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The Role of Carbon Emissions, Energy Consumption, and Electrification on Quality of Life in BRICS Nations

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Abstract

Introduction: Global concerns about climate change and sustainable development have intensified the search for pathways that reconcile economic growth with human well-being. In this context, the BRICS nations (Brazil, Russia, India, China, and South Africa) stand at the forefront of global sustainability challenges. This study therefore investigated the relationship between carbon emission intensity, energy consumption, electrification, and quality of life from 2000 to 2020.

Methods: The study employed a novel non-parametric Method of Moments Quantile Regression (MMQR) to explore heterogeneous effects across the life expectancy distribution. The Feasible Generalized Least Squares (FGLS) method and the Dumitrescu–Hurlin panel causality tests were used for robustness checks.

Results: The analysis reveals that higher carbon intensity consistently undermines the quality of life, with its detrimental effects being 2.4 times higher in lower life expectancy quantiles. Energy consumption enhances quality of life, particularly in areas with lower health baselines, peaking at a gain of +0.09 years of life expectancy. However, its benefits taper off and may even reverse at higher levels of life expectancy. Electrification exhibits a strongly positive and rising effect, ranging from negligible at the lowest quantiles to an increase of +0.45 years in life expectancy at higher quantiles.

Conclusion: This study concludes that carbon emission intensity consistently reduces quality of life across the BRICS economies, while energy consumption yields diminishing and potentially adverse health impacts over time. However, electrification increasingly enhances quality of life. The study urges policymakers to move beyond uniform climate targets and adopt quantile-specific decarbonization strategies.

Keywords: Carbon emission intensity, Energy consumption, Environmental health, Life expectancy, Sustainable development

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Introduction

The escalating climate crisis has brought sustainability and the quality of life to the forefront of developmental discourse, particularly among the BRICS nations (Brazil, Russia, India, China, and South Africa). These countries represent a critical bloc in global sustainability discussions, collectively accounting for approximately 40% of the world's population and 25% of its GDP (1,2). As such, they face the dual challenge of pursuing socio-economic development while curbing environmental degradation. Central to this challenge is the intricate relationship between environmental quality and the well-being of citizens. This relationship is increasingly evident, with factors such as carbon emissions, energy consumption patterns, and access to electricity playing pivotal roles in shaping quality of life (3-5).

Carbon emission intensity has a profound, multidimensional impact on human well-being across ecological, economic, social, and health systems (6,7). Fossil fuel combustion, deforestation, and industrial processes emit GHGs (primarily CO_2), driving global warming and destabilizing planetary systems, with disproportionate burdens on vulnerable populations (8,9). Elevated emissions are closely linked to poorer public health due to co-pollutants such as $PM_{2.5}$, NO_x, and SO_2, which increase risks of respiratory and cardiovascular diseases (7,9,10). Long-term exposure elevates mortality from COPD, lung cancer, and stroke, and the WHO estimates around 7 million premature deaths annually from air pollution, with low- and middle-income countries especially affected.

Access to reliable and affordable energy underpins healthcare, education, productivity, and innovation, yet sources, distribution, and efficiency shape unequal outcomes and environmental resilience. Fossil-fuel-based electricity and transport in high-income countries contribute to outdoor air pollution linked to roughly 4.2 million premature deaths annually (11–14). In low-income households, biomass fuels for cooking cause indoor air pollution responsible for an estimated 3.8 million deaths annually, disproportionately harming women and children (15). Climate change compounds these burdens, while energy use also enables improvements via smart grids, efficient appliances, and EVs (16,17). However, efficiency gains can spur a rebound effect without behavioral or regulatory checks, and rising demand from data centers and cryptocurrency mining raises ethical concerns about luxury versus basic needs (18–20).

Electrification can directly improve health by displacing hazardous fuels that emit toxic pollutants like carbon monoxide and fine particulates (21,22). The WHO estimates that household air pollution from such fuels causes 3.2 million premature deaths annually, which electrification can mitigate through clean cooking and LED lighting, alongside enabling vaccine refrigeration, equipment sterilization, and operation of life-saving devices in healthcare settings. Yet, where grid power relies on coal, oil, or natural gas, electrification may worsen environmental degradation and outdoor air pollution, increasing cardiovascular morbidity and mortality, particularly in densely populated or industrial areas (23,24).

This study addresses the critical challenge of reconciling economic growth with environmental sustainability in BRICS nations, where rapid industrialization has driven up carbon emission intensity, energy consumption, and electrification rates. Existing studies often assume uniform relationships between environmental degradation factors and health outcomes, overlooking quantile-specific threshold effects. This study uniquely contributes to knowledge in this regard by employing a non-parametric Method of Moments Quantile Regression (MMQR), offering granular insights to inform targeted decarbonization policies and promote environmental health equity. For instance, Brunner and Maruyama (25) identified a critical CO_2 threshold (5 t/capita) beyond which further emissions confer no additional quality-of-life gains— yet, BRICS nations like China (8.4 t/capita) and South Africa (7.5 t/capita) have long since surpassed this limit. Moreover, while prior studies have examined the individual effects of carbon emissions, energy consumption, and electrification on quality of life, they rarely account for their interdependent dynamics within the unique socio-economic and governance contexts of BRICS nations. Linear models and variable isolation in studies by Dam et al. (26), Brunner & Maruyama (25), and Samour & Adebayo (27) mask heterogeneous effects across development and pollution quantiles. By contrast, our MMQR approach captures how these variables jointly shape quality of life at varying thresholds of economic and environmental degradation.

Literature review

Previous studies have demonstrated the dual role of energy systems: on one hand, fossil fuel-driven growth exacerbates environmental degradation and health risks; on the other hand, renewable energy adoption and equitable electrification can significantly enhance quality of life. From the perspective of carbon emissions' impact on quality of life, numerous studies have consistently demonstrated that elevated CO_2 emission levels correlate with reduced life expectancy due to pollution-related illnesses and ecosystem degradation. For instance, Karimi-Alavijeh et al. (28) in G-7 and Khan et al. (29) in 31 developing nations—while Brunner and Maruyama (25) identify a per-capita 5-metric-ton CO_2 threshold beyond which quality-of-life gains cease, a result reverberated by Weitensfelder et al. (30) for energy-use saturation. In BRICS, relationships are nonlinear and stage-dependent: Ul-Haq et al. (3) report an N-shaped ecological footprint–biofuel CO_2 link; Dam et al. (26) note fossil dependence ties income growth to both emissions and life expectancy; Ma et al. (31) project large emissions cuts from coal-to-renewables/nuclear shifts; Aderinto (32) finds higher carbon intensity reduces life expectancy and raises child mortality; Zardoub (4) documents differing short- vs long-run effects as structures evolve.

Evidence across regions underscores persistent negative health effects of CO_2 and carbon intensity and the moderating role of institutions and technology. Mookherjee and Dutta (33) found long-run bidirectionality and regional imbalances in per-capita CO_2 and life expectancy; Caglar et al. (34) argued that BRICS energy systems are not yet mature enough to offset carbon intensity; BRICS-specific estimates also show a negative, significant effect of CO_2 on life expectancy (9). Similar patterns arise in Latin America and Africa (35,36), and across BRICS and Asia–Africa (37,38), with region-specific asymmetries and EKC-consistent dynamics shaped by government effectiveness and green innovation (39,40). Dam et al. (26) further highlighted feedbacks from rising life expectancy and income into environmental metrics.

