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Renewable Energy Transition and Life Expectancy in the BRICS Countries

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Abstract
This study aims to investigate the impact of disaggregated renewable energy sources on life expectancy in the BRICS nations from 1990 to 2023, using linear, non-linear and non-parametric models. This research challenges long-held beliefs about the impact of renewable energy on human health. It reveals the intricate links between different energy sources and life expectancy in the BRICS countries. Based on the QPNARDL results, hydropower is found to harm life expectancy. Based on the PNARDL model, its impact varies across countries. Based on the SQR and PCSE models in the BRICS nations, however, it appears to have a positive impact on life expectancy. According to the QPNARDL, SQR and PCSE models, wind energy reduces life expectancy in BRICS nations. However, the PNARDL model shows that wind energy has a positive impact on life expectancy in Brazil and China, and a negative impact in India and Russia. Other Renewables, including bioenergy, boost life expectancy in the BRICS nations based on the SQR and PCSE models, while hurting life expectancy based on the QPNARDL and PNARDL models. The results suggest that the impact of renewable energy sources on life expectancy varies between countries and models. These findings have significant implications for policymakers managing the transition to renewable energy; they emphasise the importance of informed, evidence-based decision-making. The study recommends promoting hydropower, wind energy and other renewable energy sources, such as bioenergy, in the BRICS countries to increase life expectancy.

Keywords
Life expectancy, Disaggregated Renewable Energy, BRICS Nations, Linear and Nonlinear Approaches.

JEL: I8, Q4, Q42, Q54, Q55.

1. Introduction

Life expectancy is often used as a key metric for assessing health status in many countries today. (Kur, 2024). Although there is ample research on the transition from non-renewable to renewable energy sources, countries are legally obliged to adhere to the Paris Agreement in order to address the effects of climate change and global warming. Osei-Kusi et al. (2024) emphasize the importance of implementing region-specific strategies for sustainable development, taking into account the unique environmental and economic challenges faced by each region. The aim of this study is to investigate the impact of the transition to renewable energy on life expectancy in BRICS countries.

Şenyapar (2023) notes that energy is the driving force behind all industries, a vital component of development and an essential part of everyday life, which must be balanced with the growing demand for electricity, while also minimising our reliance on fossil fuels. Majeed et al. (2021) argue that promoting renewable energy can increase life expectancy and reduce mortality rates, thus improving health outcomes and helping to achieve climate goals. Although many studies have emphasised the positive impact of renewable energy on life expectancy, research by Fahlevi et al. (2023) and Salehnia et al. (2022) suggest that hydropower can have a negative effect on life expectancy. This sparked debate among scholars and academics as to which renewable energy source boosts life expectancy, highlighting the most important question of this study. Figure 1 below illustrates life expectancy trends in the BRICS countries from 2000 to 2022, based on data obtained from the World Development Indicators.

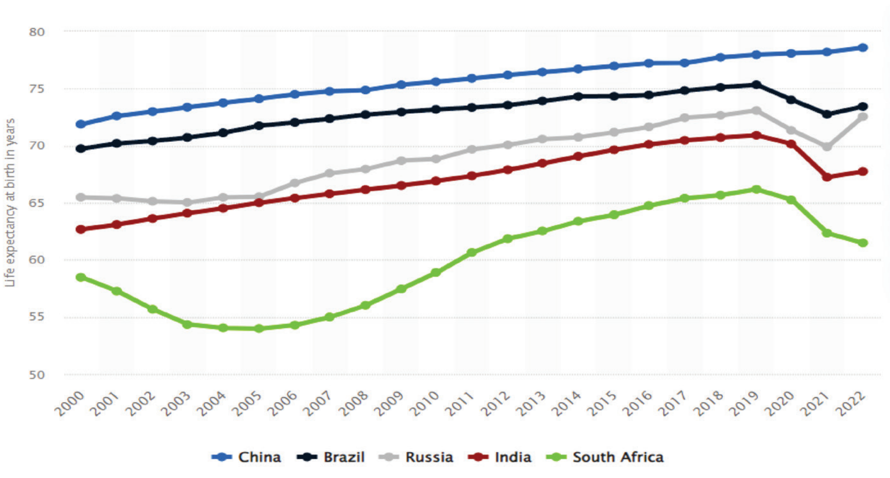

Figure 1. BRICS countries' life expectancy at birth from 2000 to 2022. *Source*: Adapted from WDI (2024)

Globally, the average life expectancy at birth increased from 67.6 years in 2000 to 72.75 years in 2020 (WDI, 2024). Among the BRICS countries, life expectancy exceeded the global average in Brazil and China, whereas it was lower in India and South Africa. In Russia, life expectancy was also lower in 2017. According to WDI (2024), life expectancy at birth has increased in the BRICS nations over the last twenty years. However, South Africa experienced a decline of almost three years between 2000 and 2005 due to HIV/AIDS, and Russia saw a slight decrease of nearly six months between 2000 and 2003 due to unhealthy habits such as alcohol or substance abuse. WDI data show that China has the longest life expectancy at 78.02 years. Brazil comes in second with 76.02 years, followed by Russia with 73.34 years. India is fourth with 72.24 years and South Africa is fifth with 66.31 years. Kur et al. (2024) explain in their study that the main contributor to the increase in life expectancy is renewable energy consumption.

According to the International Energy Agency (2020), the primary source of renewable electricity in the BRICS countries varies by nation. Overall, hydroelectric power is the main contributor, accounting for 55% of renewable electricity generation. Brazil, Russia and China notably have abundant hydroelectric resources. Wind power accounts for 25% of total renewable energy consumption in BRICS, with India and China investing heavily in this technology and leading the industry to growth. Solar power accounts for around 15%; India, China and South Africa are experiencing increased adoption of solar power, driven by rising investment and falling costs. Biomass, geothermal and other renewable sources account for the remaining 5% of renewable electricity in the BRICS countries (International Energy Agency, 2020). It is important to note that these countries are in different regions with varying climates and weather conditions, which determine the suitability of each renewable energy source.

Further data from the IEA (2020) indicate that Brazil is the largest producer of hydropower, accounting for 80% of its electricity generation. Russia is second, with 60% of its electricity generated from hydropower, while India relies primarily on wind (40%) and solar power (30%). The data also show that China generates 40% of its electricity from hydropower, 30% from wind and 20% from solar power, while South Africa generates 40% from wind and 30% from solar power. These results suggest that Brazil and Russia’s favourable drainage systems and climates allow them to generate more from hydropower. By contrast, India, China and South Africa must utilize wind and solar power to a greater extent.

Osei-Kusi et al. (2024) emphasize that climate change, brought on by the widespread release of carbon emissions, is a serious issue that needs to be tackled immediately. It harms public health, lowering life expectancy rates and increasing global temperatures. This study is conducted amid growing interest in understanding the impact of the transition to renewable energy on the BRICS nations’ health outcomes and willingness to comply with the Paris Agreement to mitigate the negative effects of climate change. To understand the complexities of the impact of renewable energy transition on life expectancy, it is important to investigate which renewable energy source has the most positive impact on life expectancy in the BRICS countries.

Şenyapar (2023) suggests that the advantages and additional benefits of renewable energy make transitioning from non-renewable sources a sensible choice for regions heavily reliant on coal production. This will also help to combat climate change by reducing greenhouse gas emissions. While some nations are offering incentives to speed up this shift, additional incentives should be introduced to encourage end consumers to adopt renewable energy sources as part of their commitment to climate change prevention agreements. Romanello et al. (2022) outline the health benefits of renewable energy, which include reduced air pollution and greenhouse gas emissions, improved water quality and a healthier environment. This results in a lower incidence of respiratory and other diseases.

The impact of each renewable energy source was not examined separately in the recent studies by Dam et al. (2023), Segbefia et al. (2023) and Kur (2024). Existing research aggregates renewable energy sources, overlooking the unique health impacts of specific sources, i.e. solar, wind, hydro, and other renewables on life expectancy in the BRICS countries. The intricacies of studying the impact of renewable energy on life expectancy in the BRICS countries necessitate a quantitative exploration. This can be achieved by employing a nonparametric quantile nonlinear autoregressive distributed lags (QNARDL) model to check whether the effects of renewable energy on life expectancy are consistent across different quartiles. The importance of transition to renewable energy has been thoroughly proven by existing literature. This study will build on this by using a panel-corrected standard error (PCSE) model to verify the robustness of the quantile regression results and ensure that policy formulation is based on strong empirical evidence.

The study is conducted at a time when all countries are legally bound to adhere to the Paris Agreement on climate change, which aims to mitigate its impact of on life expectancy. If we fail to address the effects of climate change, the consequences are likely to be devastating for BRICS and the whole world. These include high temperatures, polluted air, increased CO_2 emissions, respiratory issues and a deterioration in public health and productivity. The results of this study reveal conflicting views on the transition to renewable energy. They will inform decisions on health policy and renewable energy investments at the national and BRICS regional levels and contribute to sustainable development strategies shedding light on the health benefits of specific renewable energy sources. The study uses data collected from secondary sources between 1990 and 2023. The rest of the study is structured as follows: Section 2 reviews the empirical literature on the impact of the transition to renewable energy on life expectancy. Section 3 discusses data collection and variable descriptions, followed by methodology and data analysis in Section 4. Section 5 presents the results and interpretations, and Section 6 provides the conclusion and recommendations.

2. Literature Review

This section reviews the empirical literature on the relationship between renewable energy and life expectancy, covering everything from time series to panel data studies. In order to investigate the relationship between renewable energy and health outcomes, Majeed et al. (2021) used 2SLS and GMM models on panel data from 155 countries. Their results show that renewable energy, economic growth, trade and urbanization increased these countries' life expectancy; renewable energy appeared to reduce their mortality rates and incidence of tuberculosis. The study also calls for the increased use of renewable energy in order to enhance public health and achieve climate goals. Using a stochastic production frontier model, Rodriguez-Alvarez (2021) finds that investment in renewable energy boosts life expectancy, while PM10, PM2.5 and NOx have a negative effect on life expectancy in Europe. They recommend that social and environmental policies should aim to improve health and well-being.

