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Article

Energy Poverty, Human Capital, and the Long-Run GDP-per-capita Relationship in Nigeria: An ARDL Analysis

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Abstract

This study examines the long-run association between energy poverty, human capital and the level of real GDP per capita in Nigeria using 40 annual observations (1985-2024). Energy poverty is an equal-weighted composite deprivation index (electricity access, clean-cooking access, electricity consumption per capita), normalised by min-max and entered in logs (lnEP; higher values mean greater deprivation). Unit-root tests classify lnGDPPC, lnK, lnTO and inflation as I(1) or I(0)/I(1) but leave lnEP and lnHC unresolved (first differences not clearly stationary), so all bounds-test inference is conditional on I(1) behaviour. An ARDL(1,1,1,1,1) error-correction model without human capital (Case III, k = 4) gives a bounds F-statistic of 8.82, above the Pesaran-Shin-Smith upper 1% bound (5.06) and a simulated finite-sample upper 1% bound (6.30); the long-run lnEP coefficient is −0.80 (95% CI −1.12 to −0.49), the total association. With lnHC added (k = 5), F = 3.80 is inconclusive against the finite-sample 5% upper bound (4.48) and the lnEP multiplier is positive and imprecise (0.85; 95% CI −1.45 to 3.16). A re-specified dynamic human-capital equation gives a long-run lnEP coefficient of −0.21 (p = 0.044). The product-of-coefficients indirect effect is −0.45 (Sobel 95% interval −1.20 to 0.30); the block-bootstrap intervals for the indirect and total effects are far wider and include zero, so a large indirect share is not supported and H4 is not accepted. Adding a 1996 intercept shift removes the long-run relationship, and results depend on the sample and estimator. The evidence is therefore exploratory and associational rather than causal. Every estimate is conditional on the equal-weighted composite index, and its robustness to index construction (alternative weights, leave-one-component-out indices and separate component indicators) has not been established. No mediated share is reliably estimated, because the indirect-effect intervals include zero.

Keywords

Energy poverty, Human capital, GDP per capita, ARDL bounds test, Pathway (mediation) decomposition, Nigeria, Endogenous growth theory

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1. Introduction

One of the most formidable structural constraints confronting economic development in sub-Saharan Africa is energy poverty, and Nigeria is no exception. Despite Nigeria being the largest economy in the African continent and the foremost petroleum producer, Nigeria paradoxically struggles with one of the most acute energy access deficits globally. World Bank data indicate that roughly two-fifths of Nigerians still lacked access to electricity in 2023 [1], and dependence on traditional biomass for cooking remains widespread, a severe dimension of energy poverty that undermines household welfare and productivity.

The endogenous growth paradigm developed a well-established theoretical linkage between energy and economic growth [2,3]. Energy, as a complementary input to both physical and human capital, facilitates productivity-enhancing activities including education, healthcare delivery, and innovation. The endogenous growth theory is fundamentally impaired when access to modern energy services is denied, as is prevalent in energy-poor contexts: the accumulation of human capital, a primary engine of growth and development, is constrained. Workers cannot acquire the digital skills demanded by contemporary knowledge economies, children cannot study after dark, and health facilities cannot function optimally (see the discussion of health and education channels in Singh and Inglesi-Lotz [4]).

Yet, extant literature predominantly treats the energy-growth nexus in a reduced-form, bilateral framework that neglects the mediating role of human capital (for example, Longe et al., [5]; Olarinde and Adeniran [6]), despite the intuitive logic of this transmission mechanism. This omission is both theoretically and empirically consequential, particularly for a country like Nigeria, where there is a striking disconnect between the severity of energy poverty and the pace of human-capital development. Nigeria ranks 161st of 193 countries on the 2023/24 Human Development Index (HDI value 0.548 for 2022, in the low human development category) [7], lagging far behind the country's resource endowment.

This gap is addressed by this study by incorporating the energy poverty-growth relationship within a human-capital-augmented endogenous growth framework. Specifically, we investigate four hypotheses: H1: energy poverty is negatively associated with the long-run level of real GDP per capita in Nigeria; H2: energy poverty reduces human capital accumulation; H3: human capital is positively associated with the long-run level of real GDP per capita; and H4: human capital constitutes a channel through which energy poverty is associated with GDP per capita (a pathway decomposition, not a validated causal mediation effect; see Sections 3.4 and 6.6). Because the evidence reported below is exploratory, each hypothesis is graded as supported, partly supported or not supported in Section 7.1. All results are conditional on a single equal-weighted composite measure of energy poverty, and the pathway estimate is reported with intervals that include zero; both qualifications apply wherever the findings are summarised (Sections 4.2, 6.6, 7.1 and 7.3).

The study employs a comprehensive empirical strategy encompassing Autoregressive Distributed Lag (ARDL) bounds cointegration testing, long-run Ordinary Least Squares (OLS) and Dynamic Ordinary Least Squares (DOLS) estimation, error-correction modelling, a pathway (mediation) decomposition with Sobel and block-bootstrap intervals, and structural-stability analysis, over the period 1985-2024. The window ends in 2024 because the 2025 observation in the working dataset lies outside the data vintage and its index value is zero by construction (Section 4.2); the window starts in 1985 because that is the first year of the annual series.

The remainder of this paper is structured as follows. Section 2 reviews the relevant theoretical and empirical literature. Section 3 presents the theoretical framework and model specifications. Section 4 describes the data and variables. Section 5 outlines the econometric methodology. Section 6 presents and discusses the empirical results. Section 7 concludes with policy implications and limitations.

2. Literature Review

2.1 Empirical Literature

The empirical energy-growth literature for Nigeria and sub-Saharan Africa is large but varies in method, sample, and in how energy poverty and human capital are measured; each study carries limitations that this paper does not resolve. Singh and Inglesi-Lotz [4] estimated fixed-effects and GMM models for fourteen sub-Saharan countries over 1990-2016 and found that access to electricity contributes positively to growth, with a relatively small direct effect; they note that health, education and income-generating benefits of access, which are not estimated in their model, may carry further effects. This is the channel the present paper probes in a single-country time-series setting.

Evidence on Nigeria is mostly energy-consumption based. Longe et al. [5] used a nonlinear ARDL model for 1981-2018 and found that electricity consumption raises growth significantly in the short run but insignificantly in the long run, while capital formation is positive and significant in both. Olarinde and Adeniran [6] applied ARDL bounds testing to 1990-2016 data and reported feedback causation between growth and energy consumption, which warns that reverse causality from income to energy access cannot be dismissed. Ogbeide-Osaretin [8] found that modern energy sources reduce poverty in Nigeria while fuelwood and coal raise it. None of these studies models human capital as a transmission channel.

Work linking human capital and energy mostly runs in the other direction. Yao et al. [9] report that higher human capital reduces energy consumption in an OECD panel, and Churchill et al. [10] find a negative long-run link in six centuries of

United Kingdom data. These studies concern energy use rather than energy deprivation and say little about growth, but they show that the human capital-energy relation is plausibly bidirectional, which matters for the interpretation of any single-direction pathway.

2.2 Human Capital as a Mediating Channel

The specific mediating role of human capital in the energy-growth relationship has attracted growing scholarly attention. Fouquet and Pearson [11] review historical energy transitions and stress that they unfold over long periods, which is relevant to the slow adjustment speeds estimated below. Micro-level studies show that electrification can change development outcomes: Dinkelman [12] finds that rural electrification raised female employment in South Africa, and Lipscomb et al. [13] find sizeable positive effects of electrification on a composite development index in Brazil. Such household- and district-level findings provide grounding for the macro-level pathway investigated here, but a macro time-series association cannot by itself confirm the mechanisms they document.

Despite this progress, a gap remains in testing, within a unified time-series framework for Nigeria, whether human capital accounts for a substantial share of the total estimated pathway from energy poverty to GDP per capita.

2.3 Theoretical Underpinnings

The relationship between energy and economic growth is theoretically grounded in two principal traditions. The neoclassical growth model [14] treats energy as an intermediate input into production but relegates it to an exogenous factor whose long-run influence on output is negligible. In contrast, the endogenous growth theory of Romer [2] and Lucas [3] offers a more accommodating theoretical home, in which knowledge, skills, and human capital - which generate sustained per-capita income growth without diminishing returns - are accumulated with the facilitation of energy.

Specifically, the human-capital-augmented growth model [15] demonstrates that economies with higher human-capital stocks grow faster, conditional on their savings rates and technology. Energy poverty, by constraining educational attainment and health outcomes, is hypothesised to diminish the human-capital stock and, through this channel, to be associated with slower long-run growth. This transmission - from energy poverty, to reduced human capital, to reduced GDP per capita - constitutes the pathway hypothesis (H4) that underpins this study; we treat it as a hypothesised, exploratory pathway rather than an established causal mediation mechanism (see Section 3.4).

3. Theoretical Framework and Model Specification

3.1 Theoretical Framework

This study embeds the energy poverty-growth relationship within the Lucas [3] and Romer [2] endogenous growth framework, augmented by the Mankiw, Romer and Weil [15] human-capital model. The formal production function is:

$$Y_t = A_t \cdot K_t^{\alpha} \cdot H_t^{\beta} \cdot L_t^{(1-\alpha-\beta)}$$

where Y is aggregate output, A is total factor productivity, K is physical capital, H is human capital, L is labour, and α and β are output elasticities. Energy does not enter this production function directly. Energy poverty is treated as an exogenous shifter of the human-capital-accumulation technology (Equation 2 below) rather than as a direct input into the aggregate production function above; the empirical GDP-per-capita equation (Equation 1) is a reduced-form specification motivated by, but not mechanically derived from, this production function. Gross fixed capital formation as a percentage of GDP (lnK) is an investment-flow proxy, not a measure of the physical-capital stock. Labour-force participation (lnLF) is a labour-supply variable, distinct from labour input, hours or employment; it is not used in any estimate reported in this paper.

Distinguishing the roles of the variables, the variables used in this study are grouped as follows (Table 1):

Table 1. Classification of study variables.

