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Non-renewable Energy Consumption and Life Expectancy in Oil-producing Countries in Africa: The Conditional Role of Income Level

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Abstract

This study examines the impact of non-renewable energy consumption on life expectancy in selected oil-producing countries in Africa with focus on the conditional role of income level. Panel unit root based on the first-generation tests under the assumption of cross-sectional independence and panel co-integration anchored on Kao (1999) were conducted. To ensure more precision on the stated nexus, both the measures of non-renewable energy and life expectancy are disaggregated. Based on the empirical analyses, the following findings emanated. First, the impacts of non-renewable energy (fuel, coal, gas, and fossil fuel) were found to be negative and statistically significant on life expectancy. Second, income exerts a positive and statistically significant influence on life expectancy. Third, the impacts of non-renewable energy when the conditional role of income is taken into consideration are found to be positive for the most significant models. Fourth, CO2 emission negatively and significantly influences life expectancy. These aforementioned results are closely related to both the Fully Modified OLS and Dynamic OLS estimators. The study concludes that since non-renewable energy consumption negatively influences life expectancy in the oil-producing countries in Africa, it is therefore suggested that policies should be geared towards discouraging its consumption. This can be done by subsidizing cleaner energy sources, intensifying on educating the populace regarding the dangers inherent in consuming non-renewable energy, and embarking on capital projects that will empower people to have increased income that will enable them to sufficiently transit from non-renewable to renewable energy.

Keywords: Non-Renewable Energy, Life Expectancy, Oil Producing Countries, Income Level
JEL Classification: Q3, Q52, I10, Q40

1. Introduction

The central role of energy to man, his environment, and economic development is hard to overemphasize. Among countless reasons, the majority of activities in the modern economy in terms of production, transportation, and home appliances which cannot function effectively without the use of energy can easily be noticed. More so, as affirmed by Awodumi and Adewuyi (2020), the persistent increase in growth rates recorded globally in recent times particularly among the emerging economies further accentuates the importance of energy resources. Nevertheless, energy consumption has its many benefits as well as its associated and costs effects.

For example, an improved and sustainable quality of life requires a good amount of energy resources (Pasten & Santamarina, 2012), so as every source of energy is associated with several challenges of which health risks are highly demanding (Smith, Frumkin, Balakrishnan, Butler, Chafe, Fairlie & McMichael, 2013). Of the different kinds of energy available for man use, nonrenewable energy, even though highly associated with damaging carbon emission, environmental degradation and other life-threatening health challenges still remains the most consumed. (Bekun , Alola & Sarkodie, 2019; Hanif , Raza, Gago-de-Santos & Abbas, 2019; Shahbaz, Gozgor, Adom, Hammoudeh & Shahbaz, 2019).

The assertion that the consumption of non-renewable (NRE) energy has some health damaging implications can be supported from three perspectives. First, the literature has affirmed a direct relationship between the volume of production and energy use in contributing to the increase in carbon emission which by extension deteriorates the environment and healthy lifestyle (Awodumi & Adewuyi, 2020; Chaabouni & Saidi, 2017). Second, research has shown that the rise in the incidences of life threatening diseases like tuberculosis, measles and increase in mortality rates especially among women and children can be linked to the consumption of NRE from coal, gas, and fuel for domestic purposes (such as cooking, heating, and lightening) (Asghar, Wang & Zaidi, 2020).

Third, the level of income has been empirically advanced as a key determinant of the choice and quality of energy consumption (Smith et al. 2013) with the cheapest being non-renewable energy. Third, ones level of income has been empirically cited as a key determinant of the type of energy choice one makes (Smith et al. 2013) with the cheapest being non-renewable energy. This assertion is well supported by the energy ladder hypothesis, which asserts a positive relationship between income level and the consumption of cleaner energy that is human and environmental friendly (Hossier, 2004). Based on this proposition, it is no gainsaying to aver that the difference in the quality of energy consumption and the associated health implication constitute one of the major lines of differences between the developed and developing nations' life expectancy rate where the former has been noted to outperform the latter.