Using Driscoll and Kraay's Standard Error and Feasible Generalised Least Squares Model, Rahman and Alam (2022) found that renewable energy, economic growth, good governance and urbanisation boosted life expectancy, while CO_2 emissions reduced it in ANZUS-BENELUX countries. They recommended that future studies should include determinants such as nutritional intake, access to proper hospital services and general living conditions. Ibrahim and Ajide (2021) used an FMOLS model to find that non-renewable energy and CO_2 reduced life expectancy, while income and renewable energy increased it. They recommended large investments in renewable energy to improve health in selected oil-producing countries in Africa.

Using VECM, DOLS and Granger models, Liu and Zhong (2022) found that health expenditure and renewable energy boosted life expectancy in China. They argue that the government should introduce incentives to encourage the consumption and generation of renewable energy in order to help achieve the Sustainable Development Goal of improving life expectancy. According to Somoye et al. (2023), who used ARDL and NARDL models, positive shocks to non-renewable and renewable energy sources boost life expectancy in Nigeria; applying cleaner technologies to non-renewable sources and promoting renewables can improve health. Using a two-step system, GMM, fixed effects and FMOLS models, Ibrahim et al. (2021) show that non-renewable energy reduces life expectancy and the human development index, while increasing the infant mortality rate in Sub-Saharan Africa. They recommend policies that will help to stop the increase in the use of non-renewable energy and raise people's incomes, thereby improving their quality of life.

Ibrahim et al. (2022) use a nonlinear two-step system GMM model to find that non-renewable energy has a negative impact on the human development index, life expectancy and income, while having a positive impact on education. They suggest that future studies should focus on the impact of renewable energy consumption on quality of life. Dam et al. (2023) conclude that renewable energy and economic growth increase life expectancy in BRICS-T countries using a panel quantile regression model; policymakers therefore should promote renewable energy in order to extend life expectancy. Moreso, Wang et al. (2023) find that increased consumption of renewable energy boosts life expectancy in a panel of 121 countries, as determined by a fixed effects model and a non-linear panel threshold model. They recommend integrating health and renewable energy policies to maximize the health benefits of renewable energy. Warsame (2023) uses kernel-regularized least squares and Granger models to show that renewable energy, urbanization and economic growth increase life expectancy, citing an increase in renewable energy investment as a way to improve health outcomes without compromising economic growth or life expectancy in Somalia. Segbefia et al. (2023), utilising CS-ARDL and the Granger causality model, find that renewable energy, human capital, technological innovation and economic growth increase life expectancy in NAFTA economies; therefore, stakeholders and policymakers should collaborate to reduce air pollution and transition to cleaner energy sources in order to increase life expectancy.

With the Toda–Yamamoto Granger causality model, Yılmaz and Şensoy (2023) found no evidence of causality from renewable energy to life expectancy in Turkey. However, they did find that life expectancy caused an increase in renewable energy. They argue that policymakers should prioritise public health outcomes and promote sustainable energy in their energy policies. Using a CS-ARDL and Driscoll and Kraay standard error model, Dai et al. (2024) show that sustainable economic growth, human capital and renewable energy increase life expectancy in Nordic countries, whereas CO_2 emissions have a negative effect. The government should therefore adopt a comprehensive and balanced approach to economic growth, sustainable development and public health. Karimi-Alavijeh et al. (2024) use a method of moments quantile regression to demonstrate that, in G7 countries, renewable energy consumption, health expenditure and urbanisation increase life expectancy, while CO_2 emissions decrease it. The potential of renewable energy sources should be recognized; this will lead to the introduction of policies, such as tax-related regulations, to encourage green energy investment.

Somoye *et al.* (2024) using ARDL and NARDL models conclude that renewable energy consumption improves life expectancy in Nigeria and recommend the continuous support of renewable energy. Nica *et al.* (2023) show that increased renewable energy consumption, health expenditure, and institutional quality index improve life expectancy in Eastern European countries, using CS-ARDL and Quantile regression models on data spanning from 1990 to 2021. They suggest that the countries in Eastern Europe should transition from fossil fuels to renewable energy. Using a CS-ARDL model on data spanning from 1997 to 2019, Polcyn et al. (2023) found that a higher rate of energy use and health expenditure improved life expectancy in 46 Asian countries. The authors recommend using renewable energy and increasing health expenditure to reduce CO_2 emissions and improve life expectancy.

Using GMM, IV and BOLS models on data spanning from 2005 to 2015, Azam and Adeleye (2024) found that renewable energy consumption, per capita income and health expenditure improved life expectancy in 36 selected Asian and Pacific countries, which means that these regions need policies aimed at reducing CO_2 emissions and increasing health expenditure to improve life expectancy. According to rather controversial results obtained by Fahlevi *et al.* (2023) using panel quantile regression on data spanning from 2000 to 2018, hydropower, economic growth, and CO2 emissions negatively affect life expectancy in Asia. Future studies should therefore consider second-generation models when analyzing the relationship between renewable energy and life expectancy rather than the quantile regression. Using an ARDL model on data spanning from 1988 to 2018, Hendrawaty et al. (2022) found that, in Asian countries, renewable energy consumption positively influenced life expectancy, while economic growth had the opposite effect, so economic growth must be environmentally friendly and reduce energy consumption through a transition to renewable energy sources, in order to improve life expectancy.

The findings by Ebhota *et al.* (2023) who used a DSK approach also show that renewable energy consumption has a positive impact life expectancy in MINT countries. To boost life expectancy, these countries need to improve renewable energy consumption, economic growth, and human capital. Using panel quantile regression on data spanning from 2000 to 2018, Salehnia et al. (2022) found that hydropower negatively impacted life expectancy in a sample of 100 countries. This suggests the need for increased investment in renewable energy generation. The authors recommend that future studies consider using non-linear and dynamic econometric models to gain new insights. Osei-Kusi et al. (2024) employed a fixed-effects logit (FGLC) and propensity score matching (PCSE) model with panel data from 84 countries in sub-Saharan Africa (SSA), the Middle East and North Africa (MENA) and Eastern Europe and Central Asia (ECA) from 1990 to 2020, revealing a positive correlation between energy consumption, carbon production and life expectancy. This indicates the need for policies that promote renewable energy sources, improve energy efficiency and reward the use of green technologies, thus encouraging environmentally friendly behaviour.

Furthermore, Guo et al. (2024) used a moment quantile regression model to demonstrate that renewable energy, gross domestic product, urbanisation and industrialisation increase life expectancy, whereas CO_2 emissions have the opposite effect. They recommend that governments and policymakers prioritise renewable energy and sustainable urbanisation in order to mitigate the adverse effects of CO_2 emissions from non-renewable energy sources on health. The results of Guo et al. (2024) also show that renewable energy, urbanisation, GDP and industrialisation reduce the infant mortality rate, while CO_2 emissions increase it in the short and long term. Kur (2024) examined a panel of 45 Sub-Saharan African (SSA) countries using GMM and PMG models on data from 2000 to 2019. They found that increased renewable energy consumption was associated with higher life expectancy in these countries, and they recommended adopting an appropriate energy mix to reduce non-renewable energy consumption.

Considering the provided literature, most studies used CS-ARDL and quantile regression models, but their results contradict each other. There are few studies focusing on the impact of renewable energy on health issues in the BRICS countries. The study by Dam et al. (2023) is the only one to focus on the impact of renewable energy on health using a quantile regression model in BRICS-T rather than BRICS only. Salehnia *et al.* (2022), and Fahlevi *et al.* (2023) highlight the need to use second-generation nonlinear and dynamic models for future research on the relationship between renewable energy and life expectancy. Contrary to the mainstream view in literature that renewable energy improves life expectancy, some studies, such as those by Salehnia et al. (2022) and Fahlevi et al. (2023), suggest that hydropower has a negative impact on life expectancy. Existing research aggregates renewable energy sources, overlooking the unique impact of each of them on life expectancy in the BRICS countries. These sources include solar, wind and hydro power, as well as other renewables. This study will deepen our understanding of the health benefits of renewable energy and thus support the health and sustainability of the BRICS nations and contribute to the achievement of the Sustainable Development Goals. It will also inform renewable energy policy and public health strategies, guide healthcare planning and resource allocation, and help climate change mitigation.

This study addresses the following questions based on the gaps identified in the literature: What impact does renewable energy have on life expectancy in the BRICS countries? Which renewable energy source has the greatest impact on life expectancy in BRICS countries? Is the impact of disaggregated renewable energy on life expectancy consistent across different quartiles? What role does economic growth play in life expectancy of the BRICS nations? Are there non-linear relationships between renewable energy and life expectancy in the BRICS countries? What are the policy implications of disaggregated renewable energy for life expectancy in the BRICS countries? This study uses a quantile non-linear autoregressive distributed lag (QPNARDL) model to examine the non-linear relationships between the variables, a PNARDL model for comparative analysis within each BRICS nation, the panel-corrected standard error (PCSE) and a simultaneous quantile regression model to check robustness.

The QPNARDL model is particularly useful for identifying nonlinear relationships between variables that differ across quantiles. It is also flexible enough to handle quantile-specific analysis and panel data, enabling analysis of multiple cross-sectional units over time. Furthermore, it incorporates both autoregressive and distributed lag components, which makes it possible to capture short-term and long-term relationships between variables. By contrast, the PNARDL model recognises nonlinear relationships between variables, offering short-term dynamic analysis specific to each country and long-term homogeneity analysis. The SQR model is be used to check the robustness of the results from the QPNARDL and PNARDL models. It offers quantile-specific analysis and estimates simultaneous equations on multiple quantiles. It can also accommodate various distributions and error structures, making them flexible enough for modelling complex relationships. Finally, the PCSE model can correct for standard errors that account for heteroskedasticity, autocorrelation and cross-sectional dependence. It can also perform robustness checks on the results from the QPNARDL and PNARDL models, account for panel-specific effects and improve estimation efficiency. These models provide a methodological innovation that enables researchers to comprehensively and robustly examine the impact of disaggregated renewable energy sources on life expectancy, offering a novel contribution to existing literature which typically focuses on economic or environmental outcomes in developed countries.

3. Data collection and variable definitions

This section discusses data collection, as well as the description and sources of the variables. The study follows a quantitative research methodology, and the variables were collected from reputable online statistical sources as shown in Table 1 below. Variables for the five BRICS countries (Brazil, Russia, India, China and South Africa) were collected from 1990 to 2023. The study uses of EViews and Stata18 for computations.