Role	Variables
(i) Production-function primitives (theoretical)	K (physical capital), H (human capital), L (labour), A (total factor productivity)
(ii) Determinants of human-capital accumulation (Equation 2)	Energy poverty (lnEP), education expenditure (lnEDU), health expenditure (lnHE), digital/ICT access (lnICT)
(iii) Variables in the GDP-per-capita equation (Equation 1)	Energy poverty (lnEP), human capital (lnHC; excluded in the total-effect model), capital-deepening proxy (lnK), trade openness (lnTO), inflation (INF)
(iv) Variable not used in estimation	Labour-force participation (lnLF), near-constant (standard deviation 0.006) and partly back-cast before 1990; retained in the dataset only for descriptive and unit-root purposes

Source: Author's computation.

3.2 Baseline Long-Run Model

The baseline long-run model expresses the natural logarithm of the level of real GDP per capita (lnGDPPC) - not GDP-per-capita growth—as a function of energy poverty, human capital, physical-capital-deepening, trade openness, and inflation:

$$lnGDPPC_t = \alpha_0 + \alpha_1 lnEP_t + \alpha_2 lnHC_t + \alpha_3 lnK_t + \alpha_4 lnTO_t + \alpha_5 INF_t + \varepsilon_t \quad (1)$$

Expected signs: $\alpha_1 < 0,\ \alpha_2 > 0,\ \alpha_3 > 0,\ \alpha_4 > 0,\ \alpha_5 < 0$. This is a long-run level relationship: the short-run ARDL-ECM (Equation (4)) captures period-to-period changes, which approximate but are not identical to a growth-rate specification. The total-effect counterpart of Equation (1), which omits lnHC, is written as Equation (1′):

$$lnGDPPC_t = \alpha_0' + \alpha_1' lnEP_t + \alpha_3' lnK_t + \alpha_4' lnTO_t + \alpha_5 INF_t + \varepsilon_t' \quad (1')$$

3.3 Human Capital Accumulation Equation

The second equation models the determinants of human-capital accumulation, positioning energy poverty as a structural barrier:

$$lnHC_t = \beta_0 + \beta_1 lnEP_t + \beta_2 lnEDU_t + \beta_3 lnHE_t + \beta_4 lnICT_t + \mu_t \quad (2)$$

Expected signs: $\beta 1 < 0,\ \beta_2 > 0,\ \beta_3 > 0,\ \beta_4 > 0$. The Penn World Table (PWT) human-capital index used as the dependent variable is built from average years of schooling and assumed returns to education [16]; it does not include health. Education and health expenditure shares appear on the right-hand side as inputs to schooling and to health capital [17]. Public spending both shapes and responds to measured human capital and economic performance, so reverse causality cannot be excluded in this single-equation specification. Equation (2) is estimated in a dynamic ARDL form (Section 5.3) because the static form fails serial-correlation and functional-form tests (Section 6.5).

3.4 Mediation/Pathway Framework

Following the product-of-coefficients logic of Baron and Kenny [18] and Hayes [19], the pathway decomposition of the estimated total association of energy poverty with GDP per capita is built from the long-run multipliers of Equations (1), (1′) and (2):

$$Total\ association\ (TE) = \alpha_1'\ (directly\ estimated\ from\ Equation 1',\ mediator\ excluded) \quad (3a)$$

$$Indirect\ (human-capital)\ effect\ (IE) = \beta_1 x\ \alpha_2 \quad (3b)$$

$$Direct\ effect\ (DE) = \alpha_1 (from\ Equation\ 1,\ mediator\ included) \quad (3c)$$

The total effect is not defined algebraically as DE + IE, because that sum is not a separately estimated total effect. TE is estimated directly from the model that excludes lnHC, and the algebraic sum DE + IE and the difference TE - DE are reported only as consistency checks (Section 6.6). Combining the coefficients requires strong assumptions: (i) each long-run relation is a stable cointegrating relation in its own right; (ii) the lnEP coefficient in Equation (2) is not contaminated by serial correlation, misspecification or endogeneity; (iii) long-run multipliers from two equations estimated on different effective samples (1986-2024 and 1987-2024) and with different lag structures are commensurable; (iv) there is no unmeasured confounding of the energy poverty-human capital and human capital-income relations, and no reverse feedback from income to either. These are the sequential-ignorability-type conditions required for causal mediation [20]. They are not tested here, so the product β_1 x α_2 is a conditional statistical decomposition and not a structural or causal mediation estimate. Sampling uncertainty is reported with Sobel [21] delta-method and moving-block bootstrap intervals (Section 5.4), not stepwise significance tests.

3.5 Dynamic ARDL-ECM Specification

To capture short-run dynamics and error correction, the study employs the unrestricted error-correction model (UECM) underlying the ARDL bounds-testing procedure:

$$\begin{aligned}\Delta lnGDPPC_t = {} & \gamma_0 + \lambda\, lnGDPPC_{(t-1)} + \delta_1 lnEP_{(t-1)} + \delta_2 lnHC_{(t-1)} + \delta_3 lnK_{(t-1)} + \delta_4 lnTO_{(t-1)} + \delta_5 INF_{(t-1)} \\ & + \varphi_1 \Delta lnEP_t + \varphi_2 \Delta lnHC_t + \varphi_3 \Delta lnK_t + \varphi_4 \Delta lnTO_t + \varphi_5 \Delta INF_t + \varepsilon_t\end{aligned} \quad (4)$$

The long-run multipliers are recovered as $-\delta_i / \lambda$, with standard errors from the delta method. A negative and statistically significant λ is consistent with adjustment toward the estimated long-run relation, conditional on the validity of that relation and the rest of the dynamic specification. The total-effect counterpart of Equation (4), which omits lnHC and ΔlnHC, is written as Equation (4′):

$$\begin{aligned}\Delta lnGDPPC_t = {} & \gamma_0' + \lambda' lnGDPPC_{(t-1)} + \delta_1' lnEP_{(t-1)} + \delta_3' lnK_{(t-1)} + \delta_4' lnTO_{(t-1)} + \delta_5' INF_{(t-1)} \\ & + \varphi_1' \Delta lnEP_t + \varphi_3' \Delta lnK_t + \varphi_4' \Delta lnTO_t + \varphi_5' \Delta INF_t + \varepsilon_t'\end{aligned} \quad (4')$$

Equation (4′) is the total-effect UECM estimated as Model B (mediator excluded) in Table 5 and in the Model B column of Table 6. It is the error-correction counterpart of the static total-effect model in Equation (1′), in the same way that Equation (4) is the counterpart of Equation (1). The subscripts follow Equation (4) so that corresponding coefficients can be compared directly, and the primes denote coefficients of the model that excludes lnHC. Its long-run multipliers are recovered as $-\delta_i' / \lambda$, again with delta-method standard errors.

4. Data and Variable Measurement

4.1 Data Sources

The study utilises annual time-series data for Nigeria covering 1985-2024 (T = 40 observations; the UECM effective sample is 1986-2024, n = 39). Data are sourced from the World Development Indicators (WDI) [1], the International Energy Agency [22], the PWT [16], the Central Bank of Nigeria (CBN) Statistical Bulletin [23], and the International Telecommunication Union [24]. The working dataset extends to 2025 (41 rows); the 2025 row is excluded from the primary sample and used only in a sensitivity check (Section 6.4). Table 2 lists the indicator series and records, from inspection of the working dataset, every treatment of missing, back-cast, interpolated, floored and spliced observations. Appendix B (Table S2) lists these treatments observation by observation (variable, years affected, type of treatment and evidence, and use in estimation) so that each can be audited. The replication package contains, for every series, the source identifier and the data vintage, together with a flag for each treated observation and code that reproduces the estimates in the descriptive statistics, the estimates and the analytic quantities reported in Sections 4.2 and 6.4 to 6.6 from the working dataset.

Table 2. Indicator series, coverage and data treatment.

Variable	Source series	Treatment observed in the working dataset
lnGDPPC	GDP per capita, constant 2015 US$ (WDI: NY.GDP.PCAP.KD)	Complete 1985-2024; no treatment.
lnEP	Equal-weighted composite of access to electricity (% pop., EG.ELC.ACCS.ZS), access to clean cooking fuels (% pop., EG.CFT.ACCS.ZS) and electric power consumption (kWh p.c.)	Min-max bounds span 1985-2025: index = 1.000 in 1985 and 0 in 2025 (recorded as 0.0001, ln = -9.210, a zero-replacement floor). 2025 is excluded from the primary sample. Annual values in Appendix A (Table S1).
lnHC	Human capital index (PWT, hc)	PWT version 10 hc ends in 2019. Growth of lnHC drops from about 0.026 to 0.016 per year after 2019, so 2020-2024 values are an extension of the source series. A 1985-2019 sensitivity sample is reported (Section 6.4).
lnK	Gross fixed capital formation, % of GDP (WDI: NE.GDI.FTOT.ZS)	Complete; level drop of 0.44 log points in 2013 is consistent with GDP rebasing or series splicing (Section 6.2).
lnLF	Labour force participation rate, total (WDI: SL.TLF.CACT.ZS)	1986-1992 values fall by a constant 0.0015 log points a year (the 1985-86 fall is twice as large), consistent with a linear back-cast; 1996 and 1997 are identical. Not used in estimation.
lnTO	Trade (exports + imports)/GDP (WDI: NE.TRD.GNFS.ZS)	Complete; upward jump of 0.40 log points in 2000 (Section 6.2).
INF	Inflation, consumer prices, annual % (WDI: FP.CPI.TOTL.ZG)	Complete.
lnEDU	Government expenditure on education, % of GDP (WDI: SE.XPD.TOTL.GD.ZS)	Recorded to one decimal place (range 0.4% to 2.5% of GDP), hence step-like; falls from 1.7% in 2022 to 0.5% in 2023 and 0.4% in 2024; this discontinuity is not adjusted for.
lnHE	Current health expenditure, % of GDP (WDI: SH.XPD.CHEX.GD.ZS)	1985-2005 values change by 0 or +0.1 percentage point a year (1.8% to 3.6%; 1996 and 2002 repeat the previous year), a pattern consistent with interpolation between sparse observations; later values are one-decimal annual observations.
lnICT	ICT-access indicator per 100 inhabitants (ITU); see scale check in the next column	Floor of 0.01 per 100 (ln = -4.605) for 1985-1997; observed values from 1998. Scale check: recorded values reach 47.4 per 100 (2015) and 42 per 100 (2025), which is the range of internet use as a share of the population and far above any plausible fixed-broadband penetration for Nigeria, so the series is interpreted as internet-use intensity.