Renewables generally enhance life expectancy, while non-renewables harm it, though effects vary by context, income, and institutional quality. Wang et al. (41) and Uzoechina et al. (42) showed renewables prolong life expectancy; in BRICS, Samour and Adebayo (27) reported renewables improve environmental quality, but non-renewables and external debt offset gains; Aderinto (32) reported similar West Africa patterns, while Caglar et al. (34) and Al-Mulali (43) emphasized infrastructure gaps and coal dependence. Quantile/nonlinear evidence is mixed: hydroelectricity can reduce life expectancy at lower quantiles but benefit higher ones (38,44); renewable benefits strengthen above income thresholds (41) and with strong institutions (45), yet may net to neutral when ecological demands and debt are considered (46). Electrification's welfare impacts depend on grid composition and stage of development: institutional quality and renewable electrification raise life expectancy (45), coal-heavy grids harm lower-quantile health (35), electricity underpins social sectors (47,48), and "clean electrification" is advocated to decouple growth from emissions (37,42). Cross-country evidence shows large gains from new technologies in developing settings (5), but diminishing returns at high electricity use (49), implying that access is essential but context determines durable well-being benefits.

Across emerging economies, evidence shows that sectoral sources, macroeconomic dynamics, and technological options jointly shape the emissions–development–well-being nexus: municipal wastewater treatment plants can be nontrivial and spatially concentrated emitters of CH_4 and CO_2, implying that quality-of-life gains from urban sanitation require decarbonized processes and energy inputs to avoid hidden climate costs (50); at the macro level, shocks to economic growth, financial development, and FDI raise CO_2 emissions, with short- to medium-run effects dominated by the FDI and long-run contributions led by growth, consistent with an Environmental Kuznets Curve pattern that emphasizes the need for strong environmental governance and green finance to decouple growth from carbon intensity (51); and on the technology frontier, functionalizing activated carbon can raise CO_2 adsorption capacity by roughly 35% (albeit with regeneration-related decline), pointing to scalable, lower-cost carbon capture options that can complement electrification and industrial decarbonization strategies (52).

Unlike earlier studies that employed linear models or isolated individual factors, e.g., Uzoechina et al. (42) and Wang et al. (41), Cravioto et al. (48), this research pioneers the application of MMQR in BRICS, capturing how the interplay of these variables differentially affects quality of life at low, median, and high quantiles of emissions whilst dissecting the heterogeneous impacts across socio-economic and environmental strata. In doing so, this study bridges the policy–praxis gap and provides a scalable framework for balancing development with ecological resilience in BRICS economies.

Materials and Methods

This study investigated the role of carbon emission intensity, energy consumption, and electrification on quality of life, using life expectancy at birth as a proxy. Our analysis spans the period 2000 to 2020, a time of rapid economic transformation, surging energy demand, and growing environmental pressures across the BRICS economies. This timeframe also coincides with intensified global efforts towards the United Nations Sustainable Development Goals (SDGs), particularly those related to good health and well-being (SDG 3), affordable and clean energy (SDG 7), and sustainable cities (SDG 11).

To ensure data reliability and global comparability, data were systematically sourced from three globally recognized databases: The World Bank Development Indicators (WDI), the Energy Information Administration (EIA), and the United Nations Conference on Trade and Development (UNCTAD). The search strategy specifically targeted annual data from each of the BRICS nations, focusing on the key indicators: carbon emission intensity, energy consumption, electrification, and life expectancy at birth. These variables are further presented in Table 1. The inclusion criteria required that only BRICS countries be considered, with complete annual data available for the periods under study for all variables. Moreover, only data from the three sources were included to maintain high standards of data integrity and comparability. Conversely, the exclusion criteria eliminated any indicator with incomplete time series data across the study period.

The dependent variable, which is quality of life, is measured by life expectancy at birth (in years), obtained from the WDI. Life expectancy is a robust proxy for societal well-being, encapsulating the long-term health and economic consequences of environmental and socio-economic conditions (25,36).

Three core independent variables were included to capture the environmental determinants of life sustainability. Carbon emission intensity is measured as kilograms of CO_2 equivalent per 2021 PPP-adjusted dollar of GDP, sourced from the WDI. This metric reflects the environmental cost of economic output in BRICS nations. Prior studies, e.g., Kaya et al. (9) and Zhang et al. (40), emphasized the harmful implications of carbon emission-intensive economic growth, noting that rising carbon intensity erodes life expectancy by contributing to air pollution and climate-related health risks. Energy consumption is represented by the total annual energy use, obtained from the EIA. While energy use fuels industrialization and infrastructural development, its quality-of-life impact depends critically on the underlying energy mix (25,26). Electrification is proxied by the percentage of the population with access to electricity, also drawn from the WDI. Greater electrification reduces indoor air pollution and fire hazards, and enables clean cooking technologies (4,32).

To empirically assess how the identified environmental mechanisms shape quality of life in the BRICS nations, this study employs a log-linear specification that captures both the elasticity and distributional effects of the selected key environmental indicators on life expectancy. The baseline model is specified as follows:

$$\begin{aligned} LnLiExptit &= \alpha 0 + \alpha 1 LnCo2Emit + \alpha 2 LnENERGit \\ &+ \alpha 3 LnELECTRit + \alpha 4 LnURBNZit + \alpha 5 LnPRODCit + \varepsilon it \end{aligned} \tag{1}$$

In the specified model, the dependent variable is the natural logarithm of life expectancy at birth (Ln*LiExpt*), serving as a proxy for quality of life across BRICS nations. Ln*Co2Em* is the natural logarithm of carbon emission intensity, Ln*ENERG* depicts the natural logarithm of total annual energy consumption, Ln*ELECTR* represents the natural logarithm of access to electricity, Ln*URBNZ* represents the natural logarithm of urban population, while Ln*PRODC* indicates the natural logarithm of productive capacities. The model also includes a constant term (α_0) and an error term (ε_{it}) assumed to be independently and identically distributed. All the variables are transformed into natural logarithmic form to interpret the estimated coefficients as elasticities and to stabilize the variance of the dataset for robust econometric estimation.

To further ensure the robustness of our estimates and address potential statistical issues common in multi-country datasets, we employ a multi-stage estimation procedure as illustrated in Figure 1. First, we test for cross-sectional dependence (CD), recognizing that BRICS nations are likely interlinked through economic, environmental, and policy channels. We apply Pesaran's CD test (53), which is well suited to panels with many cross-sectional units and periods. The test statistic is defined as the average of pairwise correlation coefficients of residuals from individual regressions:

$$CD = \frac{\sqrt{2\mathrm{T}}}{\mathrm{N}(\mathrm{N}-1)}\left(\sum_{i-1}^{n-1}\sum_{K=I+1}^{N} Pik\right) \tag{2}$$

where Pik denotes the estimated pairwise correlation of residuals between countries i and k. A significant CD statistic implies that the presence of cross-sectional dependency necessitates estimators that can account for such structure.