Table 1. Data collection and sources

Variables	Description	Unit	Source
LE	Life expectancy at birth, total (years)	Years	World Bank
Hydro	Electricity generation from hydropower	Terawatt-hours	Our World in Data powered by Oxford
Wind	Electricity generation from wind power	Terawatt-hours	Our World in Data powered by Oxford
Nuclear	Electricity generation from nuclear	Terawatt-hours	Our World in Data powered by Oxford
Other-RE	Electricity generation from other renewables, including bioenergy	Terawatt-hours	Our World in Data powered by Oxford
Economic Growth (LEG)	GDP per capita growth (annual %)	%	World Bank

Source: Author's compilation

Dependent variable:

- **Life expectancy** – Life expectancy at birth indicates the number of years a newborn infant would live if the patterns of mortality prevailing at the time of its birth were to stay the same throughout its life. This variable has been used as a dependent variable in the studies by Beyene and Kotosz (2021), Fahlevi *et al*. (2023), Hendrawaty *et al.* (2022), Liu and Zhong (2022), Ibrahim *et al.* (2021), Ibrahim *et al.* (2022), Selhenia *et al.* (2022), Polcyn *et al.* (2023), Kur (2024), and Osei-Kusi *et al.* (2024).

Independent variables:

- **Hydro** refers to hydropower as a source of renewable energy. It is measured in terawatt-hours of the total electricity generated by hydropower. This variable was used in the studies by Fahlevi *et al.* (2023) and Salehnia *et al.* (2022).
- **Wind** refers to wind power as a source of renewable energy. It is measured in terawatt-hours of the total electricity generated by wind power.
- **Nuclear** refers to nuclear power as a source of renewable energy. It is measured in terawatt-hours of the total electricity generated by nuclear power.
- **Other renewables** refer to other sources of renewable power including bioenergy. It is measured in terawatt-hours of the total electricity generated by other renewable sources including bioenergy power.

Control variables:

- **Economic growth** - Annual percentage growth rate of GDP per capita based on constant local currency. GDP per capita is gross domestic product divided by midyear population. GDP at purchaser's prices is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for the depreciation of fabricated assets or for the depletion and degradation of natural resources. This variable was used in the studies by Majeed *et al.* (2021), Salehnia *et al.* (2022), Osei-Kusi *et al.* (2024), Beyene and Kotosz (2021), Hendrawaty *et al.* (2022), and Fahlevi *et al.* (2023).

4. Methodology and data analysis:

4.1. Theory and model

The basis for estimating the variables in this study stems from the health production function of Grossman (2017) which analyses the relationship between health outcomes and various inputs, such as medical care, lifestyle, and environment. Smith and Dunt (1992) emphasize that in this context, human capital, created through various foundations, can be viewed as a crucial aspect of human well-being. In this study, life expectancy is the dependent variable that represents health outcomes. Most studies, including those by Dam et al. (2023), Polcyn et al. (2023) and Segbefia et al. (2023), use life expectancy as a proxy for health in the modified health production function of Smith and Dunt (1992), in which they hypothesized the relationship between combinations of medical and non-medical inputs and the resulting output. The health production function proposed by Smith and Dunt (1992) is therefore represented as

$$HO = f(M.E) \tag{1}$$

Here, HO refers to health outcome, M to medical resources, and E to non-medical resources. Smith and Dunt (1992), Dam *et al.* (2023), Polcyn *et al.* (2023), and Fahlevi *et al.* (2023) emphasize that the health production function comprises health production, health system, resource input, and socioeconomic, financial, and physical factors contributing to overall health. Barro (2001) stated that health outcomes could be evaluated based on social, economic and physical factors. This suggests that we can use renewable energy as a control variable in this study. Decisions relating to health, such as drinking alcohol, smoking cigarettes, and dietary choices, suggest that individuals can influence their health outcomes through various factors. This study's empirical model is shaped by the theoretical framework developed by Dam et al. (2023), Fahlevi et al. (2023), Segbefia et al. (2023) and Polcyn et al. (2023). It can be represented by the equation

$$LE = f(Hydro_{1t}, Wind_{2t}, Nuclear_{3t}, Other\_RE_{4t}, LEG_{5t}) \quad (2)$$

where LE is life expectancy, wind is wind energy, hydro is hydropower, nuclear is nuclear power, Other_RE is other renewable energy sources including bioenergy, and LEG refers to economic growth. This study uses these variables to investigate the impact of disaggregated renewable energy sources on life expectancy in the BRICS nations, in line with the study's objective. GDP that reflects government health spending is a proxy for economic growth, as suggested by Wang et al. (2023).

4.2. Panel Unit root

The study also performs the Breitung (2000), Breitung and Das (2005) unit root test to make sure that the variables do not contain a unit root. Breitung (2000) proposed a *t*-ratio test statistic for testing panel unit root. Suppose that panel data y_{it} is generated by the following model:

$$y_{it} = \mu_i + \beta_i t + x_{it} \quad (3)$$

Where the unobserved error term x_{it}

$$x_{it} = \rho_i x_{it-1} + \varepsilon_{it} \quad (4)$$

The null hypothesis, which tests for the presence of a unit root in all cross-sectional units, is specified as

$$H_0 : p_i = 1 \textit{ for all } i. \quad (5)$$

If the probability value of the computed statistic is less than the probability value at any level of significance (1%, 5%, and 10%) the null hypothesis is rejected in favor of the alternate hypothesis implying that there is no unit in the variable. The IPS unit root test of Im, Pesaran, and Shin (2003) relaxes the assumption of first-order AR coefficients and allows for heterogeneity in the alternate hypothesis. It involves the Fisher-ADF and Fisher-PP test with two combined p_i test statistics. The null hypothesis is that there is a unit root. The ADF-Fisher and ADF-Choi equations are specified as

$$ADF - Fisher\ x^2 = -2\sum_{i=1}^{N} log(\rho_i) \rightarrow x^2(2N) \quad (6)$$

$$ADF - Choi\ Z = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} \varnothing^{-1}(\rho_i) \rightarrow N(0,1) \quad (7)$$

Where, $\varnothing^{-1}$ represents the reciprocal of the cumulative function of standard normal distribution. If the probability value of the computed statistic is less than the probability value at any level of significance (1%, 5%, and 10%) the null hypothesis is rejected in favor of the alternative hypothesis implying that there is no unit in the variable.

4.3. Panel cointegration

The study performs cointegration tests to check for the presence of long-run relationships between the variables. Considering the following panel regression model:

$$y_{it} = x'_{it}\beta + z'_{it}\gamma + e_{it} \tag{8}$$

Where y_{it} and x_{it} are I(1) and non-cointegrated. For $z_{it} = \{\propto_{it}\}$, Kao (1999) proposed Dickey-Fuller (DF) and Augmented Dickey-Fuller (ADF) type unit root tests for e_{it} as a test for the null of no cointegration. The DF and ADF types can be calculated from the fixed residuals as follows:

$$\hat{e}_{it} = \rho\hat{e}_{it-1} + v_{it} \tag{9}$$

$$\hat{e}_{it} = \rho\hat{e}_{it-1} + \sum_{j=1}^{p}\vartheta_j\Delta\hat{e}_{it-j} + v_{itp} \tag{10}$$

Where $\hat{e}_{it} = \tilde{y}_{it} - \tilde{x}_{it}\hat{\beta}$ and $\tilde{y}_{it} = y_{it} - \overline{y}_i$.To test for the null hypothesis of no cointegration, the null hypothesis can be specified as follows:

$$H_0 : \rho = 1. \tag{11}$$

If the probability value of the computed statistic is less than the probability value at any level of significance (1%, 5%, and 10%) the null hypothesis is rejected in favor of the alternative hypothesis implying that there is co-integration among the variables. The study will also perform the Pedroni (2001) test for the null hypothesis of no cointegration in a panel data model that allows for considerable heterogeneity. The first test of Pedroni (2001) involves averaging test statistics for cointegration in the time series across cross-sections. The second involves averaging in pieces so that the limiting distributions are based on limits of pairwise numerator and denominator terms. The first set of statistics includes a form of the average of Phillips and Ouliaris (1990) statistic as

$$\tilde{Z}_\rho = \sum_{i=1}^{N}\frac{\sum_{t=1}^{T}\left(\hat{e}_{it-1}\Delta\hat{e}_{it} - \grave{\lambda}_i\right)}{\left(\sum_{t=1}^{T}\hat{e}_{it-1}^2\right)} \tag{12}$$

If the probability value of the computed statistic is less than the probability value at any level of significance (1%, 5%, and 10%) the null hypothesis is rejected in favor of the alternative hypothesis implying that there is co-integration among the variables. The study will also perform Westerlund (2006, 2008) test under the null hypothesis of cointegration that allows for the possibility of multiple structural breaks in both level and trend cointegrated panels. This test is general enough to allow for endogenous regressors, serial correlation, and an unknown number of breaks that may be located at different dates for different cross-sections. Considering the multidimensional time-series variable y_{it} which is observable for $i = 1, \ldots \ldots, N$ cross-sectional and $t = 1, \ldots, T$ time-series observations. The following equations are specified for data generating process:

$$y_{it} = z'_{it}\gamma_{ij} + x'_{it}\beta_i + e_{it} \tag{13}$$

$$e_{it} = r_{it} + u_{it} \tag{14}$$

$$r_{it} = r_{it-1} + \phi_i u_{it} \tag{15}$$

Where $x_{it} = x_{it-1} + v_{it}$ is a K-dimensional vector of regressors and z_{it} is a vector of deterministic components. The null hypothesis that all individuals in the panel are cointegrated can be stated as

$$H_0 : \phi_i = 0 \text{ for all } i = 1, \ldots, N \tag{16}$$

If the probability value of the calculated statistic is lower than the probability value at any significance level (1%, 5%, and 10%) the null hypothesis is rejected. This will indicate the presence of heterogeneous co-integration among the variables in favor of the alternate hypothesis.