A close examination of the health indicators across selected regions of the world reveals that much is still left to be done in Africa (see Figures 1a & b). A further comparison of income levels indicates the Africa region is equally ranked lowest among others (see Figure 2). In essence, the question of whether the low-income level characterizing the developing nations like Africa is responsible for the supposed over-dependence on non-renewable energy consumption and the consequential health challenges embattling the region remains a puzzle for empirical justification. Consequently, the primary aim of this study is to investigate how the consumption of non-renewable energy such as coal, oil, and gas impacts on life expectancy in oil-producing countries in Africa. The study further extends the frontier of knowledge by probing the conditional role of income level.

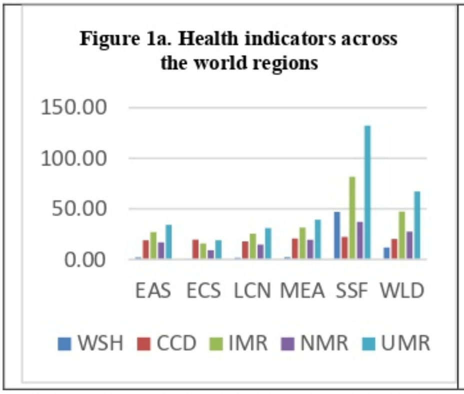


Figure 1a. Health indicators across the world regions

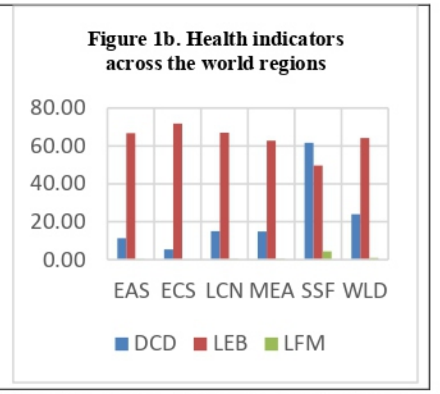
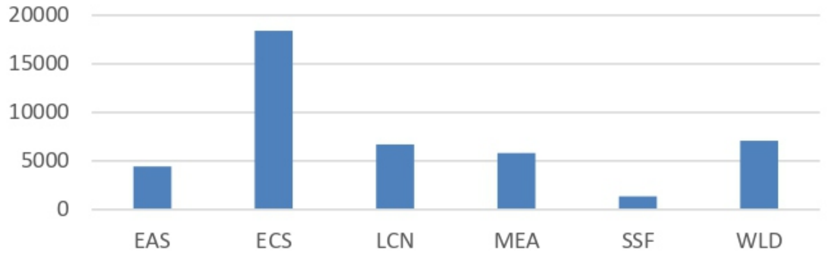


Figure 1b. Health indicators across the world regions

Note: WSH= Mortality rate attributed to unsafe water, unsafe sanitation, and lack of hygiene (per 100,000 population). CCD=Mortality from CVD, cancer, diabetes, or CRD between exact ages 30 and 70 (%). IMR=Mortality rate, infant (per 1,000 live births). MMR=Mortality rate, neonatal (per 1,000 live births). UMR=Mortality rate, under-5 (per 1,000 live births). DCD =Cause of death, by communicable diseases and maternal, prenatal, and nutrition conditions (% of total). LEB=Life expectancy at birth, total (years). LFM=Lifetime risk of maternal death (%). .EAS=East Asia & Pacific. ECS=Europe & Central Asia. LCN=Latin America & Caribbean. MEA==Middle East & North Africa. SSF=Sub-Saharan Africa. WLD=World.
Source: Authors Computation, 2022

Figure 2. Income distribution across the world regions



Note: EAS=East Asia & Pacific. ECS=Europe & Central Asia. LCN=Latin America & Caribbean. MEA==Middle East & North Africa. SSF=Sub-Saharan Africa. WLD=World.
Source: Authors Computation, 2022