Secondly, we employ Swamy's test (54) to examine random coefficient heterogeneity, i.e., whether slope coefficients differ across countries. Swamy's test is particularly useful for validating heterogeneous-slope estimators like MMQR, since it accounts for structural differences among the BRICS economies. The test statistic is given as follows:

$$\tilde{S} = \sum_{i=1}^{N}\left(\hat{\delta}_i - \tilde{\delta}_{WFE}\right)' \frac{X_i' M_\tau X_i}{\tilde{\sigma}_i^2}\left(\hat{\delta}_i - \tilde{\delta}_{WFE}\right) \tag{3}$$

where $\hat{\delta}_i$ is the individual slope coefficient for country i, $\hat{\delta}_i$ is the pooled coefficient, and $_{WFE}$ is the covariance matrix of $\hat{\delta}_i$. A significant Q suggests slope heterogeneity across the panel. Next, we apply Pesaran and Yamagata's slope homogeneity test (55), which yields two powerful test statistics: delta-tilde (Δ) and the deviation-correlated delta-tilde (Δ_adj). These tests are essential for determining whether heterogeneity in slope coefficients might affect the consistency of estimators across countries. The test statistics are defined as follows:

$$\tilde{\Delta} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - k}{\sqrt{2k}}\right) \tag{4}$$

$$\tilde{\Delta}_{adj} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - k}{\sqrt{\frac{2k(T-k-1)}{T+1}}}\right) \tag{5}$$

where $\tilde{S}$ is the slope homogeneity statistic, k is the number of regressors, and N is the number of countries. If either statistic is significant, the null hypothesis of slope homogeneity is rejected, justifying the use of estimators that allow for parameter heterogeneity.

Next, to assess the stationarity of our variables, we apply Pesaran's Cross-sectionally Augmented Dickey-Fuller (CADF) and the Cross-sectionally Imputed Panel Stationarity (CIPS) tests (50). Both procedures account for cross-sectional dependence by augmenting standard ADF regressions with cross-sectional averages. The CADF equation is written as:

$$\Delta y_{it} = \alpha_i + b_i y_{it-1} + c_i \bar{y}_{t-1} + d_i \Delta \bar{y}_t + \varepsilon_{it} \tag{6}$$

The CIPS test statistic is then computed as the average of individual CADF statistics:

$$CIPS = \frac{1}{N}\sum_{i=1}^{N} t_i(N,T) \tag{7}$$

If the test statistic is below the critical value, the null hypothesis of a unit root is rejected, suggesting stationarity.

Once stationarity is established, we examine long-run equilibrium relationships using the Pedroni (56) and Westerlund (57) cointegration tests. Pedroni's approach employs both within-dimension and between-dimension statistics to accommodate heterogeneity across countries.

Table 1. Variable Description

Variable	Acronym	Data Description	Source
Quality of life	Ln_LiExpt	Measured by life expectancy at birth, total (years)	The World Bank Development Indicators
Carbon Emission Intensity	Ln_Co2Em	Carbon intensity of GDP (kg CO_2e per 2021 PPP $ of GDP)	The World Bank Development Indicators
Energy Consumption	Ln_ENERG	Total annual energy consumption	The Energy Information Administration (EIA)
Electrification	Ln_ELECTR	Electricity access (% of population)	The World Bank Development Indicators
Urbanization	Ln_URBNZ	Urban population (% of total population)	The World Bank Development Indicators
Productive Capacities	Ln_PRODC	UNCTAD's Overall Productive Capacities Index (PCI)	UNCTAD

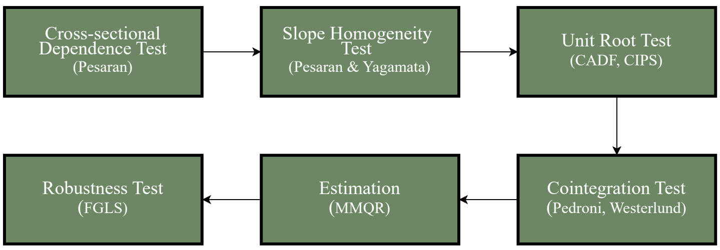

Figure 1. Econometric outline

Westerlund's test, based on the error-correction model, is robust to cross-sectional dependence. The general error-correction form used in Westerlund's procedure is:

$$\Delta Yi,t = \mu'i\, d\, t + \lambda i\left(Yi,\ t-1-\ \beta'iXi,t-1\right) + \sum_{j=1}^{k}\varnothing ij\Delta Yi,\ t-\ \mathrm{j} + \sum_{j=1}^{k} yij\Delta Xi,t-\ \mathrm{j} + \ \varepsilon i,\ t \quad (8)$$

Yi denotes the error-correction term that determines the presence of cointegration.

Finally, to estimate effects across the conditional distribution of life expectancy, we apply the Method of Moments Quantile Regression (MMQR) of Machado and Silva (58). MMQR accommodates both slope heterogeneity and cross-sectional dependence, and it captures non-linear relationships at different points of the dependent variable. This makes it ideally suited for assessing inequalities in quality-of-life outcomes across the BRICS nations. The MMQR specification is as follows:

$$Q_{yit}(\tau \mid K_{it}) = (\varphi_i + \lambda_i q(\tau)) + K'_{it}\phi + L_{it}\lambda q(\tau) \quad (9)$$

where $Q_{yit}(\tau \mid K_{it})$ is the τ-th conditional quantile of life expectancy, L_{it} is the vector of explanatory variables, and $\lambda q(\tau)$ depicts the quantile-specific slope parameters. This flexible approach provides deeper insights into how variables like carbon intensity, energy consumption, and electrification impact quality of life across different segments of the distribution (e.g., lower vs higher life expectancy nations).

Results

From the summary statistics in Table 2, quality of life has a mean value of 4.227 and a modest standard deviation of 0.093. This tight dispersion implies that, although there are measurable differences in life expectancy across BRICS countries and over time, these differences are relatively small. This likely reflects comparable socio-economic and parallel gains in healthcare access during the study period. The mean carbon emission intensity is -1.048, with values ranging from -2.13 to -0.25, indicating substantial variation in carbon efficiency across these nations. A higher (less negative) carbon intensity value reflects higher emissions, signaling weaker environmental performance. The spread in these values stresses the differences in the structural compositions of BRICS nations, with some countries leaning more heavily on energy-intensive and emission-heavy sectors than others.

Table 2. Descriptive Statistics

Variable	Obs	Mean	Std. D.	Min	Max
Ln_LiExpt	105	4.227	0.093	3.989	4.358
Ln_Co2 Em	105	-1.048	0.596	-2.13	-0.25
Ln_ENERG	105	2.935	1.031	1.517	4.973
Ln_ELECTR	105	4.505	0.131	4.099	4.605
Ln_URBNZ	105	4.035	0.365	3.32	4.467
Ln _PRODC	105	3.851	0.13	3.479	4.078

Energy consumption has a mean value of 2.935 and a standard deviation of 1.031, reflecting pronounced disparities and uneven patterns in industrial activities, energy infrastructure, and economic scale among the BRICS nations. By contrast, electrification exhibits both a high mean of 4.505 and a narrow dispersion of 0.131. Even the minimum value of 4.099 translates to roughly 60% raw access, indicating that universal electricity coverage is largely achieved across BRICS. The limited variation suggests that, unlike carbon intensity and energy use, electrification might exert a more uniform influence on life expectancy across the sampled countries.

Figure 2 summarizes the log-transformed distributions and highlights clear minima and maxima for each variable.

Life expectancy is tightly clustered, ranging from 3.989 to 4.358, indicating limited cross-country dispersion. CO_2 emission intensity spans the widest negative range, with the maximum closer to zero reflecting countries with comparatively higher carbon intensity. Energy use shows the broadest overall spread, identifying it as the most variable input across BRICS. Electrification is high on average and near its upper bound (4.099 to 4.605), suggesting most observations are close to universal access, with a small subset nearer the minimum reflecting lagging reliability or access. Urbanization ranges from 3.32 to 4.467, with the maximum indicating highly urbanized contexts that may face congestion/pollution pressures. Productive capacity varies modestly, with the maximum marking relatively stronger institutional/economic capability. Figure 2 also effectively illustrates the central tendency and spread of each of the variables' distributions, showing no evidence of extreme outliers. To further validate the dataset's econometric reliability, we conducted a thorough multicollinearity assessment using both a correlation matrix and Variance Inflation Factors (VIF), the results of which are reported in Table 3.