Note: Vintage 2024 for all series. Treatments were identified from the working dataset and are listed observation by observation in Appendix B. Source identifiers and the data vintage are recorded in the data dictionary of the replication package. Source: Author's Computation.

4.2 Variable Measurement

Economic performance (lnGDPPC) is measured as the natural logarithm of the level of real Gross Domestic Product

(GDP) per capita at constant 2015 prices, expressed in US dollars [1]. This is the standard proxy for long-run economic performance in growth regressions [25]; this is a level, not a growth-rate, variable.

Energy poverty is operationalised as an equal-weighted, min-max normalised deprivation index built from three raw access indicators, each of which increases with better energy access: (i) access to electricity (% of population), (ii) access to clean cooking fuels (% of population), and (iii) electricity consumption per capita (kWh). For each component c and year t:

$$d(c,t) = I - \left[\left(x(c,t) - min_c \right) / \left(max_c - min_c \right) \right]$$

where $x(c,t)$ is the raw value of component c in year t, and min_c and max_c are the minimum and maximum of that component over the Nigerian series (1985-2025) in the working dataset, not an external cross-country reference. The worst-observed year is 1985 and the best-observed year is 2025 for every component, so the composite index equals 1.000 in 1985 and zero in 2025. Because each raw indicator increases with better access, $d(c,t)$ is a deprivation score in [0, 1]. The composite index is the equal-weighted average of the three deprivation scores:

$$EP_t = \left(1/3\right) x \left[d\left(electricity,t\right) + d\left(cooking,t\right) + d\left(consumption,t\right) \right]$$

and $\ln EP_t = \ln(EP_t)$. Over 1985-2024 EP lies in [0.068, 1.000] and lnEP in [-2.693, 0]. A higher value of the composite index and of lnEP (a value closer to zero) denotes greater energy poverty; a lower (more negative) lnEP denotes less energy poverty. This single definition is used throughout. The composite index falls from 1.000 in 1985 to 0.068 in 2024, so lnEP declines from 0 to -2.693 as deprivation is reduced. The decline is monotone except for a reversal in 2020 (EP rises from 0.350 to 0.401) and accelerates sharply after 2020 (EP = 0.264, 0.182 and 0.068 in 2022, 2023 and 2024). In 2025 the index equals zero and the log is undefined; the working dataset replaces it by 0.0001 (lnEP = -9.210), which is an ad hoc floor and an extreme outlier. For this reason 2025 is excluded from the primary sample, and the log of an index that approaches zero is also the source of the unit-root ambiguity discussed in Section 6.1. Equal weighting (1/3 each) follows Sadath and Acharya [26] and Nussbaumer et al. [27].

The annual composite index before and after logging is reported for every year in Appendix A and in the replication workbook. The raw component series were not part of the estimation workbook, so the sensitivity checks that require them could not be run, and the central association has not been shown to be robust to index construction. Every result involving lnEP is therefore conditional on the equal-weighted composite index (Section 7.3). The sensitivity analysis in Section 6.4 varies the functional form of the index (log or level) and the estimation window, with signs and 95% intervals reported side by side, but it does not vary the weights or the components. The checks to be run once the components are available are: (i) equal weights, a theoretically justified dimension-based scheme and, where suitable, principal-component weights; (ii) leave-one-component-out indices; and (iii) separate electricity-access, clean-cooking and electricity-consumption specifications. For each, the sign of the long-run coefficient and its 95% interval will be reported side by side. The replication package contains an input template for the three raw components and code (index_robustness.py) that implements these checks.

Human capital (lnHC) is proxied by the natural logarithm of the PWT Human Capital Index, which is constructed from average years of schooling and assumed returns to education [16]; it does not incorporate health or life expectancy. Physical-capital-deepening (lnK) is measured as the logarithm of gross fixed capital formation as a percentage of GDP [1]; this is an investment-flow share, not a capital-stock measure. Trade openness (lnTO) is the natural logarithm of the sum of exports and imports divided by GDP, a standard growth-regression control [28]. Inflation (INF) is the Consumer Price Index (CPI) annual growth rate. Education expenditure (lnEDU) is government expenditure on education as a share of GDP (log), and health expenditure (lnHE) is current health expenditure as a share of GDP (log). Digital access (lnICT) is the log of an ITU ICT-access series recorded per 100 inhabitants. Its recorded values (0.01 to 47.4 per 100) are on the scale of internet use as a share of the population, not of fixed-broadband subscriptions, and it is not a mobile-telephony indicator (Table 3).

Table 3. Descriptive statistics of variables (1985-2024).

Variable	Label	Obs.	Mean	Std. Dev.	Min.	Max.	Source
lnGDPPC	Real GDP per capita (log level)	40	6.570	0.234	6.275	6.923	WDI
lnEP	Energy poverty index (log, deprivation-coded)	40	−0.576	0.531	−2.693	0.000	WDI/IEA (composite)
lnHC	Human capital index (log)	40	0.666	0.288	0.235	1.128	PWT
lnK	Gross fixed capital formation, % GDP (log)	40	2.947	0.246	2.557	3.437	WDI
lnLF	Labour force participation (log); not used	40	4.170	0.006	4.162	4.187	WDI
lnTO	Trade openness (log)	40	3.497	0.228	3.105	3.959	WDI
INF	Inflation, CPI (%)	40	19.09	16.32	5.40	72.80	WDI/CBN
lnEDU	Education expenditure, % GDP (log)	40	0.258	0.463	−0.916	0.916	WDI
lnHE	Health expenditure, % GDP (log)	40	1.138	0.226	0.588	1.435	WDI
lnICT	ICT access per 100 (log)	40	−0.236	3.667	−4.605	3.859	ITU
EP	Energy poverty index (level)	40	0.625	0.241	0.068	1.000	composite

Note: Statistics recomputed from the working dataset for 1985-2024 (T = 40). Obs. = number of observations; Std. Dev. = standard deviation; Min. = minimum; Max. = maximum; ln = natural logarithm; WDI = World Development Indicators; IEA = International Energy Agency; PWT = Penn World Table; CBN = Central Bank of Nigeria; ITU = International Telecommunication Union. Source: Author's Computation.

5. Econometric Methodology

5.1 Unit Root Testing

Prior to estimation, we assess the stationarity properties of all variables using the Augmented Dickey-Fuller (ADF) test [29], the Phillips-Perron (PP) test (Phillips and Perron, 1988 [30]), and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test [31], with a constant in each test. The ADF and PP tests operate under the null hypothesis of a unit root, while the KPSS test maintains the null of stationarity, enabling triangulation of integration orders. The ADF lag length is selected by the Schwarz criterion with a maximum of three lags (Schwert's l4 rule for T = 40). A variable is I(2) or higher if a unit root remains in its first difference. Tests are therefore applied to levels and to first differences. Rejection of a unit root in second differences is expected for I(1) and I(2) series alike and is therefore not used for classification. The Zivot and Andrews [32] test, which allows one endogenous break, is added for lnGDPPC, lnEP and lnHC.

5.2 ARDL Bounds Test for Cointegration

The ARDL bounds-testing procedure of Pesaran, Shin, and Smith [33] is used in preference to the Johansen [34] test because it accommodates a mixture of I(0) and I(1) regressors, performs reasonably in small samples, and yields a single cointegrating vector through the conditional error-correction model. It does not accommodate I(2) variables. The bounds test is an F-test of joint significance of the lagged level variables in the UECM; if F exceeds the upper critical bound the null of no level relationship is rejected. The lag order is chosen by the Schwarz and Akaike criteria over up to three lags (ARDL(1,1,1,1,1,1) is the BIC choice for the model with lnHC), the deterministic case is Case III (unrestricted intercept, no trend), k is the number of long-run regressors (k = 5 with lnHC, k = 4 without), and the asymptotic critical values are those of Pesaran et al. (2001, Table CI(iii)). Because asymptotic bounds are unreliable at T = 40 [35], finite-sample critical values for the F- and t-statistics are also simulated for T = 40, 20,000 replications, under the null with I(0) and with I(1) regressors, and decisions are based on the finite-sample values.

5.3 Long-Run and Short-Run Estimation

The primary long-run coefficients are the ARDL/UECM-implied long-run multipliers, computed as $-\delta_i/\lambda$ from the same UECM used for the bounds test, with delta-method standard errors, t-statistics and 95% confidence intervals. As secondary, sensitivity estimators, we also report static OLS with Newey-West heteroskedasticity- and autocorrelation-consistent (HAC) standard errors [36], and Dynamic OLS (DOLS) with one lead and one lag of the first differences of the regressors [37]. Where these diverge materially from ARDL, this is reported as estimator sensitivity, not robustness. The human-capital equation is estimated as an ARDL(2,1,1,1,1) UECM selected by AIC and BIC from a grid of up to two lags, because the static form fails serial-correlation and functional-form tests; its long-run lnEP multiplier is computed in the same way.

5.4 Pathway (Mediation) Decomposition

The pathway decomposition follows the product-of-coefficients approach of Preacher and Hayes [38]. Three quantities are compared: the directly estimated total association (TE, mediator-excluded model), the direct effect (DE, mediator-included model), and the indirect product IE = $\beta_1 \times \alpha_2$ from the separate equations. Uncertainty is reported two ways: a Sobel [21] delta-method interval for the product, and a moving-block bootstrap [39]; Efron and Tibshirani [40] that re-

estimates all three UECMs on resampled blocks of five consecutive years (3,000 resamples, same blocks for every equation, years 1987-2024). Because the long-run multipliers are ratios (-δ/λ) with λ close to zero, bootstrap distributions are heavy-tailed and the percentile intervals are very wide.