4.4. Panel Regression Methods

Investigating the impact of the transition to renewable energy on life expectancy in BRICS nations, the study uses a quantile non-linear autoregressive distributed lags (QNARDL) model, as proposed by Cho et al. (2020), to estimate the relationships between the variables, enabling a comparative study of each BRICS country. The QPNARDL model can capture nonlinear relationships across different quantiles. This allows for quantile-specific analysis and the handling of panel data from multiple cross-sectional units over time. The model can also capture short-run country-specific analysis and long-run homogeneity relationships. It is also robust to outliers and non-normality. The quantile nonlinear autoregressive distributed lags model for each $\xi \in (0,1)$ used in this study can be specified as follows following Cho *et al.* (2020):

$$\Delta y_{it} = \gamma_*(\xi) + \sum_{j=1}^{p}\phi_{j*}(\xi)y_{t-j} + \sum_{j=0}^{q}(\theta_{j*}^{+}\left(\xi)'x_{t-j}^{+} + \theta_{j*}^{-}(\xi)'x_{t-j}^{-}\right) + \varepsilon_t(\xi) \tag{17}$$

Where y_{it} is the dependent variable, $x_t \equiv x_{it}^{+} + x_{it}^{-}$ is the independent variables and the quantile coefficients $(\gamma_*(\xi), \phi_{1ij}^{*}(\xi), \ldots, \phi_{pij}^{*}(\xi), \theta_{0*}^{+}(\xi)', \ldots, \theta_{q*}^{+}(\xi)', \theta_{0*}^{-}(\xi)', \ldots \theta_{0*}^{-}(\xi)')'$ can be used to explore quantile variation in the asymmetric relationship embodied by the QNARDL process (Cho *et al*., 2020). Quantile regression estimates the relationship between independent and dependent variables and a specific quantile of the dependent variable, regardless of the conditional distribution assumption. It therefore represents the quantiles, rather than the average as in traditional regressions. Quantile regression is more accurate than traditional models when the requirements for mean regression are not met, or when the focus is on the outer regions of the conditional distribution. This is why it was selected for the study. The Simultaneous Quantile Regression (SQR) model provides a flexible modeling of conditional quantiles, enabling simultaneous estimation of multiple quantiles, and robustness to outliers and non-normality. The study employs the panel-corrected standard error (PCSE) model introduced by Beck and Katz (1995) and the Simultaneous quantile regression test introduced by Bassett and Koenker (2017) for robustness checks and reliability of the results. The PCSE model can be specified as

$$y_{i,t} = x_{i,t}\beta + \epsilon_{i,t}; i = 1,\dots,N; t = 1,\dots,T \tag{18}$$

Where $x_{i,t}$ is a vector of one or more (k) exogenous variables and observations indexed by both unit (i) and time (t). The matrix of independent variables for all observations is denoted by X and the vector of observations on the dependent variable as Y. The advantage of using the PCSE model over the dynamic panel generalized method of moments (GMM) and OLS lies in solving the cross-sectional dependence, cross-panel correlation, autocorrelation, and heteroskedasticity control. This technique is robust to non-spherical errors and consists of long panels.

5. Empirical results and discussions

5.1. Descriptive Statistics

Table 2. Descriptive statistics

Variable	LE	Hydro	Wind	Nuclear	Other-RE	LEG
Mean	67.883	246.91	36.582	64.030	15.719	3.0292
Median	68.289	168.04	0.4850	15.705	1.8775	3.0080
Maximum	78.587	1321.7	885.87	434.72	198.13	13.636
Minimum	53.980	0.1460	0.0000	0.0000	0.0000	-14.614
Std. Dev.	5.7641	292.60	119.32	88.597	31.316	4.6659
Skewness	-0.3165	2.2517	4.9866	2.0267	3.4693	-0.6177
Kurtosis	2.5501	7.9073	29.887	7.1904	17.177	4.0867
JB-Stat	4.2712	314.24	5825.0	240.76	1764.6	19.175
Probability	0.1182	0.0000	0.0000	0.0000	0.0000	0.0000
Observation	170	170	170	170	170	170

Source: Author's compilation

From the data shown in Table 2 above, life expectancy and economic growth are negatively skewed, whereas hydro, wind, nuclear, and other renewables are positively skewed. The kurtosis values are greater than 2 and -2 for all the variables, indicating that the data may not be normally distributed, as it is leptokurtic. This can be seen from the significant Jarque-Bera probability at 1%. This does not threaten the study, since it assumes that the residuals from the estimated model are normally distributed. The study continues with the correlation analysis shown in Section 5.2 below.

5.2. Correlation Analysis

Table 3. Correlation Analysis

Correlation	LE	Hydro	Wind	Nuclear	Other-RE	LEG
LE	1.000000					
Hydro	0.755010	1.000000				
Wind	0.444231	0.788185	1.000000			
Nuclear	0.437977	0.635948	0.701013	1.000000		
Other-RE	0.586786	0.824971	0.930804	0.576873	1.000000	
LEG	0.214183	0.240607	0.130217	0.053206	0.104448	1.000000

Source: Author's compilation

The correlation analysis displayed in Table 3 above reveals a positive correlation between hydro, nuclear, wind, and other renewables, economic growth, and life expectancy. The correlation statistics are below 0.8, which suggests that the linear relationship between the explanatory variables and life expectancy in BRICS is weaker. This justifies the application of the nonlinear QPNARDL and PNARDL models. As shown in Section 5.3 below, the study conducted unit root tests to establish the order of integration of the variables and prevent spurious regressions.

5.3. Panel Unit Root and Stationarity Tests

The study performed second-generation panel unit root tests by Breitung (2005) and Im-Pesaran-Shin (2003) to prevent spurious regressions and ascertain the variables' integration level, assessing the model's adequacy for the study. The data in Table 4 indicates that economic growth is stationary at order zero (I (0)), whereas hydro, nuclear, wind, other renewables, and life expectancy are stationary at order one (I (1)). These findings support the deployment of the nonlinear QPNARDL model in this study to analyze how the power sector transition to renewable energy impacts the life expectancy of the BRICS countries at a more detailed level. As demonstrated in Section 5.4 below, the research determines the most suitable lags to use in the model.

Table 4. Panel Unit Root Test

Variables	Breitung-Das (2005)				Im-Pesaran-Shin (2003)			
	Without Trend		Trend		Without Trend		Trend	
	Level	Δ	Level	Δ	Level	Δ	Level	Δ
LE	3.3226 (0.9996)	-4.7311 (0.0000)	5.3917 (1.0000)	7.2603 (1.0000)	-1.3984 (0.6175)	-2.7290 (0.0034)	-1.1363 (0.8270)	-2.9685 (0.0018)
Hydro	2.3109 (0.9896)	-7.9963 (0.0000)	-0.7553 (0.2250)	-4.8320 (0.0000)	-1.5261 (0.5979)	-6.5374 (0.0000)	-2.8527 (0.0010)	-6.4748 (0.0000)
Wind	8.5135 (1.0000)	-3.4442 (0.0003)	7.9055 (1.0000)	0.5905 (0.7226)	5.0143 (1.0000)	-2.6355 (0.0061)	1.7821 (1.0000)	-4.0815 (0.0000)
Nuclear	4.3758 (1.0000)	-5.6001 (0.0000)	2.6751 (0.9963)	-5.6721 (0.0000)	0.2338 (1.0000)	-5.0561 (0.0000)	-1.7333 (0.3067)	-5.3346 (0.0000)
Other-RE	5.5184 (1.0000)	-4.0898 (0.0000)	4.1953 (1.0000)	-4.3572 (0.0000)	1.9913 (1.0000)	-4.3955 (0.0000)	-0.5899 (0.9088)	-4.8355 (0.0000)
LEG	-3.1346 (0.0009)	-5.8634 (0.0000)	-3.2339 (0.0006)	-6.3387 (0.0000)	-4.0118 (0.0000)	-8.3168 (0.0000)	-4.3186 (0.0000)	-8.2178 (0.0000)

Source: Author's computation (0.01), (0.05), (0.1) significance at 1%, 5%, and 10% respectively

5.4. Optimal Lag Selection Criterion

Table 5. Optimal Lag Length Selection

VAR Lag Order Selection Criteria Sample: 1990 - 2023						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-2447.056	N/A	4.470009	39.24890	39.38466	39.30405
1	-2266.985	339.9746	4.470008	36.94376	37.89408*	37.32982

Source: Author's computation (***), (**), (*) significance at 1%, 5% and 10% respectively

As indicated in Table 5 above, the VAR optimal lags selection criterion was used in the study to identify the best lags for the model. The SC criterion suggests that only 1 lag can be used in the model. This research uses a single lag selected by the SC criterion, which is more effective than the AIC criterion as shown by Wang and Liu (2006), Acquah (2010), and Vrieze (2012). The study conducted cointegration tests to examine long-term relationships in the model, as demonstrated in Section 5.5 below.

5.5. Panel Cointegration Test for long run relationships

Table 6. Panel Cointegration Test

Test		Statistic	Probability
Kao (1999)	Modified Dickey-Fuller t	-18.9659	0.0000***
	Dickey-Fuller t	-4.8232	0.0000***
	Augmented Dickey-Fuller t	-3.2977	0.0005***
	Unadjusted modified Dickey-Fuller t	-18.0384	0.0000***
	Unadjusted Dickey-Fuller t	-4.7714	0.0000***
Pedroni (2001)	Modified Phillips-Perron t	1.5855	0.0564*
	Phillips-Perron t	-0.0963	0.4616
	Augmented Dickey-Fuller t	-0.9204	0.1787
Westerlund (2008)	Variance ratio	1.9839	0.0239**

Source: Author's computation (***), (**), (*) significance at 1%, 5% and 10% respectively

The study includes cointegration tests by Kao (1999), Pedroni (2001), and Westerlund (2008) as described in Table 6 above. Based on the results, we reject the notion that there is an absence of cointegration between panels in favor of the alternative hypothesis of cointegration. These findings indicate the existence of long-run connections between the variables in the model. The study assesses the relationships between the variables in the model in both the short and long term. Using a disaggregated approach with the panel nonlinear autoregressive distributed lags model suggested by Cho et al. (2020) in Section 5.6 below, the study analyses the effects of the transition to renewable energy on life expectancy in BRICS countries.