The correlation matrix shows that none of the explanatory variables exhibit excessively high pairwise correlation coefficients. The highest correlation is between electrification and quality of life (0.675), followed by electrification and urbanization (0.616), both well below the commonly accepted multicollinearity threshold of 0.80. Furthermore, the VIF results strengthen this conclusion; all variables report VIF values well below the conventional threshold of 10, ranging from 1.76 for carbon emission intensity to 4.93 for electrification, with a mean VIF

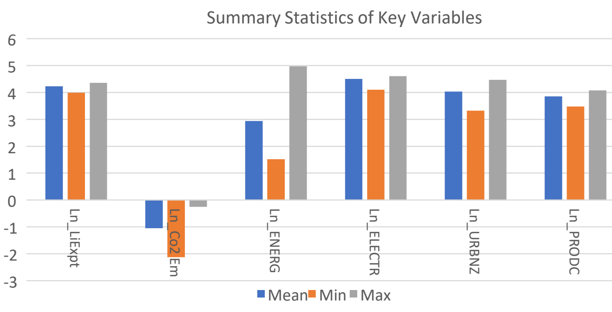

Figure 2. Bar chart visualization of the descriptive statistic results

of 3.54. These statistics indicate an acceptable level of multicollinearity among the explanatory variables. Notably, the observed correlations are consistent with theoretical expectations and prior empirical literature.

To ensure the suitability of the panel dataset for robust econometric analysis, additional pre-estimation diagnostic tests were conducted. First, the presence of cross-sectional dependence (CD) among the variables was examined. As shown in Table 4, the CD test results are statistically significant at the 1% level for all variables, with highly significant test statistics and p-values across the board. This result implies that shocks or policy changes in one BRICS country are likely to influence others, reflecting their economic and environmental interdependence. Hence, the rejection of cross-sectional independence justifies the adoption of second-generation panel data methods that accommodate such dependence.

Following the CD test, a slope homogeneity test was conducted to assess whether the slope coefficients are consistent across panel units. As presented in Table 4, both the delta-tilde ($\tilde{\Delta}$) and the adjusted delta-tilde ($\tilde{\Delta}_{adjusted}$) statistics are highly significant at the 1% level for all variables. This result confirms the presence of slope heterogeneity, indicating that the effect of each explanatory variable on quality of life varies across BRICS nations. Consequently, these findings support the adoption of estimation techniques that account for heterogeneous parameters across cross-sectional units.

The next step involved conducting unit root tests using both the CADF and the CIPS tests to examine the stationarity properties of the data. As reported in Table 5, most variables are non-stationary at level but become stationary after first differencing, indicating they are integrated of order one. Furthermore, to assess the long-run equilibrium relationship among the variables, cointegration tests were conducted (Table 6). The Pedroni test yields statistically significant results, and the Westerlund test further confirms cointegration. These results collectively suggest that despite short-run fluctuations, there is a stable long-term equilibrium relationship between quality of life and the main explanatory variables, as well as the control variables.

Given the confirmed presence of cross-sectional dependence, slope heterogeneity, cointegration, and the stationarity of variables at first order, the use of Method of Moments Quantile Regression (MMQR) is necessary. The MMQR approach facilitates the analysis of heterogeneous effects of the explanatory variables across different quantiles of the conditional distribution of quality of life. This is particularly pertinent considering the significant disparities in economic and environmental performance across BRICS countries. Moreover, MMQR is robust to outliers and non-normal error distributions and effectively captures distributional dynamics that traditional mean-based estimators overlook (58). The result of the MMQR is hence presented in Table 7.

Carbon emission intensity has a consistently negative and statistically significant impact on quality of life across all quantiles, though the magnitude of this effect declines from the 10th (-0.131) to the 90th quantile (-0.0544). Energy consumption demonstrates a positive but diminishing effect on quality of life, with a coefficient of 0.0907 at the 10th quantile (*Q*10). This implies that the initial increase in energy use, likely directed toward basic infrastructure, healthcare services, and sanitation, yields significant life-expectancy gains, particularly in the lowest-performing BRICS countries. However, this positive impact weakens progressively across the distribution and becomes statistically insignificant at the 90th quantile, reflecting

Table 3. Matrix of correlation matrix and VIF

Variables	Ln_LiExpt	Ln_Co2_Em	Ln_ENERG	Ln_ELECTR	Ln_URBNZ	Ln_PRODC	VIF	1/VIF
Ln_LiExpt	1							
Ln_Co2_Em	-0.348	1					1.76	0.567894
Ln_ENERG	0.657	0.31	1				3.4	0.294101
Ln_ELECTR	0.675	-0.13	0.429	1			4.93	0.202664
Ln_URBNZ	0.127	-0.259	-0.278	0.616	1		4.8	0.208118
Ln_PRODC	0.237	0.27	0.179	0.611	0.606	1	2.82	0.354333
Mean VIF							3.54	

Table 4. Pesaran CD and slope homogeneity tests

Pesaran CD					Slope homogeneity	
Variable	CD-test	*P*-value	corr	abs(corr)	$\tilde{\Delta}$	$\tilde{\Delta}_{adjusted}$
Ln_LiExpt	13.53***	0.000	0.933	0.933	-	-
Ln_Co2_Em	8.06***	0.000	0.556	0.556	8.685***	9.380***
Ln_ENERG	13.23***	0.000	0.913	0.913	14.751***	15.933***
Ln_ELECTR	10.99***	0.000	0.758	0.758	13.780***	14.884***
Ln_URBNZ	14.16***	0.000	0.977	0.977	25.452***	27.491***
Ln_PRODC	13.77***	0.000	0.95	0.95	8.549***	9.234***

*** represents significance at 1%.

Table 5. Unit root test results

	CADF		CIPS	
Variable	**Level**	**First difference**	**Level**	**First difference**
Ln_LiExpt	-4.746***	-1.648***	-4.213	-2.489***
Ln_Co2_Em	1.122	-2.112***	-1.273	-2.811***
Ln_ENERG	-0.464	-3.774***	-1.961***	-3.468***
Ln_ELECTR	-1.303*	-6.975***	-2.325	-4.943***
Ln_URBNZ	2.11	-0.169	0.235	-1.441
Ln_PRODC	1.844	-2.612***	-1.313	-2.933***

*, *** represent significance at 10% and 1%, respectively.

Table 6. Cointegration test results

Pedroni	Statistic	*P*-value
Modified Phillips–Perron t	2.8629***	0.0021
Westerlund	Statistic	*P*-value
Variance ratio	3.8532***	0.0001

