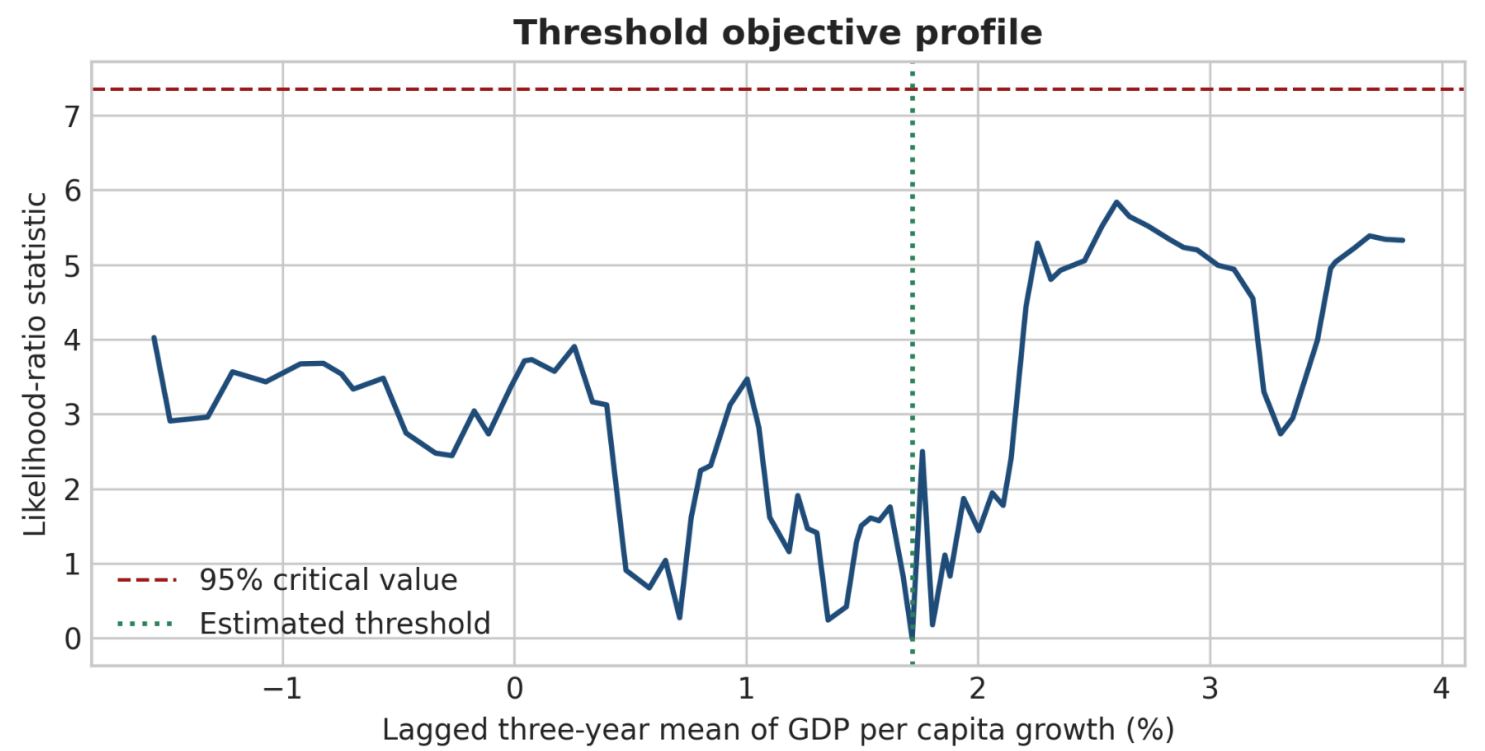


Figure 2

Threshold likelihood-ratio profile

Source: Author’s computation from World Bank WDI. Software: Python 3.12 and Matplotlib 3.10.8. The dashed line marks Hansen’s 95% profile critical value.

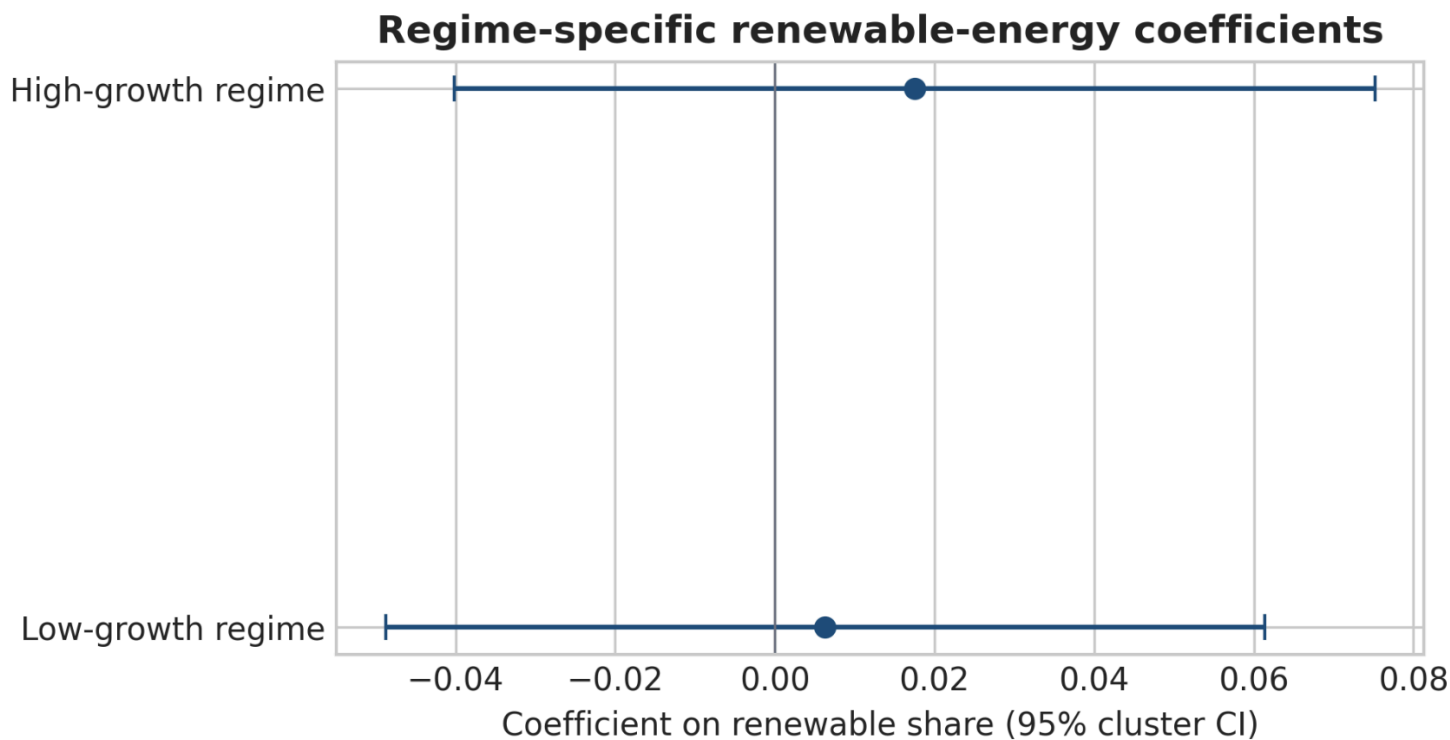


Figure 3

Regime-specific renewable-energy coefficients

Source: Author’s computation from World Bank WDI. Software: Python 3.12 and Matplotlib 3.10.8.
Intervals use country-clustered covariance estimates.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [SSARenewableGrowthDataandCodebook.xlsx](#)