5.6. Long-run relationships between renewable energy and life expectancy in BRICS

The study performed the QPNARDL model to assess the relationship between the power sector transition to renewable energy and life expectancy in the BRICS nations across different quartiles as presented in Table 7 above. The results reveal that positive and negative shocks to hydroelectric power have positive and negative impacts on life expectancy in BRICS nations, from the first to the sixth quartiles. Assuming all other factors remain equal, a 1% increase in positive or negative shocks to hydropower results in life expectancy rising or falling by between 0.08% and 0.06%, or between 0.55% and 1.68% respectively. These results imply that positive shocks to hydropower are good for life expectancy while negative shocks to hydropower are detrimental to life expectancy in the BRICS nations. These results suggest the need for policies that would have a positive impact on hydropower in order to improve life expectancy in these nations. They are consistent with those of Selhenia et al. (2022) and Fahlevi et al. (2023), who found a negative impact of hydropower on life expectancy in Asian countries.

Table 7. Quantile Panel Nonlinear Autoregressive Distributed Lags (QPNARDL) Model

	Quartiles								
Variable	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Hydro+	0.0783 (0.0008)	0.0683 (0.0056)	0.0731 (0.0050)	0.0638 (0.0130)	0.0652 (0.0208)	0.0644 (0.0473)	0.0334 (0.3660)	0.0205 (0.5315)	0.0806 (0.2750)
Hydro-	0.7589 (0.0000)	0.7476 (0.0005)	0.5493 (0.0294)	0.7796 (0.0024)	1.0868 (0.0003)	1.2065 (0.0003)	1.1688 (0.0012)	1.3193 (0.0003)	1.6816 (0.0103)
Wind+	0.0984 (0.5697)	-0.002 (0.9864)	0.1281 (0.4322)	0.1497 (0.1412)	0.1229 (0.2225)	0.1517 (0.1358)	0.1275 (0.1703)	0.1732 (0.0477)	0.4372 (0.7079)
Wind-	11.940 (0.0134)	12.249 (0.0152)	15.382 (0.0032)	18.268 (0.0024)	20.794 (0.0073)	-1.909 (0.8807)	0.4258 (0.9707)	5.1852 (0.6309)	-12.41 (0.9077)
Nuclear+	-0.2095 (0.0806)	-0.132 (0.3058)	-0.287 (0.1029)	-0.285 (0.0803)	-0.335 (0.0593)	-0.388 (0.0448)	-0.194 (0.5038)	-0.123 (0.6739)	-0.533 (0.7246)
Nuclear-	0.0800 (0.9570)	0.1052 (0.9289)	0.7289 (0.5207)	1.6977 (0.1028)	2.0407 (0.0638)	2.3188 (0.0513)	4.0899 (0.0027)	5.3536 (0.0000)	2.9161 (0.0230)
Oth-RE+	-0.1196 (0.8817)	0.2041 (0.7412)	-0.137 (0.8340)	-0.093 (0.8458)	0.2342 (0.6189)	0.1997 (0.6862)	-0.093 (0.8942)	-0.440 (0.5545)	-0.819 (0.5292)
Oth-RE-	-10.713 (0.0026)	-9.625 (0.0045)	-9.019 (0.0000)	-9.205 (0.0001)	-9.643 (0.0003)	-6.582 (0.0342)	-4.599 (0.1076)	-4.100 (0.0981)	-0.561 (0.9677)
LEG+	2.8928 (0.1276)	3.4859 (0.0164)	4.4186 (0.0006)	5.2223 (0.0000)	5.8325 (0.0000)	5.8584 (0.0000)	6.5196 (0.0000)	6.8240 (0.0000)	6.8678 (0.0000)
LEG-	0.4359 (0.7396)	1.1036 (0.3330)	1.6091 (0.1579)	1.3130 (0.1955)	1.1287 (0.2931)	0.5085 (0.6453)	-0.287 (0.8104)	-1.600 (0.2283)	-2.303 (0.2483)

Source: Author's computation (0.01), (0.05), (0.1) significance at 1%, 5%, and 10% respectively

Furthermore, there is a positive statistically significant relationship between positive shocks to wind power and life expectancy at the eighth quantile and a negative statistically significant relationship between negative shocks to wind power and life expectancy from the first to fifth quantile in BRICS nations. A 1% increase in positive or negative shocks to wind power results in life expectancy rising or falling by 0.17% or between 11.84% and 20.79%, respectively, ceteris paribus. This suggests that positive shocks to wind power have a weaker positive effect on life expectancy than negative shocks. Put simply, negative shocks to wind power have a negative influence on life expectancy in the BRICS nations.

The results show that positive and negative shocks to nuclear power result in negative effects on life expectancy at lower and higher quartiles respectively. A 1% increase in positive and negative shocks to nuclear power results in life expectancy falling between 0.29 to 0.39% from the fourth to sixth quantiles and between 2.04 to 2.92% from the fifth to ninth quantiles respectively, ceteris paribus. These results suggest that nuclear energy has a negative impact on life expectancy in the BRICS nations, highlighting the need for a policy review to improve life expectancy.

The results further show that there is a positive statistically significant relationship between negative shocks to other renewable energy and life expectancy in the BRICS nations. A 1% increase in negative shocks to other renewable energy sources significantly results in life expectancy increasing by 10.71 to 6.58% from the first quantile to the sixth quantile respectively, ceteris paribus. These results show that negative shocks to other renewable energy are good for life expectancy in the BRICS nations. The relationship becomes insignificant after the sixth quantile.

Lastly, the results reveal that positive shocks to economic growth have a positive statistically significant relationship with life expectancy in the BRICS nations. A 1% increase in positive shocks to economic growth significantly results in life expectancy rising by between 3.48 to 6.86% between the second to the ninth quantile respectively, ceteris paribus. These results imply that an increase in economic growth is good for improving life expectancy in the BRICS nations. These results are inconsistent with those of Selhenia et al. (2022), but consistent with the findings of Osei-Kusi et al. (2024), Beyene and Kotosz (2021), Hendrawaty et al. (2022) and Majeed et al. (2021), who all found that economic growth has a positive impact on life expectancy. In Section 5.7 below, the paper presents the results of comparative analysis for each of the BRICS nations.

5.7. Comparative analysis of the short-run country-specific relationships between renewable energy and life expectancy in BRICS nations

The results of the short-run, country-by-country analysis of the impact of a disaggregated renewable energy transition on life expectancy in the BRICS nations are presented in Table 8. The error correction terms are negatively statistically significant for Brazil, China, Russia and South Africa, but positively significant for India. A negative error correction term suggests negative adjustments in the short term towards long-term equilibrium, whereas in India, there is positive adjustment towards long-term equilibrium.

A negative, significant relationship between positive hydropower shocks and life expectancy is evident in Brazil, China and Russia, whereas in India, the relationship is positive and significant. A 1% increase in positive hydropower shocks results in a decline in life expectancy of 0.008%, 0.002% and 0.03% in Brazil, China and Russia respectively, whereas in India it rises by 0.005%. Conversely, negative shocks in hydropower result in an increase in life expectancy of 0.02%, 0.05% and 0.06% in Brazil, India and Russia respectively. For China, however, life expectancy declines by 0.02% under the same conditions. Comparing these coefficients reveals that negative shocks to hydropower have a greater impact on life expectancy, meaning hydropower has a positive impact on life expectancy in Brazil, India and Russia, but a negative impact in China. These results contradict those of Selhenia et al. (2022) and Fahlevi et al. (2023), who found that hydropower negatively impacted life expectancy and suggested the need for policies that boost hydropower in order to improve life expectancy in Brazil.

Table 8. Comparative Short-Run Relationships

PNARDL Short Run Relationships					
Variables	**Brazil**	**China**	**India**	**Russia**	**South Africa**
ECT	-0.007553 (0.0021)	-0.000509 (0.0000)	0.000998 (0.0000)	-0.009404 (0.0037)	-0.016816 (0.0137)
ΔHydro+	-0.007623 (0.0000)	-0.001909 (0.0000)	0.004656 (0.0000)	-0.030059 (0.0000)	-0.268969 (0.1194)
ΔHydro-	-0.018285 (0.0000)	0.016846 (0.0000)	-0.051492 (0.0000)	-0.061566 (0.0000)	-0.180614 (0.1701)
ΔWind+	0.092686 (0.0000)	0.001254 (0.0000)	-0.000198 (0.8331)	-0.155949 (0.3525)	-0.197767 (0.1724)
ΔWind-	-8.987838 (0.9985)	0.348197 (0.9326)	0.185241 (0.0129)	13.02167 (0.0010)	-0.371495 (0.9056)
ΔNuclear+	-0.096052 (0.0000)	0.000408 (0.0001)	0.034253 (0.0001)	-0.090220 (0.0000)	-0.437646 (0.0068)
ΔNuclear-	0.248637 (0.0001)	-0.005858 (0.5189)	-0.004963 (0.4901)	0.045980 (0.0000)	0.343497 (0.0094)
ΔOther-RE+	-0.016268 (0.0004)	0.004564 (0.0001)	-0.103301 (0.0000)	-2.169464 (0.6803)	-3.230266 (0.7707)
ΔOther-RE-	1.504357 (0.0000)	0.002355 (0.9964)	0.012947 (0.0820)	-6.841382 (0.9237)	9.299353 (0.8313)
ΔLEG+	0.028814 (0.0000)	0.013700 (0.0006)	-0.205315 (0.0000)	-0.035149 (0.0003)	-0.182006 (0.0002)
ΔLEG-	0.021824 (0.0005)	-0.028391 (0.0001)	0.105582 (0.0000)	-0.025188 (0.0013)	0.074501 (0.0276)

Source: Author's computation (0.01), (0.05), (0.1) significance at 1%, 5% and 10% respectively

There is a significant positive relationship between positive wind power shocks and life expectancy in Brazil and China. Assuming all other factors remain equal, a 1% increase in positive wind power shocks would lead to a 0.09% increase in life expectancy in Brazil and a 0.001% increase in China. Negative shocks to wind power can significantly decrease life expectancy by 0.18% and 13.02% in India and Russia, respectively, all other things being equal. This suggests that wind power has a positive impact on life expectancy in Brazil and China, but a negative impact in India and Russia, meaning that policies promoting wind power should be implemented in Brazil and China, but not in India and Russia.