*** represents significance at 1%.

Table 7. The results of the Method of Moments Quantile Regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Variables	**Location**	**Scale**	**Q10**	**Q20**	**Q30**	**Q40**	**Q50**	**Q60**	**Q70**	**Q80**	**Q90**
$Ln\_Co_2\_Em$	-0.0930***	0.0245**	-0.131***	-0.122***	-0.109***	-0.0962***	-0.0847***	-0.0785***	-0.0723***	-0.0670***	-0.0544**
	(0.0140)	(0.00968)	(0.0158)	(0.0137)	(0.0135)	(0.0139)	(0.0149)	(0.0155)	(0.0167)	(0.0181)	(0.0234)
Ln_ENERG	0.0570***	-0.0217***	0.0907***	0.0827***	0.0716***	0.0599***	0.0497***	0.0443***	0.0387***	0.0341**	0.0229
	(0.0107)	(0.00741)	(0.0120)	(0.0103)	(0.0105)	(0.0108)	(0.0113)	(0.0115)	(0.0122)	(0.0133)	(0.0177)
Ln_ELECTR	0.212*	0.150**	-0.0209	0.0344	0.111	0.192*	0.262**	0.300**	0.339**	0.371**	0.448**
	(0.109)	(0.0752)	(0.124)	(0.108)	(0.103)	(0.107)	(0.118)	(0.125)	(0.136)	(0.148)	(0.184)
Ln_URBNZ	-0.0394	-0.0472*	0.0337	0.0164	-0.00778	-0.0332	-0.0553	-0.0671	-0.0792*	-0.0893*	-0.113*
	(0.0377)	(0.0261)	(0.0430)	(0.0376)	(0.0357)	(0.0370)	(0.0410)	(0.0438)	(0.0475)	(0.0516)	(0.0641)
Ln_PRODC	0.139*	-0.0152	0.163*	0.157**	0.149**	0.141*	0.134	0.130	0.126	0.123	0.115
	(0.0746)	(0.0516)	(0.0861)	(0.0762)	(0.0692)	(0.0723)	(0.0828)	(0.0906)	(0.0997)	(0.108)	(0.129)
Constant	2.630***	-0.311	3.112***	2.997***	2.839***	2.671***	2.526***	2.448***	2.369***	2.302***	2.143***
	(0.303)	(0.210)	(0.346)	(0.304)	(0.285)	(0.296)	(0.330)	(0.355)	(0.387)	(0.420)	(0.517)
Observations	105	105	105	105	105	105	105	105	105	105	105

Standard errors in parentheses *** $P<0.01$, ** $P<0.05$, *$P<0.1$.

a saturation point in more advanced BRICS nations. In these contexts, further expansion of predominantly fossil-fuel-based energy systems may contribute more to pollution and climate vulnerabilities. Electrification reveals a striking quantile-dependent trajectory. It is statistically insignificant at lower quantiles (*Q*10–*Q*30) but becomes strongly positive and significant from *Q*40 onwards, with its impact peaking at *Q*90. In other words, electrification portrays a threshold dynamic and negligible impact at the lowest quantiles, giving way to strong and significant life-expectancy gains at *Q*40 and above. Figure 3 presents the quantile-specific coefficient estimates for CO_2 emissions, energy consumption, electricity access, urbanization, and production, illustrating how the magnitude and direction of their effects vary across the conditional distribution.

Discussion

Given the uniformly negative and statistically significant impact of carbon emission intensity on quality of life, with a progressive decline from the 10th to the 90th quantile. The results indicate that environmental degradation has the most severe consequences in contexts where public health systems and social protections are underdeveloped. Furthermore, the positive scale parameter indicates increasing dispersion in the relationship between CO_2 emissions and life expectancy as emissions rise. These patterns suggest targeted mitigation and health-system strengthening are most urgent in lower-quantile settings. For context, this direction aligns with prior cross-country evidence (28,29), but this study's contribution is to map and quantify the gradient of harms across the conditional life-expectancy distribution. The quantile-coefficient plot in Figure 3 illustrates this trend, showing a gradual increase in the coefficient from approximately −0.13 at the 10th percentile to −0.05 by the 90th percentile. This confirms that carbon-intensive growth inflicts the greatest toll on life expectancy in countries already at the lower end of the life-expectancy spectrum, though the negative effect

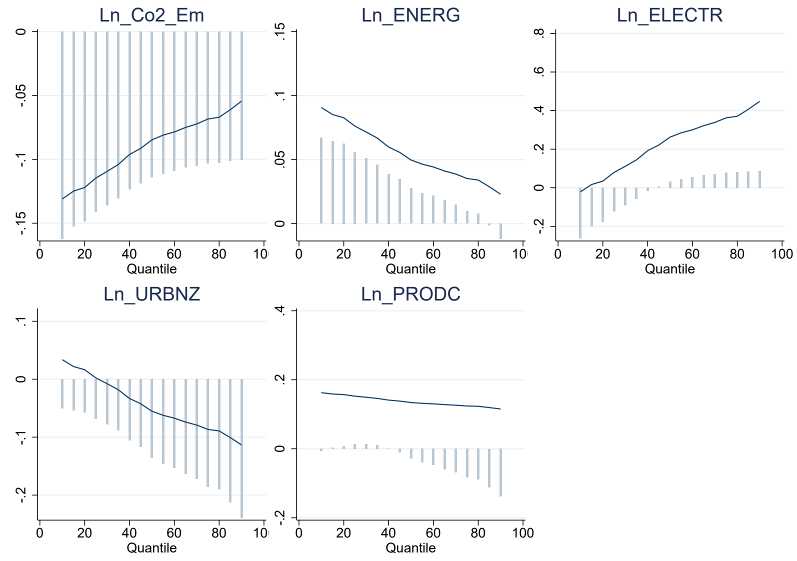

Figure 3. Quantile-coefficient plots from the MMQR estimates.

persists even at higher quantiles.

With respect to the negative scale coefficient of energy consumption, this indicates that beyond a certain point, further energy expansion offers marginal benefits and may contribute more to environmental degradation than to quality-of-life improvements. This, however, contrasts with traditional linear models and highlights the dual role of energy: a catalyst for development at low-income stages and a liability at higher levels of economic and social advancement, particularly those without a transition plan to clean energy. The study's results therefore support policies that prioritize early-stage access and efficiency, while accelerating fuel switching and demand-side management as countries move up the distribution. This pattern is consistent with threshold-type findings in the literature (3,26,41), but our novel insight is the distributional mapping of these effects within BRICS. Figure 3 illustrates this dynamic, with the quantile profile sloping downward from roughly +0.09 at Q10 to near zero at Q90. This indicates that while initial increase in energy use enhances sizeable gains where life expectancy is low, these benefits taper off in higher-life-expectancy contexts, which is consistent with a saturation or threshold effect.

The threshold dynamic result of electrification implies that mere access to electricity does not substantially improve life expectancy at lower quantiles, where infrastructural deficiencies may dilute its benefits. However, once reliability, quality, and complementary infrastructure improve, electrification begins to yield meaningful health and longevity dividends. Figure 3 presents this progression by visually confirming this progression: the effect is negligible at the lowest quantiles, begins to rise around Q30 (+0.11), and peaks at *Q*90 (+0.45). In other words, improvements in electrification deliver the most substantial gains in countries already enjoying higher life expectancy, indicating that post-access improvements, such as grid stability, energy quality, and system resilience, are essential for sustained health benefits. While prior work emphasizes reliability and adequacy (47–49), this study's added value is quantifying where along the life-expectancy distribution these gains become most pronounced in BRICS.

Regarding the control variables, urbanization reveals that early-stage urban growth may initially and marginally improve health, likely due to better access to public services and agglomeration effects. However, at higher quantiles, where urban populations are already dense, continued urban expansion may strain public services, increase pollution levels, and reduce overall life expectancy. These interpretations are directionally in line with existing arguments (34,39,40), but the contribution of this study is to localize their relevance across quantiles, clarifying where policy levers (mitigation, clean energy transitions, grid quality, urban planning, and institutional strengthening) yield the largest marginal gains.

Robustness test

To ensure that the study's findings are not biased by heteroskedasticity or contemporaneous correlation across the BRICS nations, the baseline life-expectancy model was re-estimated using Feasible Generalized Least Squares (FGLS). As presented in Table S1, the FGLS results consistently confirm that carbon emission intensity has a statistically significant and negative impact on life expectancy across all model specifications. In the single-regressor model (Column 1), a 1% increase in carbon intensity reduces life expectancy by approximately 0.11%. This negative relationship persists when energy consumption and electrification are included as additional regressors (Columns 4–5) and remains robust even under the inclusion of country fixed effects (Column 6). This finding confirms that the adverse health effects of carbon-intensive growth are not artefacts of model specification or estimation method.