5.5 Structural-Stability Analysis

Stability is examined with (i) the CUSUM and CUSUMSQ tests of Brown et al. [41] on recursive residuals of the UECM; (ii) a Bai and Perron [42]-type exhaustive search for up to three intercept shifts (partial structural change, 15% trimming), with sup-F(l+1|l) tests evaluated against critical values from a residual bootstrap of the no-break model [43]; 300 replications); (iii) Chow-type intercept-shift tests at known dates (1999 democratic transition, 2016 recession, 2020 pandemic); (iv) re-estimation of the model with step dummies at the detected breaks; and (v) recursive re-estimation of the long-run multiplier on expanding windows.

5.6 Wald Tests

Wald tests assess the statistical significance of selected long-run multipliers and joint restrictions on the lagged levels in the UECM. They are joint-significance tests of coefficient restrictions; they do not by themselves validate the theory, the identification, or a causal-mediation interpretation. The Wald statistic is asymptotically chi-squared (equivalently, F-) distributed under the null hypothesis [44].

6. Empirical Results and Discussion

6.1 Unit Root Test Results

As shown in Table 4, the evidence supports I(1) for lnGDPPC, lnK, lnTO and lnEDU, and I(0)/I(1) for inflation and health expenditure. It does not establish an integration order for the two variables that matter most. For lnEP, a unit root remains in the first difference under both ADF (p = 0.827) and PP (p = 1.000), and the Zivot-Andrews test does not reject a unit root in the first difference (p = 0.971); the cause is the sharp acceleration of the log index towards zero after 2020 (Section 4.2). For lnHC, ADF and PP do not reject a unit root in the first difference (p = 0.307 and 0.401) although KPSS does not reject stationarity of the first difference and the Zivot-Andrews test with a trend rejects for the level (p = 0.020). lnICT and lnLF split ADF and PP. It therefore cannot be asserted that every series is I(0) or I(1) with no I(2) variable. All bounds-test results below are conditional on lnEP and lnHC being at most I(1), and an I(2) regressor would invalidate the PSS critical values. The same ambiguity applies to the index in levels (ADF p = 0.308 for the first difference), so it is a property of the series and not only of the log transform.

Table 4. Unit-root tests, 1985-2024.

Variable	ADF level (p)	PP level (p)	KPSS level	ADF Δ (p)	PP Δ (p)	KPSS Δ	Classification
lnGDPPC	−1.00 (0.752)	−0.46 (0.899)	0.693*	−3.94 (0.002)	−3.97 (0.002)	0.495*	I(1)
lnEP	1.11 (0.995)	2.41 (0.999)	0.878*	−0.77 (0.827)	6.55 (1.000)	0.410	I(1); I(2)
lnHC	−3.17 (0.022)	0.66 (0.989)	0.903*	−1.95 (0.307)	−1.76 (0.401)	0.292	I(1); I(2)
lnK	−0.73 (0.838)	−0.54 (0.884)	0.569*	−4.92 (0.000)	−4.87 (0.000)	0.080	I(1)
lnTO	−2.33 (0.163)	−1.76 (0.401)	0.124	−4.38 (0.000)	−4.15 (0.001)	0.075	I(1)
INF	−2.79 (0.059)	−2.76 (0.064)	0.246	−5.88 (0.000)	−6.00 (0.000)	0.125	I(0)/I(1)
lnEDU	−0.38 (0.914)	−1.31 (0.623)	0.435	−4.73 (0.000)	−4.99 (0.000)	0.388	I(1)
lnHE	−2.83 (0.054)	−4.06 (0.001)	0.819*	−5.55 (0.000)	−5.59 (0.000)	0.443	I(0)/I(1)
lnICT	−1.35 (0.607)	−0.74 (0.837)	0.824*	−1.80 (0.382)	−4.36 (0.000)	0.176	(ADF and PP disagree on Δ)
lnLF (not used)	−1.74 (0.408)	−2.69 (0.075)	0.443	−1.60 (0.482)	−6.22 (0.000)	0.777*	(ADF and PP disagree on Δ)

Notes: Constant included. ADF = Augmented Dickey-Fuller test; PP = Phillips-Perron test; KPSS = Kwiatkowski-Phillips-Schmidt-Shin test; (p) = p-value; Δ = first difference; I(0) = integrated of order zero (stationary in levels); I(1) = integrated of order one (stationary in first differences); I(2) = integrated of order two. ADF lags by Schwarz criterion, maximum 3; PP with automatic Bartlett bandwidth; KPSS 5% critical value 0.463, * = rejects stationarity at 5%. Source: Author's Computation (Python statsmodels/arch), 2026.

6.2 Trend Analysis

Real GDP per capita (lnGDPPC) falls from 1985 to a trough around 1999, rises strongly until 2014, and then stagnates, with a dip around the 2016 recession triggered by the oil-price collapse and another in 2020 attributable to the COVID-19 pandemic (Figure 1a). The energy-poverty deprivation index declines in almost every year from 1.000 in 1985 to 0.068 in 2024, i.e. deprivation falls over the whole sample, not only after the early 2000s; the one reversal is 2020, and the decline accelerates from 2021 (Figure 1b). Because lnGDPPC falls until 1999 while EP falls throughout, the long-run association estimated below is shaped by differing trends across sub-periods, a feature that motivates the stability analysis in Section 6.8. Human capital (lnHC) displays a steady upward trajectory throughout the sample (Figure 1c). Physical-capital-deepening (lnK) exhibits cyclical behaviour, peaking around 2012 and dropping in 2013, a discontinuity consistent with GDP rebasing or series splicing; lnTO shows a comparable jump in 2000 (Figure 1d and Table 2). Inflation (INF) shows extreme volatility, peaking above 70% in 1995 and settling near 10-20% after 1999, rising again from 2021 (Figure 1e). ICT access (per 100 inhabitants, internet-use scale) is floored at 0.01 until 1997 and rises rapidly from the early 2000s (Figure 1f); it should not be read as a measure of mobile-telephony expansion.

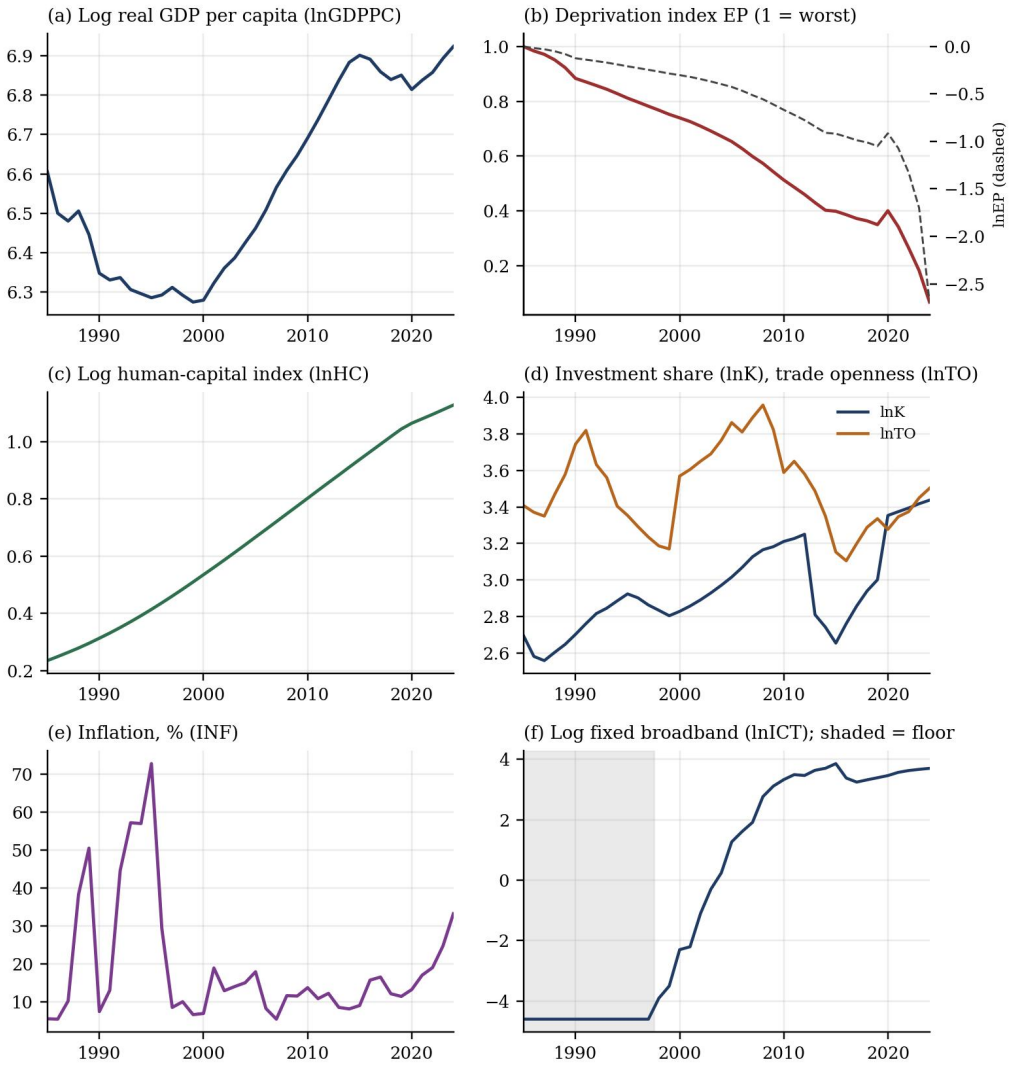


Figure 1. Trends of the variables, 1985-2024. (a) Log real GDP per capita (lnGDPPC); (b) Deprivation index EP (solid line, 1 = worst) and lnEP (dashed line); (c) Log human-capital index (lnHC); (d) Log investment share (lnK) and log trade openness (lnTO); (e) Inflation (INF, %); (f) Log ICT access per 100 inhabitants (lnICT), with the shaded area marking the floor value.