The present study contributes to the stock of extant literature in five major ways. First, a survey of extant literature revealed that the nexus between nonrenewable energy and life expectancy is still budding. This is more demanding in the case of African countries where more than 60% of the urban population do not have access to adequate electricity and thus depend on nonrenewable sources like wood and kerosene for cooking at a higher cost compared to other countries (Aliyu, Modu, & Tan, 2018). Among the cluster of countries in the African continent, the current study mainly focuses on the oil producing countries within the region where the major enhancer of economic growth is the consumption of non-renewable energy like coal, natural gas, and petroleum, its associated effects on environmental degradation (CO2 emissions) and serious health challenges (Shahbaz, Tiwari & Nasir, 2013).

Based on the existing data, the consumption of natural gas by Algeria, Angola, Egypt, Gabon and Nigeria increased from about 107.9 billion cubic feet (bcf) to closely 327bcf and 759.5 bcf in 1980, 2000, and 2015 respectively (Aliyu et al., 2017). Second, the recent efforts geared towards the attainment of sustainable health and wellbeing (SDG 3) and advocacy towards ensuring sustainable and affordable energy for all (SDGs 7) further accentuate the need for this study. Third, the role of income is fundamental in the attainment of sustainable energy and healthy life styles; this is well elucidated in the various targets of the SDGs. For instance, to achieve sustainable health and wellbeing, which are fundamental for achieving improved life expectancy, terms relating to income are clearly stated in closely five targets (i.e. 3.7; 3.8; 3.9b; and 3.9c of SDGs 3) and with affordability significantly pronounced in the quest for sustainable energy. Besides, the concept of fuel ladder is a point to be reckoned with when it comes to the role of income in the energy-health nexus. Fourth, aside from the dearth of empirical studies on the subject of interest in this study, the inclusion of the role of income level is either new or scarcely available. Fifth, the choice of Africa among the world regions can easily be understood from the disappointing performance in the health and income indicators as exposited in Figures 1 and 2. Sixth, this study extends the policy discussion on the impact of non-renewable energy on life expectancy on oil producing economies in Africa for both the aggregated (fossil fuel) and disaggregated (coal, gas, and fuel).

The road map for the rest of this study is delineated as thus: the next section dwells on the review of relevant and related literature, whereas section three presents and discusses the method, the data, the strategic model, and the estimation techniques. Section four contains the presentation and discussion of results. Section five presents conclusion, policy suggestions, and caveats

2. Succinct Review of Literature

The empirical studies explicating the relationship between non-renewable energy and life expectancy is yet to be fully exploited and when it comes to the conditional role of income in this nexus, we are not aware of any. However, to position the present study in the heart of the extant literature and equally unravel the ambiguities that have entrapped precision in the debates, some studies are reviewed on energy consumption nexus with health outcomes, quality of life, and life expectancy as appropriate.

In the most recent order, Alimi and Ajide (2020) examined the nexuses among environment, institutions, and health outcomes in sub-Saharan African countries for the period spanning 1996–2016. To achieve the study's objectives, corruption index, regulatory quality and government effectiveness were used to proxy institution. While health expenditure, life expectancy and child mortality were used to capture health outcome, carbon emission and environmental footprint were the proxy for environment. The study found that degradation measured by carbon emissions and ecological footprint reduces human life expectancy. More so, even in the presence of institution, carbon emissions are noted to escalate infant mortality rates.

In a closely related study, Ajide and Alimi (2020) found evidence for the negative and positive effects of carbon emission on life expectancy and infant mortality respectively in the Sub-Saharan African region. Nkalu and Edeme (2019) examined the impacts of environmental hazards on life expectancy in Africa with specific focus on Nigeria using a time series data spanning 1960 to 2017 by employing the generalized autoregressive conditional heteroscedasticity (GARCH). Findings from the study showed life expectancy is reduced by about seven weeks by environmental hazards associated with solid fuel consumption.