Energy consumption likewise consistently shows a positive influence on life expectancy across most model specifications, indicating that infrastructural and service benefits derived from increased energy use contribute to longer life spans. However, when country fixed effects are incorporated, the estimate turns negative, indicating that once unobserved, time-invariant national characteristics are controlled for, the marginal benefits of additional energy consumption may diminish or even reverse. This result mirrors the saturation effects identified in the earlier MMQR analysis. Similarly, the electrification variable demonstrates one of the strongest and most stable positive effects across models. Whether entered independently or alongside the other environmental metrics, greater electricity access consistently enhances life expectancy. This aligns with the quantile analysis, which indicates that reliable electrification delivers substantial longevity benefits, particularly once basic access thresholds are surpassed. Turning to controls, productive capacities and urbanization display more subtle patterns. Productive capacities yield a large positive coefficient in the simplest model and regain significance under country effects, highlighting the role of institutional and infrastructural strength. Urbanization, on the other hand, exhibits alternating marginal negative and positive directions, indicating that its net impact on life expectancy depends on the balance between the benefits of agglomeration and the environmental stresses associated with urban growth.

The study further conducted the Dumitrescu and Hurlin (59) Granger causality test as an additional robustness check to strengthen the empirical credibility of the findings. The results, presented in Table S2, reveal a unidirectional Granger causality running from energy consumption to life expectancy, confirming that changes in energy use precede and help predict variations in life expectancy. This supports the MMQR finding of energy consumption having a significant impact at lower quantiles of life expectancy, suggesting its importance in facilitating developmental outcomes, especially in countries with lower baseline living standards.

Similarly, carbon emission intensity and electrification both exhibit bidirectional causality with life expectancy, indicating a feedback loop where not only do emissions and electricity access influence health outcomes, but improvements in life expectancy also appear to affect energy and environmental decisions over time. These mutual causalities highlight the dynamic interplay between environmental sustainability and human well-being, a relationship that was also evident in the MMQR results, where both variables showed quantile-dependent effects on life expectancy.

The bidirectional causality between urbanization and life expectancy further confirms the complex, co-evolving relationship between demographic shifts and quality of life outcomes. Interestingly, the test reveals a unidirectional causality from productive capacity to life expectancy, aligning with our earlier regression findings that suggest the developmental benefits of increased productivity, albeit with diminishing returns or context-specific outcomes. The lack of reverse causality in this case may reflect that, while productivity drives better living conditions, higher life expectancy alone does not significantly increase productive capacity.

Conclusion

This study explored the complex relationship between carbon emission intensity, energy consumption, electrification, and quality of life across BRICS nations from 2000 to 2020. Employing robust methodologies like the Method of Moments Quantile Regression (MMQR) along with robustness checks through Feasible Generalized Least Squares (FGLS) and Dumitrescu and Hurlin (DH) Granger causality tests. The results indicate that carbon emission intensity exerts a significantly negative effect on life expectancy, particularly at lower quantiles, highlighting the disproportionately detrimental effect of pollution in more vulnerable populations. Energy consumption, while essential to economic growth and development, showed mixed outcomes by positively influencing life expectancy at lower quantiles, but became negative at higher ones. This points to an environmental saturation effect, where excessive or inefficient energy use undermines long-term health and sustainability. In contrast, electrification consistently demonstrated a strong positive impact across all quantiles, affirming its crucial role in enhancing living standards and climate resilience. The robustness checks with FGLS further affirmed the stability and statistical significance of the key variables, while the DH Granger causality tests also investigated temporal causality patterns. Specifically, energy consumption and productive capacity were found to Granger-cause life expectancy, while bidirectional feedback loops were identified between life expectancy and both carbon emissions and electrification. These findings reinforce the dynamic and interconnected nature of environmental-health linkages in the BRICS context.

Building on these results, the distributional patterns suggest distinct policy priorities across the life-expectancy spectrum. At the lower quantiles, the harms of carbon emission intensity are largest, and the benefits of additional energy use remain positive but fragile, while electrification effects are muted until reliability and complementary infrastructure improve. By contrast, at the higher quantiles the marginal health gains from additional energy consumption taper toward zero, electrification delivers sizable benefits conditional on quality, and the adverse effects of carbon intensity, though smaller than at the bottom of the distribution, remain statistically significant. These gradients imply that countries at the lower end require "access-and-clean-up" strategies, whereas countries at the upper end require "quality, efficiency, and large-scale decarbonization" strategies. For lower-quantile BRICS contexts, policy should first target exposure reduction and essential service delivery. This entails localized air-quality monitoring and enforcement in high-risk urban and industrial zones, rapid deployment of end-of-pipe controls for SO_2/NO_x/PM, and near-term substitution away from biomass and kerosene through clean cooking and basic electrification. Expanding grid connections or decentralized renewable systems should be paired with minimum reliability standards, lifeline tariffs, and service-based electrification of clinics, vaccine cold chains, water, and sanitation. Because energy use still yields measurable health gains at these quantiles, efficiency standards for appliances and buildings can lock in low-emission demand growth, while primary health interventions (e.g., respiratory and cardiovascular screening, heat-health action plans) mitigate the immediate health burden of pollution. Institutional investments in monitoring, environmental enforcement, and local maintenance capacity are essential to sustain these gains.

For higher-quantile BRICS contexts, the policy emphasis should shift from access expansion to quality, demand management, and accelerated decarbonization. The tapering returns to energy consumption call for comprehensive efficiency policies, time-of-use tariffs, stringent appliance and building codes, industrial energy-management systems, and vehicle standards, to counter rebound effects. Electrification policy should prioritize grid modernization, flexibility, and resilience: storage, demand response, renewable firming, and climate-proofing of networks to ensure that the large potential health dividends of electrification are realized. To reduce the persistent harms of carbon intensity, countries should implement carbon pricing or caps with robust Measurement, Reporting, and Verification (MRV), retire coal on an expedited schedule, electrify industrial heat where feasible, and deploy low-emission freight and urban low-emission zones. Complementary financial instruments (green bonds, blended finance) and just-transition programs can de-risk investment and support affected workers and regions. Across both quantile groups, policy design should be explicitly distributional. Subnational dashboards linking life expectancy, exposure, electrification quality, and service access can guide the geographic targeting of interventions. Equity safeguards (such as targeted transfers, affordability protections, and distributional impact assessments) help align climate and energy policies with health co-benefits. Coordinated governance across energy, health, environment, and urban ministries is critical to translate quantile-specific evidence into integrated programs that maximize longevity gains while reducing carbon intensity.

This study is subject to several limitations that warrant careful interpretation of the findings. First, the analysis relies on country-level, log-transformed aggregates for key constructs. While these measures facilitate comparability across BRICS economies and over time, they inevitably mask within-country heterogeneity, subnational disparities, and potential measurement error. Data availability and harmonization constraints may also affect cross-country comparability across years. Second, model specification choices may shape the results. Quantile estimates are sensitive to functional form, covariate selection, and the treatment of nonlinearities, lags, and potential structural breaks. While the specification aims to capture key dynamics, it may not fully reflect complex adjustment paths, technological shocks, or policy regime shifts within the sample period. Relatedly, electrification is proxied primarily by access or coverage; this does not fully capture reliability, affordability, fuel mix, or service quality, which may attenuate effect sizes or shift their distribution across quantiles. Lastly, the temporal and policy context is evolving. Rapid deployment of renewables, changing grid quality, and health system shocks (e.g., pandemics) may alter the relationships documented here. The results therefore reflect the period studied and should not be presumed invariant to subsequent policy or technological change.