There are significant positive and negative relationships between positive nuclear energy shocks and life expectancy in the BRICS nations. A 1% increase in positive shocks to nuclear energy results in life expectancy increasing by 0.0004% and 0.03% in China and India, respectively, while it decreases by 0.10%, 0.09% and 0.44% in Brazil, Russia and South Africa, respectively, ceteris paribus. Conversely, a 1% increase in negative shocks to nuclear energy results in a significant decrease in life expectancy of 0.25%, 0.05% and 0.34% in Brazil, Russia and South Africa, respectively. These results suggest that nuclear energy does not contribute to life expectancy in Brazil, Russia and South Africa, but could be promoted in China and India as it is beneficial there. In light of these findings, nuclear energy policies in the BRICS countries should be revised to enhance life expectancy.

Considering other renewable energy sources, a significant negative relationship exists in Brazil and India, whereas in China it is positive. A 1% increase in positive shocks to other renewable energies, including bioenergy, results in a 0.02% decrease in life expectancy in Brazil and a 0.10% decrease in India, while it increases by 0.005% in China, ceteris paribus. Moreover, a 1% increase in negative shocks to other renewable energy sources results in a decline in life expectancy of 1.50% and 0.01% in Brazil and India, respectively, all other things being equal. In light of these findings, it can be concluded that other renewable energy sources, including bioenergy, have a negative impact on life expectancy in Brazil and India. Consequently, policies relating to these sources must be revised to enhance life expectancy.

The relationships between economic growth and life expectancy in the BRICS countries also appear to be rather different. According to Table 8, a 1% increase in positive economic growth shocks results in a 0.03% increase in life expectancy in Brazil and a 0.01% increase in China, but decreases by 0.21%, 0.04% and 0.18% in India, Russia and South Africa respectively, all other things being equal. A 1% increase in negative economic shocks would lead to a 0.03% increase in life expectancy in China and Russia, and a 0.02%, 0.11% and 0.07% decrease in Brazil, India and South Africa respectively, ceteris paribus. These results show that economic growth does not improve life expectancy in Brazil, Russia, South Africa and India, but does in China. They are inconsistent with those obtained by Osei-Kusi et al. (2024), Beyene and Kotosz (2021), Hendrawaty *et al.* (2022), and Majeed *et al.* (2021) who found a positive impact of economic growth on life expectancy. Section 5.8 below presents the results of the diagnostics tests.

5.8. Diagnostics Tests

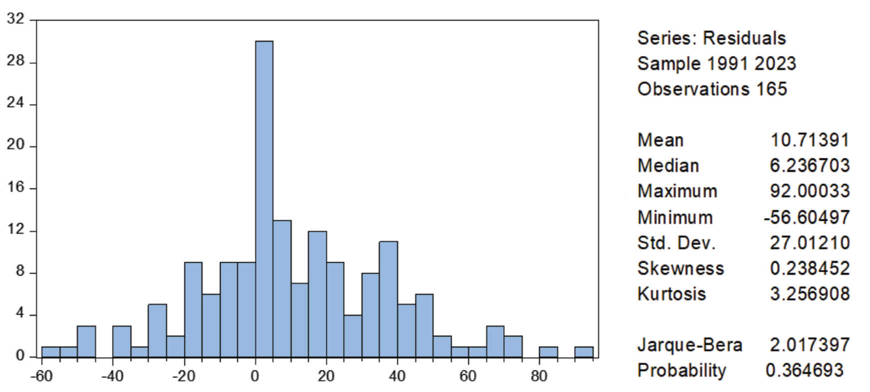

Figure 2. Residuals histogram normality test. *Source*: Author's computation

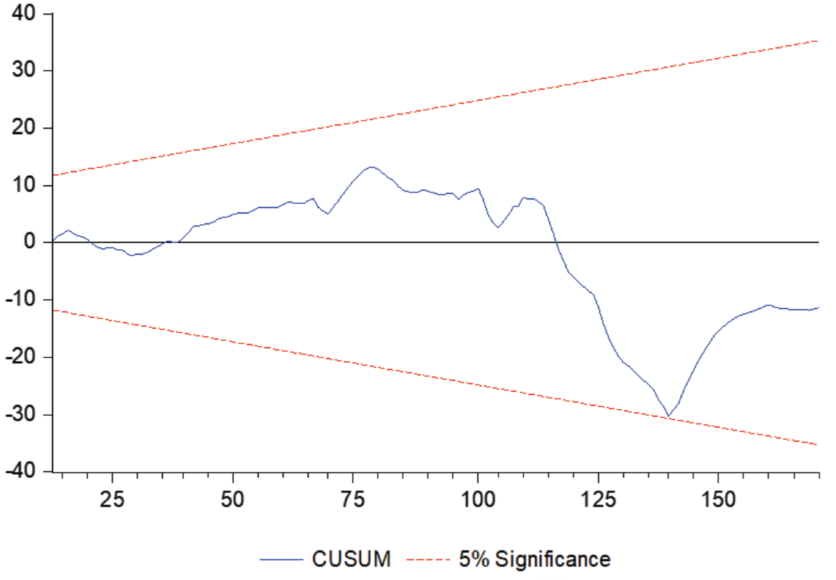

Figure 3. CUSUM model stability test. *Source*: Author's computation

The study performed nonlinear CUSUM and residual histogram normality tests, as shown in Figures 2 and 3 above. The results of the histogram normality test show a Jarque–Bera statistic of 2.01 and a probability of 0.36, indicating that the null hypothesis that the residuals from the model are normally distributed cannot be rejected. We can therefore conclude that the residuals from the model are normally distributed and that the results are reliable for formulating policies and making recommendations. Furthermore, the CUSUM test results show that the model is stable, as the trend line is within the 5% critical bounds according to Ploberger and Krämer (1992). The study continues with the robustness check, as outlined in Section 5.9 below.

5.9. Robustness Check

The study performed Simultaneous Quantile Regression, as shown in Table 9 above, to check the robustness of the results obtained in Sections 5.6 and 5.7. The values of the pseudo R^2 increase from 0.47 to 0.56 between the first and ninth quantiles, indicating that the results at the higher quantiles are more reliable than those at the lower quantiles. The results suggest a significant positive correlation between hydropower and life expectancy in the BRICS countries across the quantile range. A 1% increase in hydropower results in a 0.02% increase in life expectancy between the first and eighth quantiles, and a 0.11% increase between the first and eighth quantiles, ceteris paribus. These findings contradict those of Selhenia et al. (2022) and Fahlevi et al. (2023), who found a negative impact of hydropower on life expectancy. Taking these results into account, one could argue that hydropower has a positive impact on life expectancy in BRICS nations, and therefore policies that increase hydropower must be promoted. However, it should be noted that the impact of hydropower on life expectancy varies across different quantiles.

Table 9. Simultaneous Quantile Regression Model

Simultaneous Quantile Regression									
Variables	Quartiles								
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Hydro	0.0215 (0.000)	0.0187 (0.000)	0.0160 (0.000)	0.0162 (0.000)	0.0145 (0.000)	0.0139 (0.000)	0.0105 (0.000)	0.114 (0.000)	0.0094 (0.000)
Wind	-0.102 (0.000)	-0.079 (0.000)	-0.065 (0.000)	-0.061 (0.000)	-0.058 (0.000)	-0.059 (0.000)	-0.045 (0.000)	-0.044 (0.000)	-0.041 (0.000)
Nuclear	0.0321 (0.027)	0.0166 (0.017)	0.0107 (0.272)	0.0118 (0.119)	0.0186 (0.005)	0.0212 (0.000)	0.0199 (0.000)	0.0219 (0.000)	0.0194 (0.000)
Oth-RE	0.2107 (0.000)	0.1826 (0.000)	0.1727 (0.000)	0.1565 (0.000)	0.1590 (0.000)	0.1559 (0.000)	0.1394 (0.000)	0.1332 (0.000)	0.1299 (0.000)
LEG	-0.028 (0.843)	0.0033 (0.967)	0.0757 (0.138)	0.0503 (0.304)	0.0544 (0.336)	0.1101 (0.111)	0.1706 (0.000)	0.1991 (0.000)	0.2322 (0.000)
PseudoR2	0.4717	0.4789	0.4817	0.4964	0.5058	0.5105	0.5240	0.5448	0.5615
Observ.	170	170	170	170	170	170	170	170	170

Source: Author's computation (***), (**), (*) significance at 1%, 5% and 10% respectively

There is a significant negative relationship between wind power and life expectancy in the BRICS countries. The impact is stronger at lower quantiles and weaker at higher ones, since a 1% rise in wind power results in a 0.10% to 0.04% decrease in life expectancy in the first and ninth quantiles respectively, all other things being equal. These results suggest that wind power does not contribute to increased life expectancy in the BRICS nations, and that policies on wind power must be revised to improve life expectancy. The results are consistent with those in Tables 7 and 8 and are reliable for policy formulation and recommendations. This calls for the current wind power policies in these countries to be revised so that they can boost life expectancy.

Other renewable energy sources, including bioenergy, have a significant positive impact on life expectancy in the BRICS nations. These impacts appear stronger at lower quantiles and weaker at higher quantiles, since a 1% increase in other renewable energy sources results in an increase of between 0.21% and 0.13% at the first and ninth quantiles, respectively, ceteris paribus. However, these results are inconsistent with those presented in Table 7, which show stronger negative effects at lower quantiles and weaker effects at higher quantiles. They imply that other renewable energy sources, such as bioenergy, are beneficial to life expectancy in BRICS nations and should be promoted. Nuclear energy was also found to have a significantly positive impact at lower and higher quantiles, but an insignificant impact between the third and fourth quantiles. These results contradict those presented in Table 7, which show significantly stronger negative impacts at higher quantiles. In terms of economic growth, there is only a positive and stronger significance from the seventh to the ninth quantile. These results suggest that caution should be exercised when attempting to boost life expectancy through economic growth in the BRICS countries. Table 10 below, presents the results of robustness checks using the panel-corrected standard error model.