6.3 ARDL Bounds Test for Cointegration

The mediator-excluded model rejects the null of no level relationship: F = 8.82 exceeds the 1% upper bound whether asymptotic (5.06) or simulated (6.30), although the t-statistic on λ lies between the finite-sample bounds, so the conclusion rests on the F-test and on the assumption that all regressors are at most I(1), which Section 6.1 shows is unresolved for lnEP (Table 5). The mediator-included model does not give clear evidence: F = 3.80 marginally exceeds the asymptotic 5% upper bound (3.79) but is below the finite-sample value (4.48). A large F-statistic is in any case not a substitute for break analysis or finite-sample validation (Section 6.8). The evidence for the existence of a level relationship is stronger than the evidence for the size or sign of any single coefficient.

Table 5. Bounds tests, mediator-excluded and mediator-included models.

	Model B: mediator excluded (Eq. 4′)	**Model A: mediator included (Eq. 4)**
Lag order; deterministic case	ARDL(1,1,1,1,1); Case III	ARDL(1,1,1,1,1,1); Case III
Sample (n); regressors k	1986-2024 (39); k = 4	1986-2024 (39); k = 5
F-statistic	8.82	3.80
PSS asymptotic 5% bounds I(0)/I(1)	2.86 / 4.01	2.62 / 3.79
PSS asymptotic 1% bounds I(0)/I(1)	3.74 / 5.06	3.41 / 4.68
Simulated finite-sample 5% bounds (T = 40)	3.21 / 4.59	2.96 / 4.48
Simulated finite-sample 1% bounds (T = 40)	4.51 / 6.30	4.24 / 6.19
F-test decision (finite-sample)	Reject no level relationship at 1%	Inconclusive at 5%
Error-correction coefficient λ (t; p)	−0.146 (−3.36; 0.002)	−0.098 (−1.85; 0.076)
Simulated 5% t-bounds I(0)/I(1)	−2.89 / −4.08	−2.87 / −4.28
t-test decision	Inconclusive	Does not reject

Notes: F tests the lagged levels of lnGDPPC and all regressors. Finite-sample values are from 20,000 Monte Carlo replications (random-walk or white-noise regressors, T = 40, Case III). Source: Author's Computation, 2026; asymptotic values from Pesaran, Shin and Smith (2001), Table CI(iii).

6.4 Long-Run and Short-Run Estimates

Without lnHC the long-run lnEP multiplier is −0.803 (SE 0.154, p <0.001): greater energy deprivation is associated with a lower long-run level of GDP per capita, consistent with H1. Adding lnHC changes the picture entirely: the lnEP multiplier becomes 0.851 (SE 1.124) and the lnHC multiplier is 2.199 (SE 1.538, p = 0.164), both statistically insignificant. The two regressors are strongly collinear (correlation −0.88 in levels; VIF 4.9 for lnEP and 6.3 for lnHC), so the data cannot separate their long-run effects precisely. lnLF is not used in any estimate because it is nearly constant (Table 6).

Table 6. Mediator-excluded and mediator-included ARDL equations side by side.

Term	**Model B: mediator excluded (Eq. 4′)**	**Model A: mediator included (Eq. 4)**
Constant	0.598* (0.311)	0.343 (0.385)
lnGDPPC(t-1) [λ]	−0.146* **(0.043)**	−0.098* (0.053)
lnEP(t-1)	−0.117* **(0.035)**	0.084 (0.089)
lnHC(t-1)	-	0.217* (0.124)
lnK(t-1)	0.033 (0.033)	0.010 (0.044)
lnTO(t-1)	0.064 **(0.025)**	0.039 (0.028)
INF(t-1)	−0.000 (0.000)	−0.000 (0.000)
ΔlnEP	0.083 **(0.040)**	−0.074 (0.070)
ΔlnHC	-	2.025 (1.592)
ΔlnK	−0.113 **(0.051)**	−0.077 (0.054)
ΔlnTO	0.010 (0.044)	−0.017 (0.043)
ΔINF	0.000 (0.000)	0.001* (0.000)
R-squared; n	0.645; 39	0.719; 39
Long-run multipliers: estimate (SE); 95% CI		
LR lnEP	−0.803* **(0.154); [−1.12, −0.49]**	0.851 (1.124); [−1.45, 3.16]
LR lnHC	-	2.199 (1.538); [−0.96, 5.35]
LR lnK	0.228 (0.258); [−0.30, 0.76]	0.105 (0.478); [−0.88, 1.09]
LR lnTO	0.439 **(0.208); [0.01, 0.87]**	0.392 (0.276); [−0.17, 0.96]
LR INF	−0.003 (0.002); [−0.01, 0.00]	−0.001 (0.003); [−0.01, 0.01]

Notes: OLS estimates of the UECMs (Equations 4′ and 4), unrestricted intercept, 1986-2024. Long-run multipliers = -δ/λ, delta-method SEs, t-based 95% intervals. * p<0.01, p<0.05, * p<0.10 (p-values of lagged-level coefficients are those of the UECM regression; for multipliers, of the delta-method t-test). Source: Author's Computation, 2026.

Across estimators the mediator-excluded lnEP coefficient is consistently negative (−0.35 OLS, −0.80 ARDL, −0.74 DOLS), but the mediator-included coefficient changes sign with the estimator (ARDL 0.85, OLS −0.14, DOLS −0.69), and the DOLS estimates with lnHC rest on only 16 residual degrees of freedom. The human-capital multiplier is positive across estimators but significant only in static OLS (0.63, p = 0.005), so H3 is not robustly supported. These divergences are reported as fragility, not as confirmation (Table 7).

Table 7. Long-run lnEP and lnHC estimates by estimator (1985-2024).

Coefficient	ARDL long-run	Static OLS (HAC, 2 lags)	DOLS (1 lead, 1 lag)
lnEP, mediator excluded	−0.803 (0.154)*	−0.352* **(0.121)**	−0.735* **(0.100)**
lnEP, mediator included	0.851 (1.124)	−0.138 **(0.064)**	−0.692 (0.693)
lnHC, mediator included	2.199 (1.538)	0.630* **(0.222)**	0.383 (0.998)

Notes: Standard errors in parentheses. ARDL = autoregressive distributed lag; OLS = ordinary least squares; HAC = heteroskedasticity- and autocorrelation-consistent standard errors; DOLS = dynamic ordinary least squares; lnEP = log energy poverty index; lnHC = log human capital index. DOLS uses 37 observations (16 residual degrees of freedom with lnHC; 20 without). Source: Author's Computation, 2026.

Without lnHC the long-run lnEP multiplier stays between about -0.51 and -0.94 in log specifications and between -1.3 and -1.4 with the index in levels, whatever the sample, but with lnHC it is positive or insignificant in every row. The sign of the total association is therefore stable across samples, whereas its magnitude, and the existence of a separate direct effect, are not. The estimate also weakens when a second lag of the dependent variable is added (-0.51, SE 0.34). In that variant the 95% interval (−1.21 to 0.19) includes zero. Table 8 shows that the sign of the total association is stable to the sample window and to the log or level form of the index; it is silent on the weights and components of the index, so it does not establish robustness to index construction.

Table 8. Sensitivity of the ARDL long-run lnEP multiplier to sample and specification.

Sample / specification	Model	n	F	λ (t)	LR lnEP (SE)	LR lnHC (SE)	95% CI, LR lnEP
1985-2024 (primary)	lnEP+HC	39	3.80	−0.098 (−1.85)	0.851 (1.124)	2.199 (1.538)	[−1.45, 3.16]
1985-2024 (primary)	lnEP	39	8.82	−0.146 (−3.36)	−0.803 (0.154)	-	[−1.12, −0.49]
1985-2025 (2025 floor 0.0001 kept)	lnEP+HC	40	5.27	−0.113 (−2.21)	0.169 (0.527)	1.327 (0.823)	[−0.91, 1.25]
1985-2025 (2025 floor 0.0001 kept)	lnEP	40	8.40	−0.136 (−3.09)	−0.724 (0.154)	-	[−1.04, −0.41]
1985-2019 (PWT hc native years)	lnEP+HC	34	1.85	−0.164 (−1.45)	1.061 (1.411)	2.627 (2.056)	[−1.86, 3.99]
1985-2019 (PWT hc native years)	lnEP	34	6.92	−0.170 (−3.09)	−0.727 (0.157)	-	[−1.05, −0.40]
1990-2024	lnEP+HC	34	8.80	−0.087 (−1.57)	0.589 (0.934)	2.029 (1.351)	[−1.35, 2.53]
1990-2024	lnEP	34	9.31	−0.060 (−1.00)	−0.939 (0.298)	-	[−1.55, −0.32]
1985-2022 (before index collapse)	lnEP+HC	37	2.39	−0.088 (−1.55)	1.298 (2.082)	2.750 (2.869)	[−2.99, 5.59]
1985-2022 (before index collapse)	lnEP	37	8.27	−0.166 (−3.57)	−0.799 (0.137)	-	[−1.08, −0.52]
1985-2024, EP in levels	EP+HC	39	2.66	−0.110 (−2.15)	0.761 (1.620)	1.604 (1.306)	[−2.56, 4.08]
1985-2024, EP in levels	EP	39	9.93	−0.140 (−3.72)	−1.378 (0.260)	-	[−1.91, −0.85]
1985-2025, EP in levels	EP+HC	40	2.98	−0.113 (−2.22)	−0.238 (0.957)	0.845 (0.859)	[−2.20, 1.72]
1985-2025, EP in levels	EP	40	9.82	−0.137 (−3.66)	−1.316 (0.250)	-	[−1.83, −0.81]
1985-2019, EP in levels	EP+HC	34	1.42	−0.134 (−1.10)	0.875 (2.727)	1.805 (2.119)	[−4.78, 6.53]
1985-2019, EP in levels	EP	34	9.44	−0.137 (−2.86)	−1.410 (0.292)	-	[−2.01, −0.81]
ARDL p=2 (1985-2024)	lnEP+HC	38	3.25	−0.051 (−0.98)	1.631 (2.612)	2.890 (3.236)	[−3.75, 7.01]
ARDL p=2 (1985-2024)	lnEP	38	4.08	−0.066 (−1.54)	−0.508 (0.342)	-	[−1.21, 0.19]

Notes: n = number of observations in the estimation sample; F = bounds F-statistic; λ (t) = error-correction coefficient (t-statistic); LR = long-run multiplier; SE = standard error; CI = confidence interval; lnEP+HC = mediator-included model; lnEP = mediator-excluded model; EP = energy poverty index in levels; lnHC = log human capital index. 'EP in levels' replaces lnEP by the index itself (no logarithm, no floor needed in 2025 beyond the recorded 0.0001). The 1985-2025 rows keep the floored 2025 observation. 'ARDL p=2' adds a second lag of the dependent variable. The last column gives the 95% interval (t-based, delta method) of the long-run coefficient on lnEP or EP. The table varies the sample window, the functional form of the index and the lag order only; it does not vary the index weights or components. Source: Author's Computation, 2026.