Asghar et al., (2019) investigated the extent to which human capital in Pakistan is impacted by the nexuses among non-renewable energy (NRE) consumptions, environmental pollution, and mortality rate. The study employed Autoregresive Distributive Lag (ARDL) model data spanning 1995 to 2017 to determine the existence of cointegration and long-run dynamics. Empirical findings from the study revealed that non-renewable energy (gas, coal, and oil) amplifies air pollutants, measles, cases of tuberculosis, and mortality rate and consequently impede improvements in human capital.

Shobande (2019) investigated the extent to which energy use impacts on infant mortality rate in selected 23 economies in Africa by employing the Generalized Method of Moment (GMM) on panel dataset from 1999 to 2014. Empirical results provided substantial evidence for the negative impacts of energy use on infant mortality rates. More so, while environmental pollution was found to compound child mortality rate, earnings from the rent of natural resources reduces infant mortality rate.

Akinlo and Sulola (2019) investigated the causal relationship between government health expenditure, under-5 mortality, and infant mortality rates from 2000 to 2008 in 10 selected economies of the sub-Saharan African region. the empirical results revealed that while public health expenditure exerts positive impacts on under-five and infant mortality, income proxy by GDP per capita, health support in the form of external aid, prevention programs on HIV, and progress in the coverage of immunization all exerted negative effects on under-five and infant mortality. However, the impact of health expenditure has been noted to be very significant in reducing some diseases, which could aggravate the rates of mortality at all levels (Becchetti, Conzo & Salustri, 2017).

The spatial effects of a cluster of energy sources for cooking and heating on life expectancy constitute the core of interest to Wang and Luo (2018) in China. The research findings from the study provided evidence for diverging impacts of energy indicators on life expectancy. For instance, while a positive nexus was found between household energy consumption and life expectancy at birth, negative effects were recorded for domestic coal and biomass fuel nexuses. In close contact with the above studies are those, which evaluate the impact of energy use on quality of life. Whether improved quality of life can significantly enhance life expectancy remains an open debate for future empirical verification. Hence, few of the studies in this line of thought are reviewed thus.

Nadimi and Tokimatsu (2018) examined the nexus between energy consumption (electricity) and quality of life between 2005 and 2013 for a panel of 112 countries by employing panel cointegration approach. The empirical findings, which emanated from the study, revealed that energy consumption is not significant enough to influence variation in the quality of life. Conversely, Nadimi, Tokimatsu, and Yoshikawa (2017) investigated the impactful relationship between energy consumption and quality of life with consideration for poverty level between 2003 and 2013 in both developed and developing economies. Findings from the study showed that while a statistically significant impacts of energy consumption on quality of life was recorded, they differ in terms of signs (positive and negative) in relation to the different indicators of energy consumption employed.

By employing a microeconomic level quantitative method, Chen,Yao, Hu and Lin (2017) investigated how energy consumption impacts the quality of life of some selected cities in Japan (Nagasaki, Isahara and Omura). The authors relied on the Constant Elasticity of Substitution (CES) model to assess consumers' demand for public transport, car tours, and non-mobility goods for eighty-eight traffic analysis at an optimum utility level. The simulation analysis conducted by the study revealed that energy use provides evidence for traces of significant impacts on quality of life. The empirical findings, which emanated from the work of Bridge, Adhikari and Fontenla (2016) on the functional association between electricity, income, and quality of life in Nepal provided evidence for positive but insignificant impacts of electricity consumption on health.

That notwithstanding, additional evidence from the study suggested that when it comes to determinants of quality of life, electricity consumption is highly fundamental and non-negligible. This good news on energy consumption-quality of life nexus was further corroborated by Al-Mulali (2016). In his analysis, the author evaluated the direction of causal impact between energy consumption and quality of life for a period spanning 1990 to 2009 in 198 selected countries using Canonical Co-integrating Regression (CCR). The result, which emerged from the study, showed that not less than 70% of the countries investigated, experienced significant improvements in quality of life from energy consumption.