Table 10. Panel Corrected Standard Error (PCSE) Model

Linear Regression, Correlated Panels Corrected Standard Errors (PCSEs)
Panels: Correlated (balanced)
Number of Observations: 170
Number of groups: 5
Autocorrelation: No autocorrelation

Variables	Coefficient	Standard Error	z	P > z
Hydro	0.0093955	0.0028957	6.96	0.000***
Wind	-0.0405674	0.0108358	-11.88	0.000***
Nuclear	0.0193625	0.0027059	5.00	0.000***
Other-RE	0.1299125	0.0477585	10.50	0.000***
LEG	0.2321529	0.6068558	1.85	0.064*

Estimated covariances: 15	R-Squared: 0.7128
Estimated autocorrelations: 0	Wald chi2(5): 391.01
Estimated coefficients: 6	Prob > chi2: 0.0000

Source: Author's computation (***), (**), (*) significance at 1%, 5% and 10% respectively

The study performed a robustness check using the panel-corrected standard error model shown in Table 10 above. The R-squared value of 0.7128 indicates a good fit, meaning that the model explains 71.28% of the variation in life expectancy results. The results reveal that, ceteris paribus, a 1% increase in hydropower leads to a 0.01% increase in life expectancy in BRICS nations. These results imply that hydropower has a positive impact on life expectancy in the BRICS nations and should be promoted for this reason. These findings are consistent with those in Tables 9 and 7, but inconsistent with the studies of Selhenia et al. (2022) and Fahlevi et al. (2023), who found a negative impact of hydropower on life expectancy. Conversely, wind power negatively affects life expectancy in the BRICS nations since a 1% increase in wind energy significantly decreases life expectancy by 0.04%, ceteris paribus. These results indicate that wind energy is not good for life expectancy in the BRICS nations and the current policies on wind energy must be revised to boost their life expectancy. The results are consistent with those presented in Tables 7, 8 and 9, which show that wind energy has a negative impact on life expectancy in the BRICS nations.

Concerning other renewable energy sources, such as bioenergy, it can be seen that a 1% increase in bioenergy leads to a 0.21% increase in life expectancy, all other things being equal. These results suggest that bioenergy is beneficial for life expectancy in BRICS countries and should be promoted to increase it. These results are consistent with those presented in Tables 7 and 9 above, which show that other renewable energy sources also boost life expectancy. To increase life expectancy, these countries' governments must design policies that promote the generation and consumption of bioenergy. As shown in Table 10 above, nuclear energy and economic growth also significantly contribute to increasing life expectancy. These results are consistent with those of Osei-Kusi et al. (2024), Beyene and Kotosz (2021), Hendrawaty et al. (2022) and Majeed et al. (2021), who also found a positive impact of economic growth on life expectancy. In Section 6 below, the study continues with the conclusions and policy recommendations.

6. Summary and Implications

This study investigated how the transition to renewable energy impacted life expectancy in the BRICS countries between 1990 and 2023. The theoretical foundation was firmly based on a modified health production function, which was used to answer the study's question of which renewable energy source contributes the most to life expectancy in BRICS nations. The study employed four estimation methods: the QPNARDL model for nonlinear relationships; the PNARDL model for short-run, country-specific comparisons; the Simultaneous Quantile Regression model to check the robustness of the QPNARDL model; and the PCSE model to check the robustness of the panel results overall, with no autocorrelations. The study was conducted at a time when all countries were legally bound to comply with the Paris Agreement on climate change.

The empirical results from these panel models revealed that the impact of disaggregated renewable energy in BRICS nations varies and cannot be generalized. Contrary to mainstream literature suggesting that renewable energy boosts life expectancy, the results showed that wind energy had a negative impact, while hydropower and other renewable energy sources, including bioenergy, had a positive impact, based on the results from the QPNARDL, SQR and PCSE models. The comparative results of the PNARDL model on a cross-country basis reveal the following: wind energy has a positive impact in Brazil and China, but a negative impact in India and Russia. Hydropower has a positive impact on India and a negative impact on China, while its impact is mixed in Brazil and Russia, where positive shocks do not contribute to life expectancy while negative shocks boost it. Other renewables have a negative impact in Brazil and India, and a positive impact in China. The study found no evidence that renewable energy sources boost life expectancy in South Africa, as the results were insignificant. These results imply the need to revise renewable energy transition policies, especially in South Africa, to boost life expectancy.

The policy implications depend on the impact of disaggregated renewable energy on life expectancy in the BRICS nations, a topic that was thoroughly investigated in this study. Firstly, the QPNARDL model indicates that hydropower has a significant negative effect on life expectancy. The PNARDL model produces mixed results for different countries, whereas Simultaneous Quantile Regression and PCSE indicate that hydropower increases life expectancy. Based on these models, it is recommended that hydropower is promoted in all the BRICS countries to increase life expectancy. This can be achieved by increasing investment in hydropower infrastructure to boost generation and consumption. Brazil, India and Russia, which have favourable hydrological conditions, could build more dams to generate hydroelectricity and boost life expectancy.

Secondly, the results from the QPNARDL, SQR and PCSE models show that wind energy has a positive effect on life expectancy in Brazil and China, but a negative effect in India and Russia. This suggests that BRICS governments need to revise their current policies on wind energy to boost life expectancy. This could be achieved by increasing funding for wind energy research and development. Thirdly, the results of the QPNARDL and PNARDL models show that other renewable energy sources, such as bioenergy, have a negative impact on life expectancy, whereas the robustness results of the SQR and PCSE models show that they have a positive impact. The PNARDL model shows that bioenergy negatively affects life expectancy in Brazil and India. Based on the robust results from the SQR and PCSE models, it can be inferred that the promotion of bioenergy must be prioritized within the BRICS group, with Brazil and India revising their policies to boost life expectancy.

Fourthly, rigorous policies must be implemented to address the impact of nuclear energy on life expectancy in the BRICS countries. According to the PNARDL findings, life expectancy is significantly lower in South Africa, Russia and Brazil. However, the robustness results of the SQR and PCSE models indicate an increase in life expectancy. Taking both findings into account, the study suggests promoting nuclear energy because it helps reduce air pollution and greenhouse gas emissions, which are significant health concerns. Although economic growth has a positive influence on life expectancy, further improvement requires it to be directed through a green economy.

This research project involves analyzing cross-country panel data to compare the short-term impact of different renewable energy sources on life expectancy in each of the BRICS nations. The primary aim of the study was to explore the impact of the transition to renewable energy on life expectancy in the BRICS countries, using various panel data and nonparametric models. Based on the study's empirical results, hydropower and renewable energy sources such as bioenergy are the most effective ways to enhance life expectancy in the BRICS nations, and should therefore be prioritized in order to boost life expectancy and mitigate the adverse effects of climate change.

7. Conclusion

This study investigated the impact of the disaggregated renewable energy transition on life expectancy in the BRICS nations from 1990 to 2023. The empirical results from the QPNARDL, PNARDL, SQR, and PCSE models reveal that the impact of disaggregated renewable energy sources on life expectancy varies across countries and models. The key findings of the study can be summarised as follows: Firstly, hydropower has a positive impact on life expectancy in the BRICS nations, particularly in India. Secondly, the impact of wind energy is mixed, with a positive effect in Brazil and China, but a negative effect in India and Russia. Thirdly, other renewable energy sources, including bioenergy, have a positive impact on life expectancy, except in Brazil and India.

Based on the empirical results, this study recommends promoting hydropower generation and consumption in the BRICS countries to increase life expectancy. Wind energy policies should be revised to boost life expectancy, particularly in India and Russia. Bioenergy promotion should be prioritised in Russia, China and South Africa, while policies in Brazil and India should be revised. The study also recommends to promote nuclear energy, considering its advantages in reducing air pollution and greenhouse gas emissions. The study acknowledges the limitation of excluding the impact of solar power on life expectancy. Future studies should consider using non-stationary models to explore the novel impact of disaggregated renewable energies, including solar power, on life expectancy. In conclusion, this study provides new insights into the impact of the transition to renewable energy on life expectancy in the BRICS nations. The findings emphasise the need for policies tailored to specific renewable energy sources to improve life expectancy and mitigate the negative impacts of climate change.

Data availability statement: The data underpinning the analysis reported in this paper are available on reasonable request from the corresponding author.

References

Acquah, H. D. G. (2010). Comparison of Akaike information criterion (AIC) and Bayesian information criterion (BIC) in selection of an asymmetric price relationship. *Journal of Development and Agricultural Economics*, 2(1), 1-6.

Azam, M., & Adeleye, B. N. (2024, February). Impact of carbon emissions sources on life expectancy in Asia and the Pacific region. In *Natural Resources Forum* (Vol. 48, No. 1, pp. 35-57). Oxford, UK: Blackwell Publishing Ltd. https://doi.org/10.1111/1477-8947.12303

Barro, R. J. (2001). Human capital and growth. *American economic review*, *91*(2), 12-17. https://doi.org/10.1257/aer.91.2.12

Bassett, G. W., & Koenker, R. (2017). A quantile regression memoir. In *Handbook of Quantile Regression* (pp. 3-5). Chapman and Hall/CRC.

Beck, N., & Katz, J. N. (1995). What to do (and not to do) with time-series cross-section data. *American political science review*, *89*(3), 634-647. https://doi.org/10.2307/2082979

Beyene, S. D., & Kotosz, B. (2021). Empirical evidence for the impact of environmental quality on life expectancy in African countries. *Journal of Health and Pollution*, *11*(29), 210312. https://doi.org/10.5696/2156-9614-11.29.210312

Breitung, J. (2001). The local power of some unit root tests for panel data. In *Nonstationary panels, panel cointegration, and dynamic panels* (pp. 161-177). Emerald Group Publishing Limited. https://doi.org/10.1016/S0731-9053(00)15006-6

Breitung, J., & Das, S. (2005). Panel unit root tests under cross-sectional dependence. *Statistica Neerlandica*, *59*(4), 414-433. https://doi.org/10.1111/j.1467-9574.2005.00299.x

Cho, J. S., Greenwood-Nimmo, M. J., & Shin, Y. (2020). *Estimating the nonlinear autoregressive distributed lag model for time series data with drifts*. Mimeo, University of York.