6.5 Human Capital Accumulation Equation

As shown in Table 9, the static equation shows strong serial correlation (Breusch-Godfrey p = 0.0001; Durbin-Watson 0.91) and fails RESET (p = 0.018), so its coefficients, including $\beta_1 = -0.294$, cannot be relied on, and HAC errors do not repair this. A dynamic ARDL(2,1,1,1,1) equation, selected by AIC and BIC, is used instead; it passes the serial-correlation (p = 0.187 at two lags), functional-form (p = 0.923) and normality (p = 0.825) tests but still fails Breusch-Pagan (p = 0.003); heteroskedasticity remains unresolved. The dynamic long-run lnEP multiplier is $\beta_1 = -0.205$ (SE 0.097, p = 0.044), smaller in size than the static value. The sign is negative in every variant, including a common-period static estimate for 2000-2019 (−0.64), a static estimate for 1985-2019 (−0.57) and a dynamic estimate for 1985-2019 (−0.40) (this variant has a positive adjustment coefficient, $\lambda = 0.002$, and a 95% interval of −1.28 to 0.49, so it supports sign consistency only), but its size ranges from about -0.2 to -0.6. The adjustment coefficient is very small ($\lambda = -0.019$), so the ratio is imprecise, and the block-bootstrap interval for β_1 (−1.11 to 0.65) includes zero. H2 is therefore partly supported. Education expenditure and health expenditure enter positively; ICT access is insignificant. Potential endogeneity of public expenditure and human capital, and mechanical overlap between the schooling-based hc index and education spending, remain unaddressed.

Table 9. Human-capital equation, static and dynamic specifications.

	Static OLS (HAC), n = 40	**Dynamic ARDL(2,1,1,1,1) long-run, n = 38**
lnEP	−0.294*** (0.068)**	−0.205 (0.097)**; [−0.40, −0.01]**
lnEDU	0.147*** (0.052)**	0.320 (0.101)*****
lnHE	0.286*** (0.051)**	0.448 (0.099)*****
lnICT	0.014 (0.010)	−0.015 (0.011)
Adjustment coefficient λ (t)	-	−0.019 (−3.71)
Bounds F (k = 4); simulated 5%/1% upper	-	19.52; 4.59 / 6.30
Breusch-Godfrey, 2 lags: LM (p)	18.27 (0.0001)	3.36 (0.187)
Ramsey RESET: F (p)	6.18 (0.018)	0.01 (0.923)
Jarque-Bera (p)	13.34 (0.001)	0.38 (0.825)
Breusch-Pagan (p)	-	26.76 (0.003)
Max. VIF (lnICT)	14.56	-

Notes: OLS = ordinary least squares; HAC = heteroskedasticity- and autocorrelation-consistent; ARDL = autoregressive distributed lag; n = number of observations; λ (t) = adjustment coefficient (t-statistic); LM = Lagrange multiplier; RESET = regression equation specification error test; VIF = variance inflation factor. Static column reports HAC standard errors; diagnostics use conventional OLS residuals. Dynamic column: long-run multipliers with delta-method SEs; estimated 1987-2024. * p<0.01, p<0.05. Source: Author's Computation, 2026.

6.6 Pathway (Mediation) Decomposition

The directly estimated total association is TE = −0.803 (analytic 95% interval [−1.12, −0.49]). The mediator-included direct effect is DE = 0.851 (interval [−1.45, 3.16]), and the indirect product is IE = (−0.205) x (2.199) = −0.452, with a Sobel interval of [−1.20, 0.30], which includes zero. The block-bootstrap intervals are far wider (IE: [−11.5, 10.8]; TE: [−2.28, 1.99]) and also include zero, because λ is close to zero in many resamples and the multipliers are ratios (Table 10).

Table 10. Total association, direct effect and indirect product.

Component	**Source**	**Point estimate**	**Analytic 95% interval**	**Block-bootstrap 95% interval**
Total association, TE	Model B, long-run lnEP	−0.803	[−1.12, −0.49]	[−2.28, 1.99]
Direct effect, DE	Model A, long-run lnEP	0.851	[−1.45, 3.16]	[−13.69, 11.86]
Channel β_1 (EP to HC)	Dynamic HC equation	−0.205	[−0.40, −0.01]	[−1.11, 0.65]
Channel α_2 (HC to GDPPC)	Model A, long-run lnHC	2.199	[−0.96, 5.35]	[−18.96, 17.07]
Indirect product IE = β_1 x α_2	Separate equations	−0.452	[−1.20, 0.30] (Sobel)	[−11.53, 10.75]
Consistency check: DE + IE	Algebraic sum	0.399	-	-
Consistency check: TE - DE	Difference method	−1.654	-	[−14.73, 13.55]
Point-estimate ratio IE/TE	-	56%	-	not reliably estimated

Notes: TE comes from a separately estimated model that excludes lnHC (Table 6, Model B); DE, α2 from Model A; β1 from Table 9. Bootstrap: 3,000 moving-block resamples (block length 5), percentile intervals. Source: Author's Computation, 2026.

The three routes do not agree. The sum DE + IE is 0.40, positive, whereas the directly estimated TE is −0.80; the difference TE - DE is −1.65, about three times the product IE. Combining coefficients from separate equations with different effective samples, lag structures and diagnostics does not reproduce the total association, and the discrepancy is itself evidence that the product is not interpretable as a mediated share. The point-estimate ratio IE/TE is about 56%; it is conditional on the ARDL estimator, the separate-equation assumptions of Section 3.4 and the composite index, and its bootstrap interval spans both signs, so it must not be read as a reliably estimated proportion. A ratio computed against a total defined as DE + IE would not be meaningful for the same reason. The dynamic human-capital equation, on which β_1 rests, still fails the Breusch-Pagan test, shows a very small adjustment speed, and is affected by possible endogeneity. The product is conditional on these assumptions, not a structural or causal mediation estimate, and H4 is not supported. These qualifications (indirect-effect intervals that include zero under both the Sobel and the bootstrap approach, an indirect product that does not reproduce the directly estimated total association, and no reliably estimated mediated share) apply wherever the pathway result is summarised in this paper.

6.7 Wald Tests

Table 11 reports Wald tests of the long-run restrictions and of the joint significance of the lagged levels. The null that the long-run lnEP multiplier is zero is rejected in the mediator-excluded model (W1: $\chi^2(1) = 27.22$, $p < 0.001$) but not in the mediator-included model (W2: $\chi^2(1) = 0.57$, $p = 0.455$), and the long-run lnHC multiplier is not statistically significant (W3: $\chi^2(1) = 2.04$, $p = 0.164$). The joint null that the lagged levels of lnEP and lnHC are both zero is not rejected in Model A (W4: $F = 2.03$, $p = 0.150$), whereas the joint null on the lagged level and the contemporaneous difference of lnEP is rejected in Model B (W5: $F = 5.57$, $p = 0.009$). In the human-capital equation, the long-run lnEP coefficient is significant at the 5% level (W6: $\chi^2(1) = 4.48$, $p = 0.044$). As stated in Section 5.6, these are joint-significance tests only and do not validate the theory, the identification or a causal-mediation interpretation.

Table 11. Wald tests.

Test	Null hypothesis	Statistic	p-value
W1: lnEP, Model B	LR lnEP = 0	27.22 (χ^2_1)	<0.001
W2: lnEP, Model A	LR lnEP = 0	0.57 (χ^2_1)	0.455
W3: lnHC, Model A	LR lnHC = 0	2.04 (χ^2_1)	0.164
W4: lnEP and lnHC levels, Model A	$\delta_1 = \delta_2 = 0$ (UECM)	F = 2.03	0.150
W5: lnEP level and difference, Model B	$\delta_1 = \varphi_1 = 0$ (UECM)	F = 5.57	0.009
W6: EP to HC channel	LR lnEP = 0, HC equation	4.48 (χ^2_1)	0.044

Notes: Long-run tests use delta-method standard errors. As stated in Section 5.6, these are joint-significance tests only. Source: Author's Computation, 2026.

6.8 Diagnostic Tests and Structural Stability

Table 12 shows Model B passes the Breusch-Godfrey test at one and four lags ($p = 0.402$ and 0.109) and narrowly at two lags ($p = 0.060$), is not rejected for normality or RESET, and shows marginal heteroskedasticity (Breusch-Pagan $p = 0.080$) and an ARCH effect at two lags ($p = 0.005$). Model A fails serial correlation at two and four lags ($p = 0.0007$ and 0.004), fails normality ($p = 0.024$) and shows an ARCH effect at two lags. Model A is therefore the less reliable specification and its long-run multipliers should not be used for the pathway calculation without qualification. Many observations are influential (2013, 2020 and 2024 have high leverage), and the condition indices are large because the model contains trending level regressors. HAC standard errors make inference robust to given forms of heteroskedasticity and autocorrelation but do not repair misspecification.