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Competing Interests
The author declares no conflict of interest.

Ethical Approval
The author hereby verifies that all data extracted and utilized in this study were of high originality from the respective databases, and no data from the study have been or will be published separately elsewhere.

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Supplementary Files
Supplementary file 1 contains Tables S1 and S2.

References

1. Xuan D, Jiang X, Fang Y. Can globalization and the green economy hedge natural resources? Functions of population growth and financial development in BRICS countries. Resour Policy 2023;82:103414. doi:10.1016/j.resourpol.2023.103414
2. Su CW, Huang SW, Tao R, Haris M. Does economic overheating provide positive feedback on population health? Evidence from BRICS and ASEAN countries. Front Public Health 2021;9:661279. doi:10.3389/fpubh.2021.661279
3. Ul-Haq J, Visas H, Umair M, Hye QM, Khanum S. Toward sustainable development: exploring the relationship between economic fitness and carbon emissions in BRICS. Sustain Futur 2024;7:100226. doi:10.1016/j.sftr.2024.100226
4. Zardoub A. Impact of economic growth, renewable energy consumption and energy intensity on CO2 emissions in BRIC countries: an application of CS-ARDL. J Infrastruct Policy Dev 2024;8(8):4312. doi:10.24294/jipd.v8i8.4312
5. Nadimi R, Tokimatsu K. Modeling of quality of life in terms of energy and electricity consumption. Appl Energy 2018;212:1282-94. doi:10.1016/j.apenergy.2018.01.006
6. McAlister S, Morton RL, Barratt A. Incorporating carbon into health care: adding carbon emissions to health technology assessments. Lancet Planet Health 2022;6(12): e993-9. doi:10.1016/s2542-5196(22)00258-3
7. Hensher M. Incorporating environmental impacts into the economic evaluation of health care systems: perspectives from ecological economics. Resour Conserv Recycl 2020;154:104623. doi:10.1016/j.resconrec.2019.104623
8. Li J, Irfan M, Samad S, Ali B, Zhang Y, Badulescu D, et al. The relationship between energy consumption, CO2 emissions, economic growth, and health indicators. Int J Environ Res Public Health 2023;20(3):2325. doi:10.3390/ijerph20032325
9. Kaya F, Voumik LC, Rashid M, Akter S, Khan SH, Salehi M,

et al. Energy choices to health outcomes: a multidimensional analysis of risk in BRICS via PMG-ARDL approach. PLoS One 2024;19(12): e0310558. doi:10.1371/journal.pone.0310558
10. Pradhan RP, Nair MS, Hall JH, Bennett SE. Planetary health issues in the developing world: dynamics between transportation systems, sustainable economic development, and CO2 emissions. J Clean Prod 2024;449:140842. doi:10.1016/j.jclepro.2024.140842
11. Finkelman RB, Wolfe A, Hendryx MS. The future environmental and health impacts of coal. Energy Geosci 2021;2(2):99-112. doi:10.1016/j.engeos.2020.11.001
12. Buonocore JJ, Salimifard P, Michanowicz DR, Allen JG. A decade of the US energy mix transitioning away from coal: historical reconstruction of the reductions in the public health burden of energy. Environ Res Lett 2021;16(5):054030. doi:10.1088/1748-9326/abe74c
13. Yang X. Is fossil fuel intensity adversely affecting health improvement and sustainability? Resour Policy 2025;101:105388. doi:10.1016/j.resourpol.2024.105388
14. Khatibi SR, Moradi-Lakeh M, Karimi SM, Kermani M, Motevalian SA. Catalyzing healthier air: the impact of escalating fossil fuel prices on air quality and public health and the need for transition to clean fuels. Biofuel Res J 2024;11(2):2099-104. doi:10.18331/BRJ2024.11.2.4
15. Amaefule C, Kalu IE, Udeorah S, Ebelebe LO. Fossil fuel consumption, CO2 emissions and growth in high-income countries and low-income countries. Eur J Sustain Dev Res 2022;6(3): em0190. doi:10.21601/ejosdr/12084
16. Pennington AF, Cornwell CR, Sircar KD, Mirabelli MC. Electric vehicles and health: a scoping review. Environ Res 2024;251(Pt 2):118697. doi:10.1016/j.envres.2024.118697
17. Pan S, Yu W, Fulton LM, Jung J, Choi Y, Gao HO. Impacts of the large-scale use of passenger electric vehicles on public health in 30 US metropolitan areas. Renew Sustain Energy Rev 2023;173:113100. doi:10.1016/j.rser.2022.113100
18. Tayebi S, Amini H. The flip side of the coin: exploring the environmental and health impacts of proof-of-work cryptocurrency mining. Environ Res 2024;252(Pt 1):118798. doi:10.1016/j.envres.2024.118798
19. Uma S. Blockchain and AI: disruptive digital technologies in designing the potential growth of healthcare industries. In: Rai BK, Kumar G, Balyan V, eds. AI and Blockchain in Healthcare. Singapore: Springer; 2023. p. 137-50. doi:10.1007/978-981-99-0377-1_9
20. Guo M, Huang Z, Wu L, Tan CL, Peng J, Guo X, et al. Application of blockchain technology in environmental health: literature review and prospect of visualization based on CiteSpace. Technologies 2022;10(5):100. doi:10.3390/technologies10050100
21. Khogali A, Ahmed A, Ibrahim M, Karrar K, Elsheikh M, Abdelraheem E, et al. Building power-ful health systems: the impacts of electrification on health outcomes in LMICs. Psychol Health Med 2022;27(Suppl 1):124-37. doi:10.1080/13548506.2022.2109049
22. Wallach ES, Lam NL, Nuwagira E, Muyanja D, Tayebwa M, Valeri L, et al. Effect of a solar lighting intervention on fuel-based lighting use and exposure to household air pollution in rural Uganda: a randomized controlled trial. Indoor Air 2022;32(2): e12986. doi:10.1111/ina.12986
23. Omri A, Kahouli B, Afi H, Kahia M. Impact of environmental quality on health outcomes in Saudi Arabia: does research and development matter? J Knowl Econ 2022:1-26. doi:10.1007/s13132-022-01024-8
24. Majeed MT, Luni T, Zaka G. Renewable energy consumption and health outcomes: evidence from global panel data analysis. Pak J Commer Soc Sci 2021;15(1):58-93.
25. Brunner E, Maruyama K. SP4-32 Health and sustainability: International ecological study of carbon dioxide emissions and life expectancy. J Epidemiol Community Health 2011;65(Suppl 1): A442-3. doi:10.1136/jech.2011.142976p.26
26. Dam MM, Kaya F, Bekun FV. On the nexus between real income, renewable energy consumption, and environmental sustainability on life expectancy for BRICS-T countries: accessing evidence from quantile regression. Nat Resour Forum 2024;48(4):1109-35. doi:10.1111/1477-8947.12347
27. Samour A, Adebayo TS. External debt, renewable energy, and environmental quality in BRICS countries: novel findings based on the load capacity factor. Res Sq [Preprint]. December 7, 2022. Available from: https://www.researchsquare.com/article/rs-2328886/v1
28. Karimi Alavijeh N, Ahmadi Shadmehri MT, Dehdar F, Zangoei S, Nazeer N. The role of renewable energy on life expectancy: evidence from method of moments quantile regression based on G-7 countries data. Int J Energy Sect Manag 2023;18(4):767-88. doi:10.1108/ijesm-11-2022-0001
29. Khan F, Sarwar G, Khan MA, Noor S, Rehman ZU. Assessing the link between environmental quality and life expectancy in developing nations: an empirical analysis for sustainable development. Int Soc Sci J 2025;75(256):295-310. doi:10.1111/issj.12553
30. Weitensfelder L, Moshammer H, Ataniyazova O. Energy consumption, energy distribution, and clean energy use together affect life expectancy. Sustainability 2024;16(2):678. doi:10.3390/su16020678
31. Ma X, Song C, Zhao C, Zhao Z, Deng B, Liu Z. The role of BRICS countries in the optimal low-carbon transition path for sustainable development. J Clean Prod 2024;460:142583. doi:10.1016/j.jclepro.2024.142583
32. Aderinto E. Energy consumption, environmental quality and health nexus in West African countries: implications for sustainable development. Res Sq [Preprint]. July 9, 2023. Available from: https://www.researchsquare.com/article/rs-3057950/v1
33. Mookherjee S, Dutta UP. The issue of sustainable urbanization in BRICS nations: an impact-analysis of urban energy consumption and carbon emission. In: Globalization, Income Distribution and Sustainable Development: A Theoretical and Empirical Investigation. Bingley: Emerald Publishing Limited; 2022. p. 147–59. doi:10.1108/978-1-80117-870-920221020.
34. Caglar AE, Guloglu B, Gedikli A. Moving towards sustainable environmental development for BRICS: investigating the asymmetric effect of natural resources on CO2. Sustain Dev 2022;30(5):1313-25. doi:10.1002/sd.2318
35. Sampene AK, Li C, Wiredu J. Environmental technology to stimulate life expectancy: a deep dive into the role of PM2.5 and carbon emission. Environ Int 2024;193:109118. doi:10.1016/j.envint.2024.109118
36. Beyene SD, Kotosz B. Empirical evidence for the impact of environmental quality on life expectancy in African countries. J Health Pollut 2021;11(29):210312. doi:10.5696/2156-9614-11.29.210312
37. Rahman HU, Zaman U, Górecki J. The role of energy consumption, economic growth and globalization in environmental degradation: empirical evidence from the BRICS region. Sustainability 2021;13(4):1924. doi:10.3390/su13041924
38. Younus S, Khursheed A, Afzal N. Impact of economic progress, energy consumption and carbon dioxide emissions on life expectancy: evidence from Asia and Africa. J Soc Sci Rev 2022;2(3):225-35. doi:10.54183/jssr.v2i3.115
39. Osei-Kusi F, Wu C, Tetteh S, Castillo WI. The dynamics of carbon emissions, energy, income, and life expectancy: regional comparative analysis. PLoS One 2024;19(2): e0293451. doi:10.1371/journal.pone.0293451
40. Zhang X, Hasan MM, Waris U. Assessing the nexus between natural resources and government effectiveness: role of green innovation in shaping environmental sustainability of BRICS nations. Resour Policy 2024;93:105024. doi:10.1016/j.