Dai, B., Amarteifio, E. N. A., Kyere, F., & Sampene, A. K. (2024). Examining the dynamics between economic development, tourism, renewable energy and life expectancy in the Nordic economies. *Environmental Research*, *252*, 118900. https://doi.org/10.1016/j.envres.2024.118900

Dam, M. M., Kaya, F., & Bekun, F. V. (2024). On the nexus between real income, renewable energy consumption, and environmental sustainability on life expectancy for BRICS-T countries: Accessing evidence from quantile regression. In *Natural Resources Forum* (Vol. 48, No. 4, pp. 1109-1135). Oxford, UK: Blackwell Publishing Ltd.

Ebhota, O. S., Hongxing, Y., & Sampene, A. K. (2023). Air pollution and life expectancy: New evidence from the MINT economies. *Heliyon*, *9*(12), e22396. https://doi.org/10.1016/j.heliyon.2023.e22396

Fahlevi, M., Ahmad, M., Balbaa, M. E., Wu, T., & Aljuaid, M. (2023). The efficiency of petroleum and government health services to benefit life expectancy during the inefficiencies of hydroelectricity consumption. *Environmental and Sustainability Indicators*, *19*, 100289. https://doi.org/10.1016/j.indic.2023.100289

Grossman, M. (2017). On the concept of health capital and the demand for health. In *Determinants of health: an economic perspective* (pp. 6-41). Columbia University Press.

Guo, A., Ullah, O., Zeb, A., Din, N. U., & Hussain, S. (2024). Unveiling health dynamics: Exploring the impact of CO_2 emissions, urbanization, and renewable energy on life expectancy and infant mortality in SAARC countries (1990–2022). *Natural Resources Forum*, 1–28. https://doi.org/10.1111/1477-8947.12460

Hendrawaty, E., Shaari, M. S., Kesumah, F. S. D., & Ridzuan, A. R. (2022). Economic growth, financial development, energy consumption and life expectancy: fresh evidence from ASEAN countries. *International Journal of Energy Economics and Policy*, *12*(2), 444-448. https://doi.org/10.32479/ijeep.12670

Ibrahim, R. L., & Ajide, K. B. (2021). The role of income level and institutional quality in the non-renewable energy consumption and life expectancy nexus: evidence from selected oil-producing economies in Africa. *OPEC Energy Review*, *45*(3), 341-364. https://doi.org/10.1111/opec.12212

Ibrahim, R. L., Ajide, K. B., & Omokanmi, O. J. (2021). Non-renewable energy consumption and quality of life: Evidence from Sub-Saharan African economies. *Resources Policy*, (*73)*, 102176. https://doi.org/10.1016/j.resourpol.2021.102176

Ibrahim, R. L., Julius, O. O., Nwokolo, I. C., & Ajide, K. B. (2022). The role of technology in the non-renewable energy consumption-quality of life nexus: insights from sub-Saharan African countries. *Economic Change and Restructuring*, (55), 257–284. https://doi.org/10.1007/s10644-020-09312-6

Im, K. S., Pesaran, M. H., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of econometrics*, *115*(1), 53-74. https://doi.org/10.1016/S0304-4076(03)00092-7

International Energy Agency. (2020). *Renewables 2020: Analysis and Forecasts to 2025*. https://www.iea.org/reports/renewables-2020

Karimi Alavijeh, N., Ahmadi Shadmehri, M. T., Dehdar, F., Zangoei, S., & Nazeer, N. (2024). The role of renewable energy on life expectancy: evidence from method of moments quantile regression based on G-7 countries data. *International Journal of Energy Sector Management*, *18*(4), 767-788. https://doi.org/10.1108/IJESM-11-2022-0001

Kao, C. (1999). Spurious regression and residual-based tests for cointegration in panel data. *Journal of econometrics*, *90*(1), 1-44. https://doi.org/10.1016/S0304-4076(98)00023-2

Kur, K. K. (2024). Does environmental degradation and renewable energy consumption influence health outcomes? Evidence from Sub-Saharan Africa. *Global Journal of Emerging Market Economies*, *16*(3), 411-430. https://doi.org/10.1177/09749101241238288

Liu, H., & Zhong, K. (2022). Relationship between health spending, life expectancy and renewable energy in China: A new evidence from the VECM approach. *Frontiers in Public Health*, (*10)*, 993546. https://doi.org/10.3389/fpubh.2022.993546

Majeed, M. T., Luni, T., & Zaka, G. (2021). Renewable energy consumption and health outcomes: Evidence from global panel data analysis. *Pakistan Journal of Commerce and Social Sciences (PJCSS)*, *15*(1), 58-93.

Nica, E., Poliakova, A., Popescu, G. H., Valaskova, K., Burcea, S. G., & Constantin, A. L. D. (2023). The impact of financial development, health expenditure, CO2 emissions, institutional quality, and energy Mix on life expectancy in Eastern Europe: CS-ARDL and quantile regression Approaches. *Heliyon*, *9*(11), e21084. https://doi.org/10.1016/j.heliyon.2023.e21084

Osei-Kusi, F., Wu, C., Tetteh, S., & Castillo, W. I. G. (2024). The dynamics of carbon emissions, energy, income, and life expectancy: Regional comparative analysis. *Plos one*, *19*(2), e0293451. https://doi.org/10.1371/journal.pone.0293451

Pedroni, P. (2001). Fully modified OLS for heterogeneous cointegrated panels. In *Nonstationary panels, panel cointegration, and dynamic panels* (pp. 93-130). Emerald Group Publishing Limited. https://doi.org/10.1016/S0731-9053(00)15004-2

Phillips, P. C., & Ouliaris, S. (1990). Asymptotic properties of residual based tests for cointegration. *Econometrica: journal of the Econometric Society*, 58(1), 165-193. https://doi.org/10.2307/2938339

Ploberger, W., & Krämer, W. (1992). The CUSUM test with OLS residuals. *Econometrica: Journal of the Econometric Society*, 60(2), 271-285. https://doi.org/10.2307/2951597

Polcyn, J., Voumik, L. C., Ridwan, M., Ray, S., & Vovk, V. (2023). Evaluating the influences of health expenditure, energy consumption, and environmental pollution on life expectancy in Asia. *International Journal of Environmental Research and Public Health*, *20*(5), 4000. https://doi.org/10.3390/ijerph20054000

Rahman, M. M., & Alam, K. (2022). Life expectancy in the ANZUS-BENELUX countries: The role of renewable energy, environmental pollution, economic growth and good governance. *Renewable Energy*, (*190)*, 251-260. https://doi.org/10.1016/j.renene.2022.03.135

Rodriguez-Alvarez, A. (2021). Air pollution and life expectancy in Europe: Does investment in renewable energy matter?. *Science of the Total Environment*, (*792)*, 148480. https://doi.org/10.1016/j.scitotenv.2021.148480

Romanello, M., Di Napoli, C., Drummond, P., Green, C., Kennard, H., Lampard, P., ... & Costello, A. (2022). The 2022 report of the Lancet Countdown on health and climate change: health at the mercy of fossil fuels. *The Lancet*, *400*(10363), 1619-1654. https://doi.org/10.1016/S0140-6736(22)01540-9

Salehnia, N., Karimi Alavijeh, N., & Hamidi, M. (2022). Analyzing the impact of energy consumption, the democratic process, and government service delivery on life expectancy: evidence from a global sample. *Environmental Science and Pollution Research*, *29*(24), 36967-36984. https://doi.org/10.1007/s11356-021-18180-0

Segbefia, E., Dai, B., Adotey, P., Sampene, A. K., Amoako, T., & Lamptey, C. (2023). Renewable energy, technological innovation, carbon emission, and life expectancy nexus: experience from the NAFTA economies. *Environmental Science and Pollution Research*, *30*(50), 108959-108978. https://doi.org/10.1007/s11356-023-29983-8

Şenyapar, H. N. D. (2023). A bibliometric analysis on renewable energy's public health benefits. *Journal of Energy Systems*, *7*(1), 132-157. https://doi.org/10.30521/jes.1252122

Smith, C. S., & Dunt, D. (1992). Work program of the National Centre for Health Program Evaluation. *Australian Health Review: a Publication of the Australian Hospital Association*, *15*(2), 117-123.

Somoye, O. A., Ozdeser, H., & Seraj, M. (2024, May). The asymmetric impact of fossil fuel and renewable energy consumption on life expectancy in Nigeria. In *Natural Resources Forum* (Vol. 48, No. 2, pp. 385-403). Oxford, UK: Blackwell Publishing Ltd. https://doi.org/10.1111/1477-8947.12312

Vrieze, S. I. (2012). Model selection and psychological theory: a discussion of the differences between the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). *Psychological methods*, *17*(2), 228. https://doi.org/10.1037/a0027127

Wang, Q., Wang, L., & Li, R. (2023). Does renewable energy help increase life expectancy? Insight from the linking renewable energy, economic growth, and life expectancy in 121 countries. *Energy Strategy Reviews*, (*50)*, 101185. https://doi.org/10.1016/j.esr.2023.101185

Wang, Y., & Liu, Q. (2006). Comparison of Akaike information criterion (AIC) and Bayesian information criterion (BIC) in selection of stock–recruitment relationships. *Fisheries Research*, *77*(2), 220-225. https://doi.org/10.1016/j.fishres.2005.08.011

Warsame, A. A. (2023). Environmental pollution and life expectancy in Somalia: do renewable energy, urbanization, and economic growth matter?. *Environmental Science and Pollution Research*, *30*(51), 110528-110538. https://doi.org/10.1007/s11356-023-30114-6

WDI. (2024). *World Development Indicators: BRICS countries: life expectancy at birth from 2000 to 2022*. World Bank. https://www.statista.com/statistics/741661/life-expectancy-at-birth-in-the-bric-countries/

Westerlund, J. (2006). Testing for panel cointegration with multiple structural breaks. *Oxford Bulletin of Economics and Statistics*, *68*(1), 101-132. https://doi.org/10.1111/j.1468-0084.2006.00154.x

Westerlund, J. (2008). Panel cointegration tests of the Fisher effect. *Journal of applied econometrics*, *23*(2), 193-233. https://doi.org/10.1002/jae.967

Yılmaz, E., & Şensoy, F. (2023). Investigating the causal relationship between renewable energy consumption and life expectancy in Turkey: A Toda-Yamamoto causality test. *International Econometric Review*, *15*(1), 1-11. https://doi.org/10.33818/ier.1264805