Table 12. Residual diagnostics.

Test (statistic; p-value)	Model B (mediator excluded)	Model A (mediator included)
Breusch-Godfrey LM, 1 lag (df 1)	0.70 (0.402)	0.35 (0.555)
Breusch-Godfrey LM, 2 lags (df 2)	5.62 (0.060)	14.51 (0.001)
Breusch-Godfrey LM, 4 lags (df 4)	7.57 (0.109)	15.14 (0.004)
Breusch-Pagan (df 9 / 11)	15.43 (0.080)	18.03 (0.081)
Jarque-Bera (df 2)	1.28 (0.527)	7.47 (0.024)
ARCH LM, 1 lag	0.01 (0.942)	1.55 (0.213)
ARCH LM, 2 lags	10.71 (0.005)	6.74 (0.034)
Ramsey RESET, squared fitted values: F	1.59 (0.217)	1.58 (0.221)
Ramsey RESET, squared and cubed: F	0.92 (0.412)	1.71 (0.202)
OLS-CUSUM (Ploberger-Kramer)	0.50 (0.965)	0.34 (1.000)
Durbin-Watson	1.59	1.69
Condition index (scaled regressors)	231	361
Cook's D > 4/n (years)	1986, 1988, 1990, 1996, 2013, 2020, 2024	1986, 1988, 1990, 1996, 2024
Leverage > 2k/n (years)	1990, 2013, 2024	2013, 2020, 2024

Notes: Breusch-Godfrey is the LM version with chi-squared p-values (Breusch, 1978; Godfrey, 1978); other tests: Breusch and Pagan (1979), Jarque and Bera (1987), Engle (1982), Ramsey (1969), Cook (1977). Source: Author's Computation, 2026.

Structural breaks and finite-sample uncertainty. Recursive CUSUM and CUSUMSQ plots stay inside the 5% bands (Figures 2a and 2b; maximum CUSUM ratio 0.76 of the band; maximum CUSUMSQ deviation 0.17 against an approximate band of 0.37), although the CUSUM path drifts steadily downward after 2010. The exhaustive intercept-shift search finds one candidate break, with the new regime starting in 1996 (sup-F(1|0) = 11.30; bootstrap 10%, 5% and 1% critical values 11.3, 12.9 and 21.1; bootstrap p = 0.10), significant only at about the 10% level, and no support for a second break (sup-F(2|1) = 3.04, p = 0.63; candidate date 2011). BIC prefers one or two breaks to none (−257.4 with no break, −267.0 with one, −267.5 with two). Chow-type intercept-shift tests at known dates are insignificant at 5% (1999: p = 0.157; 2016: p = 0.066; 2020: p = 0.114).

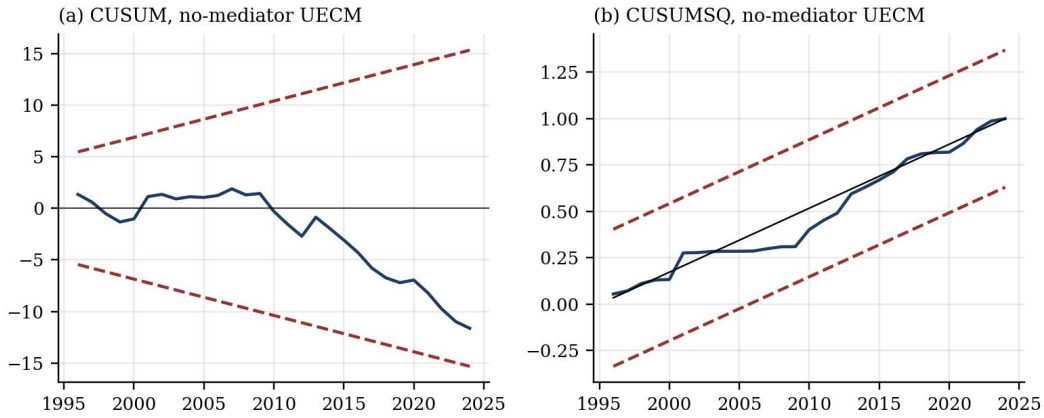


Figure 2. CUSUM and CUSUMSQ, Model B (mediator excluded). (a) CUSUM; (b) CUSUMSQ.

The long-run result is not stable to these checks. A step dummy from 1996 is itself highly significant (p = 0.002); once it is included the error-correction coefficient shrinks to −0.025 (t = −0.49) and the lnEP multiplier falls to −0.33 (SE 1.19) (Table 13). In recursive windows ending in 2005 and 2010 the adjustment coefficient is positive and the lnEP multiplier is positive; the negative multiplier appears only in windows ending in 2015 or later (Figures 3a and 3b). The cointegration and coefficient conclusions are therefore conditional on the untested assumption of a stable long-run relation across the whole sample, and the existence of a level relationship is better supported than the magnitude or sign of any individual coefficient. Because the short sample limits the power of every test above, the ARDL results are retained as exploratory evidence only; they are not treated as confirmed by the large F-statistic of Model B.

Table 13. Stability of the long-run lnEP multiplier.

Specification (Model B unless stated)	n	F	λ (t)	LR lnEP (SE)
Baseline, 1986-2024	39	8.82	−0.146 (−3.36)	−0.803 (0.154)
With step dummy from 1996 (dummy p = 0.002)	39	4.77	−0.025 (−0.49)	−0.332 (1.187)
With step dummies from 1996 and 2011	39	4.64	−0.051 (−0.97)	0.801 (1.633)
Recursive window 1985-2005	20	6.28	0.345	1.358 (1.032)
Recursive window 1985-2010	25	9.16	0.230	1.149 (1.013)
Recursive window 1985-2015	30	7.00	−0.136	−1.131 (0.388)
Recursive window 1985-2019	34	6.92	−0.170	−0.727 (0.157)
Recursive window 1985-2024	39	8.82	−0.146	−0.803 (0.154)

Notes: n = number of observations; F = bounds F-statistic; λ (t) = error-correction coefficient (t-statistic); LR lnEP = long-run multiplier of the log energy poverty index; SE = standard error; UECM = unrestricted error-correction model. Recursive windows use the Model B UECM re-estimated on 1985 to the year shown. Source: Author's Computation, 2026.

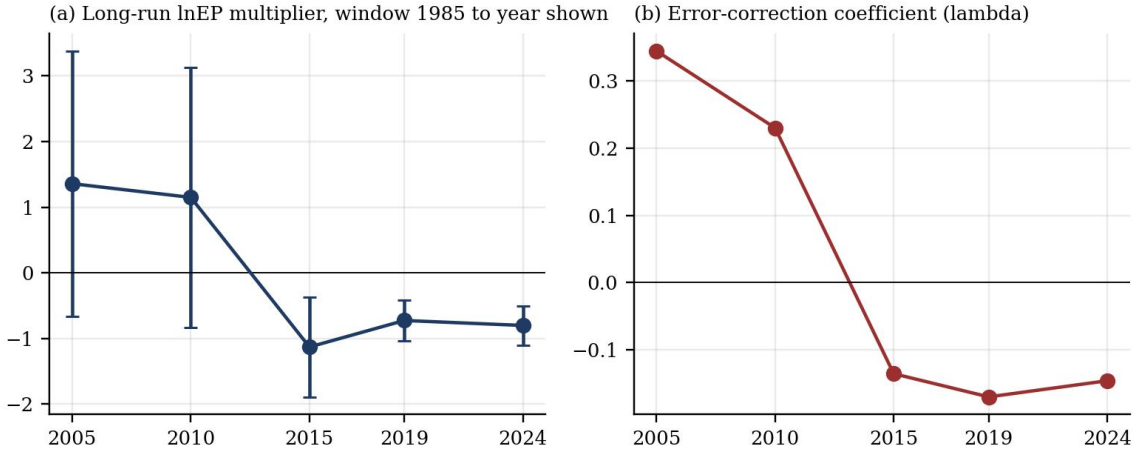


Figure 3. Recursive long-run lnEP multiplier and error-correction coefficient, Model B. (a) Long-run lnEP multiplier; (b) Error-correction coefficient.

7. Conclusion and Policy Implications

7.1 Summary of Findings

This study has examined the long-run association between energy poverty, human capital, and the level of GDP per capita in Nigeria using annual data from 1985 to 2024. Four findings emerge, all exploratory. First, unit-root tests leave the integration orders of lnEP and lnHC unresolved, so every bounds-test result is conditional on an I(1) assumption that is not established. Second, the mediator-excluded ARDL model supports a level relationship (F = 8.82) and a negative long-run association between energy deprivation and GDP per capita (−0.80); this result is conditional on the equal-weighted composite index, was not tested against alternative weightings, leave-one-component-out indices or separate component indicators (so its robustness to index construction is not established), and is not stable to an intercept shift in 1996 or to the choice of estimation window. Third, when human capital is added the evidence for a level relationship is inconclusive and the lnEP coefficient is positive and imprecise, largely because lnEP and lnHC are strongly collinear. Fourth, the pathway product (−0.45) has intervals that include zero, is inconsistent with the directly estimated total association, and does not support H4; the indirect-effect intervals include zero under both the Sobel and the bootstrap approach, so no mediated share is reliably estimated (Table 14).

Table 14. Status of the hypotheses.