In a related study, Mazur (2011), using electricity as a proxy for energy consumption investigated the effects of energy consumption on the quality of life in twenty-one advanced economies for the period spanning 1980 and 2006. The results from the empirical analyses revealed a positive and significant relationship between energy consumption and quality of life such that an increase in the former leads to corresponding improvements in the latter.

Notwithstanding the preponderance of studies alluding to the positive effects of energy use on quality of life, empirical evidence from a study by Jorgenson, Alekseyko and Giedraitis (2014) suggested the contrary. While the motivation for this study has been explicitly enunciated in the introductory section, it is worthy of note that the various ambiguities, mixed findings, and more importantly lack of consensus on the nexuses among the three main variables of interest in the study (non-renewable energy, income level, an life expectancy) in the literature make this current study a must to conduct. Further, the focus of the study on oil-producing countries in Africa is ingenuity, which is obviously scarce in the literature and highly needed in the region owing to its pursuit of sustainable development agenda by 2030 and the African growth agenda by 2063.

3. Method

3.1 Panel Unit Root Tests

Before embarking on the panel co-integration test, it is important to conduct panel unit root tests to examine the direction of integration of the panel data series. The motivation behind the panel unit root tests is based on the ground that the test is capable of simultaneously estimating data from time series and cross-sectional units (Ajide and Ridwan, 2018). Empirical evidence has established the pertinence of panel unit root tests in providing more dependable outcomes compared to the time series test Barbieri (2009). There are five prominent types of the available panel unit root test, which include Fisher-type tests using ADF, and PP tests (Maddala and Wu, 1999; Choi, 2001); Hadri (2000); Breitung (2000); Levin, Lin and Chu (2002) and Im, Pesaran & Shin (2003).

In respect to the aforementioned, this study aims to investigate the presence of a unit root among the panel of selected variables. These include: life expectancy decomposed into female (LEBF), male (LEBM), and total (LEBT), non-renewable energy both aggregated (fossil fuel) and disaggregated (fuel, coal, and gas), gross domestic product per capita (GDPPC) and carbon emission (CO2). Both the first and second-generation unit root tests are employed on all the variables across the five selected oil-producing countries in Africa.

To specify the model for the LLC and IPS, and in finding the Augmented Dickey-fuller (ADF) test for each series in the panel, emphasis is laid on the autoregressive model. Relying on the assumption that there are Nsets of series, the following can be assumed,

$$\Delta q_{it} = \delta_{ir}\mu_{tr} + \phi_i q_{i,t-1} + \sum_{j=1}^{p_i} \chi_{ij}\Delta q_{i,t-j} + \varpi_{it}, \qquad (1)$$

i=1,…,N; r=0,1,2; where:

$\mu_{t0} = 0$ or $\mu_{t1} = 1$ $\mu_{t2} = (1,t)'$ [1]where we state the null hypothesis as $\mathbf{H_0}: \phi = 0$ vs. $\mathrm{H}_1 \phi :< 0$.

Based on the assumption of IPS, we conduct the test statistic after concluding on μ_{tr} p_i and, following this, the *t*-ratios for the ϕ_i , t_{μ_i} can, thus, be accounted for and also its average, $\bar{t}_{NT} = \sum_{i=1}^{N} t_{\alpha_i} \Big/ N$ are calculated. IPS advance that we can adjust $\bar{t}_{NT}$ to arrive at an asymptotic $N(0,1)$ statistic under the null hypothesis;

$$\bar{t}_{NT}^{*} = \frac{N^{1/2}\left(\bar{t}_{NT} - N^{-1}\sum_{i=1}^{N} E(t_{\alpha_i})\right)}{\left[N^{-1}\sum_{i=1}^{N} Var(t_{\alpha_i})\right]^{1/2}} \qquad (2)$$

$\mathrm{E}(t_{\alpha_i})$ and $\mathrm{Var}(t_{\alpha_i})$ are derived by simulation.