resourpol.2024.105024
41. Wang Q, Wang L, Li R. Does renewable energy help increase life expectancy? Insight from the linking renewable energy, economic growth, and life expectancy in 121 countries. Energy Strategy Rev 2023;50:101185. doi:10.1016/j.esr.2023.101185
42. Uzoechina BI, Ezekwike JO, Ekwoh GA, Eze EA, Imoagwu PC, Edeh JN. Impact of energy consumption on life expectancy in lower-middle-income West African countries. Glob Health Econ Sustain 2024;3(1):1-13. doi:10.36922/ghes.3518
43. Al-Mulali U. Exploring the bi-directional long run relationship between energy consumption and life quality. Renew Sustain Energy Rev2016;54:824-37. doi:10.1016/j.rser.2015.10.125
44. Salehnia N, Karimi Alavijeh N, Hamidi M. Analyzing the impact of energy consumption, the democratic process, and government service delivery on life expectancy: evidence from a global sample. Environ Sci Pollut Res 2022;29(24):36967-84. doi:10.1007/s11356-021-18180-0
45. Vatamanu AF, Onofrei M, Cigu E, Oprea F. Renewable energy consumption, institutional quality and life expectancy in EU countries: a cointegration analysis. Energ Sustain Soc 2025;15(1):2. doi:10.1186/s13705-024-00507-7
46. Aladejare SA, Osagu FN. Assessing quality of life from the lens of sustainability in Africa. Res Sq [Preprint]. May 11, 2023. Available from: https://www.researchsquare.com/article/rs-2919846/v1
47. Zohuri B, McDaniel P. The electricity: an essential necessity in our life. In: Zohuri B, McDaniel P, eds. Advanced Smaller Modular Reactors: An Innovative Approach to Nuclear Power. Cham: Springer International Publishing; 2019. p. 1-21. doi:10.1007/978-3-030-23682-3_1
48. Cravioto J, Ohgaki H, Che HS, Tan C, Kobayashi S, Toe H, et al. The effects of rural electrification on quality of life: A southeast Asian perspective. Energies 2020;13(10):2410. doi:10.3390/en1310241010.3390/en13102410
49. Mazur A. Does increasing energy or electricity consumption improve quality of life in industrial nations? Energy Policy 2011;39(5):2568-72. doi:10.1016/j.enpol.2011.02.024
50. Yaghmaeian K, Panahi Fard M, Ahmadi Moghadam M, Mousavi M, Jaafarzadeh N, Omidinasab M, et al. CH4 and CO2 emissions rate of Iranian municipal wastewater treatment plants using IPCC and USEPA approaches. Environ Health Eng Manag 2024;11(2):161-6. doi:10.34172/ehem.2024.16
51. Jakada AH, Mahmood S, Ahmad AU, Muhammad IG, Danmaraya IA, Yahaya NS. Driving forces of CO2 emissions based on impulse response function and variance decomposition: a case of the main African countries. Environ Health Eng Manag 2022;9(3):223-32. doi:10.34172/ehem.2022.23
52. Haghmoradkhani A, Pardakhti A, Zahed MA. Evaluation of adsorption efficiency of activated carbon functionalized with methyl diethanolamine in carbon dioxide gas. Environ Health Eng Manag 2022;9(3):261-70. doi:10.34172/ehem.2022.27
53. Pesaran MH. A simple panel unit root test in the presence of cross-section dependence. J Appl Econ (Chichester Engl) 2007;22(2):265-312. doi:10.1002/jae.951
54. Swamy PA. Efficient inference in a random coefficient regression model. Econometrica 1970;38(2):311-23. doi:10.2307/1913012
55. Pesaran MH, Yamagata T. Testing slope homogeneity in large panels. J Econom 2008;142(1):50-93. doi:10.1016/j.jeconom.2007.05.010
56. Pedroni P. Critical values for cointegration tests in heterogeneous panels with multiple regressors. Oxf Bull Econ Stat 1999;61(S1):653-70. doi:10.1111/1468-0084.0610s1653
57. Westerlund J. Testing for error correction in panel data. Oxf Bull Econ Stat 2007;69(6):709-48. doi:10.1111/j.1468-0084.2007.00477.x
58. Machado JAF, Santos Silva JM. Quantiles via moments. J Econom 2019;213(1):145-73. doi:10.1016/j.jeconom.2019.04.009
59. Dumitrescu EI, Hurlin C. Testing for Granger non-causality in heterogeneous panels. Econ Model 2012;29(4):1450-60. doi:10.1016/j.econmod.2012.02.014