Hypothesis	Finding	Supporting evidence
H1: EP negatively associated with lnGDPPC	Partly supported, conditional on the equal-weighted index (robustness to index construction not established). Total association in Model B is −0.80 (CI −1.12 to −0.49); negative across samples and in OLS and DOLS; lost when lnHC is added or a 1996 intercept shift is allowed.	Tables 5-8, 13
H2: EP reduces human capital	Partly supported. Negative in every specification (dynamic long-run -0.21, p = 0.044), but size varies and the bootstrap interval includes zero.	Table 9
H3: HC positively associated with lnGDPPC	Not robustly supported. Positive in all estimators but insignificant in the ARDL and DOLS.	Tables 6, 7
H4: HC as a pathway from EP to GDPPC	Not supported. Indirect product has Sobel and bootstrap intervals including zero, and DE + IE does not match the directly estimated TE. No mediated share is reliably estimated.	Table 10

7.2 Policy Implications

The findings are consistent with, though they do not by themselves establish, several policy directions for Nigeria. First, the association between energy poverty and both GDP per capita and human capital suggests that energy-access expansion and human-capital investment may be usefully coordinated (the pathway estimate cannot be used to support this, since its intervals include zero), though we stop short of asserting that a specific intervention (for example, electrifying a given number of schools) will produce a particular, quantified growth effect, since that would require an identification strategy this design does not provide. Second, access to electricity should be distinguished from the reliability and quality of supply, and clean-cooking access from electricity access; the composite index used here combines these dimensions and cannot speak to which specific dimension drives the estimated association. Third, the national-level data used in this study cannot speak to regional or rural-urban heterogeneity, which is likely to be substantial in Nigeria; subnational panel data would be needed to assess distributional implications. Fourth, the slow estimated adjustment speed (λ = -0.15 in Model B) is consistent with considerable inertia in the energy-income relationship, but in view of the instability documented in Section 6.8 it should not be used to support specific policy horizons. Given the exploratory status of the evidence, these implications should be read as hypotheses for further testing rather than as recommendations resting on an established mechanism.

7.3 Limitations and Future Research

(1) Measurement uncertainty in the energy-poverty index: only the equal-weighted composite index could be analysed. Principal-components and other weighting schemes, leave-one-component-out indices, and separate electricity-access, clean-cooking and electricity-consumption specifications could not be estimated because the raw components are not in the estimation dataset; the central lnEP result is conditional on the equal-weighted index. Future work should re-estimate the models with the component-level data under transparent alternative weights (a theoretically justified scheme and, where suitable, principal components), leave-one-component-out indices and separate indicators, and report coefficient signs and uncertainty intervals side by side. The log of an index that approaches zero also produces extreme late-sample values and an ambiguous integration order, and the 2025 observation had to be excluded.
(2) Integration order and small sample: lnEP and lnHC may be I(2) or near-I(2), which would invalidate bounds-test inference; with T = 40 the multipliers are ratio estimates with wide intervals (Section 6.6), finite-sample critical values are simulated rather than derived, and structural-break tests have low power.
(3) Specification of the pathway: the indirect product combines separately estimated equations, one of which still fails the Breusch-Pagan test, with possible reverse causality and unmeasured confounding. A jointly estimated system (for example, a structural VAR or a system ARDL) with credible exogenous variation in energy access is needed for causal mediation claims. Credible exogenous variation in energy access is required to address reverse causality and confounding; household-level fixed-effects designs using the GHS-Panel waves are one possible route.
(4) Data construction: several series are interpolated, back-cast, floored or extended beyond the source vintage (Table 2); series discontinuities in lnK and lnTO suggest rebasing or splicing. Re-estimation on native-coverage years is a priority once the source files are updated. Future updates should document source identifiers and data vintages for every series and keep the treatment of interpolated, back-cast, floored, extended and spliced observations auditable, as in Appendix B.
(5) Coefficient and break stability: additional annual observations and more reliable component data are needed to assess the stability of the long-run coefficients and of the 1996 break; with T = 40 the stability results in Section 6.8 are indicative only.
(6) Aggregation bias: all series are national aggregates and cannot capture regional, rural-urban, or household-level heterogeneity in energy poverty or human-capital outcomes.

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Ethics Statement

Not applicable. This study uses only secondary, publicly available, aggregated macroeconomic time-series data (World Bank, International Energy Agency, PWT, Central Bank of Nigeria, International Telecommunication Union) and did not involve human or animal subjects, primary data collection, or identifiable personal data. No ethics committee/institutional review board approval was therefore required.

Informed Consent

Not applicable, for the same reason as the Ethics Statement above.

Data Availability Statement

The working dataset (annual, 1985-2025; the 2025 row is excluded from the primary sample), a data dictionary with source identifiers and the data vintage, observation-level treatment flags for interpolated, back-cast, floored, extended and spliced values (Appendix B), the composite energy-poverty index before and after logging for every year, the analysis code (replicate.py) and its output are supplied as supplementary files with this submission. The code reproduces the estimates in Table 3 and Tables 6-9 and the analytic quantities in Table 10; the unit-root, bootstrap and stability routines are not included in this release. The raw component series underlying the composite index are not part of the estimation dataset; an input template for them and the code for the index-robustness checks (index_robustness.py) are included, and the checks will be run when the components are added. The files can also be deposited in a persistent repository, subject to the journal policy.

Author Contributions

Conceptualisation: Askilu Jaafaru; Methodology: Askilu Jaafaru and Olugbo Joel Omwayi; Data curation: Askilu Jaafaru and Olugbo Joel Omwayi; Formal analysis: Askilu Jaafaru; Writing - original draft: Askilu Jaafaru and Olugbo Joel Omwayi; Writing - review and editing: Obadiah Jonathan Gimba, and Adofu Ilemona; Supervision: Adofu Ilemona.

Conflict of Interest

The authors declare no conflict of interest.

Generative AI Statement

Generative artificial intelligence (Claude, Anthropic) was used, at the corresponding author's direction, for language polishing and editing of the manuscript text, including grammar, formatting and phrasing. It was not used to generate the manuscript content, arguments, or original scholarly contribution. All conceptualization, economics modelling, data analysis, interpretation of results, citation selection and verification, and the conclusion and policy recommendations are the author's own. The corresponding author reviewed, edited, and takes full responsibility for the accuracy and scientific content of the manuscript.

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Appendix A: Energy-poverty composite index by year.

Table S1. Energy poverty composite index.

Year	EP	lnEP	Year	EP	lnEP	Year	EP	lnEP
1985	1.0000	0.000	1999	0.7524	−0.284	2013	0.4305	−0.843
1986	0.9838	−0.016	2000	0.7397	−0.302	2014	0.4028	−0.909
1987	0.9715	−0.029	2001	0.7263	−0.320	2015	0.3990	−0.919
1988	0.9513	−0.050	2002	0.7096	−0.343	2016	0.3864	−0.951
1989	0.9231	−0.080	2003	0.6917	−0.369	2017	0.3726	−0.987
1990	0.8836	−0.124	2004	0.6727	−0.396	2018	0.3640	−1.011
1991	0.8708	−0.138	2005	0.6533	−0.426	2019	0.3501	−1.050
1992	0.8576	−0.154	2006	0.6276	−0.466	2020	0.4008	−0.914
1993	0.8441	−0.169	2007	0.5989	−0.513	2021	0.3425	−1.071
1994	0.8282	−0.189	2008	0.5737	−0.556	2022	0.2647	−1.329
1995	0.8117	−0.209	2009	0.5430	−0.611	2023	0.1824	−1.702
1996	0.7972	−0.227	2010	0.5131	−0.667	2024	0.0677	−2.693
1997	0.7823	−0.246	2011	0.4867	−0.720	2025†	0.0001	−9.210
1998	0.7678	−0.264	2012	0.4602	−0.776			

Notes: lnEP = natural logarithm of EP; EP = equal-weighted deprivation index (1 = worst observed, 0 = best observed in 1985-2025). † 2025: index equals zero by construction; the working dataset records the floor 0.0001 (lnEP = -9.210); excluded from the primary sample. Source: Author's Computation.

Appendix B: Observation-level data-treatment register.

Each row records a treatment found by inspecting the working dataset (1985-2025). "Used" means the affected observations enter the estimates in the primary sample (1985-2024).

Table S2. Observation-level data-treatment register.

Variable	Years affected	Treatment and evidence	Use in estimation
lnEP	2025	Floored: the index is zero by construction and is recorded as 0.0001 (ln = −9.210).	Excluded from the primary sample; kept only in the Table 8 rows labelled 1985-2025.
lnEP	1985-2025	Min-max bounds are taken from the Nigerian series itself (1985 = 1.000, 2025 = 0); the index falls sharply after 2020 (EP = 0.068 in 2024), so the log approaches a singularity.	Used; source of the unit-root ambiguity (Section 6.1); 1985-2022 sample in Table 8.
lnHC	2020-2025	Extended beyond the PWT 10 series (hc ends in 2019); annual growth falls from about 0.026 to between 0.015 and 0.020 after 2019.	Used for 2020-2024 in the primary sample; 1985-2019 sample in Table 8.
lnK	2013	Level fall of 0.44 log points (3.25 to 2.81), consistent with GDP rebasing or series splicing; not adjusted.	Used; 2013 is a high-leverage year (Table 12).
lnTO	2000	Level rise of 0.40 log points (3.17 to 3.57); not adjusted.	Used.
lnLF	1985-1992	Constant fall of 0.0015 log points a year from 1986 to 1992 (the 1985-86 fall is twice as large), consistent with a linear back-cast; 1996 and 1997 are identical.	Not used in estimation.
lnEDU	1985-2025	Recorded to one decimal place, hence step-like (six repeated values: 1987, 1990, 1991, 1997, 2000, 2016); falls from 1.7% (2022) to 0.5% (2023) and 0.4% (2024); not adjusted.	Used in Equation (2) only.
lnHE	1985-2005	Annual changes of 0 or +0.1 percentage point (1.8% to 3.6%), with repeats in 1996 and 2002, consistent with interpolation between sparse observations.	Used in Equation (2) only.
lnICT	1985-1997	Floored at 0.01 per 100 (ln = −4.605); observed values from 1998; values up to 47.4 per 100 are on the scale of internet use, not fixed-broadband subscriptions.	Used in Equation (2) only; coefficient insignificant.
lnGDPPC, INF	1985-2025	Complete series; no treatment.	Used.

Note: Observations are identified from the working dataset; no treatment was altered for the estimates reported. Source: Author's Computation.