3.2 Panel Co-integration Tests

The rationale for the estimation of the panel co-integration techniques is anchored on the need to ascertain the presence of long-run relationships among a cluster of variables while controlling for heterogeneous nature of the short-run dynamics and fixed effects among the varying samples of the panel (Eregha & Mesagan, 2017). Three different tests of panel co-integration namely; Pedroni (1999, 2004), Kao (1999), and Fisher (combined Johansen) are employed in the present study.

The panel co-integration test proposed by Pedroni (1999, 2004) relies heavily on the estimated residuals from the Engle and Granger (1987) which estimates in addition to co-integrating regression, the extent of heterogeneity in the sample panel of the model. This is stated thus:

$$y_{i,t} = \delta_i + \alpha_i t + \varphi_{1i} x_{1i,t} + \varphi_{2i} x_{2i,t} + \ldots + \varphi_{Hi} x_{Hi,t} + \sigma_{i,t}\,, \qquad (3)$$

Where $i = 1,...,N$; $t = 1,...,T$ N denotes the total number of cross-sectional units in the panel, T represents the number of observations over time. Further, H denotes the number of explanatory variables. In this model, ∂_i implies the fixed-effects parameter or member-specific intercept, which differs based on individual unit in the cross-section. A similar representation is analogous to the slope coefficients and member-specific time effects $\alpha_i t$.

In the augmented version of Pedroni (1999, 2004), both the heterogeneous panel and heterogeneous group mean panel statistics are proposed in evaluating the existence of panel co-integration for two sets of statistics. In the first set, three statistics are outlined $Z_{\hat{v},N,T}$, $Z_{\hat{\rho}N,T\ 1}$ and $Z_{tN,T}$ which, are evidenced upon the pooled residuals based on the within-the dimension of the panel specified as:

$$Z_{\hat{v},N,T} = T^2 N^{3/2} \sum_{t=1}^{N}\sum_{t=1}^{T} L_{11i}^2 \hat{\ell}_{i,t1}^2 \tag{4}$$

$$Z_{\hat{\rho}N,T1} = T\sqrt{N} \sum_{i=1}^{N}\sum_{t=1}^{T} L_{11i}^2 \hat{\ell}_{i,t1}^2 {}^{1} \sum_{t=1}^{N}\sum_{t=1}^{T} L_{11i}^2 \left(\hat{\ell}_{i,t\ 1} \Delta\hat{\ell}_{i,1} \lambda_i\right) \tag{5}$$

$$Z_{tN,T} = \sigma_{N,T} \sum_{I=1}^{N}\sum_{T=1}^{T} L_{11i}^2 \hat{\ell}_{i,t1}^2 {}^{1/2} \sum_{t=1}^{N}\sum_{t=1}^{T} L_{11i}^2 \left(\hat{\ell}_{i,t\ 1} \Delta\hat{\ell}_{i,1} \lambda_i\right). \tag{6}$$

Where $\hat{\ell}_{i,t1}$ denotes the vector of residual in the Ordinary Least Square computation of equation (5)

The second statistic is based on the pooled residuals along the between-the dimension of the panel which sufficiently controls for a non-homogeneous autocorrelation parameter in the cross-section and is thus specified:

$$\tilde{Z}_{\hat{\rho}N,T}\ {}^{1} = \sum_{t=1}^{N}\sum_{t=1}^{T} \hat{\ell}_{i,t}^2 {}^{1} \sum_{t=1}^{T} \left(\hat{\ell}_{i,t\ 1} \Delta\hat{\ell}_{i,t} \lambda_i\right) \tag{7}$$

$$\tilde{Z}_{tN,T}{}^{1} = \sum_{t=1}^{N}\sum_{t=1}^{T} \hat{\ell}_{i,t}^2 1 {}^{1/2} \sum_{t=1}^{T} \left(\hat{\ell}_{i,t\ 1} \Delta\hat{\ell}_{i,t} \lambda_i\right) \tag{8}$$

The above-stated models compute the group means of the specific time-series statistics. Based on this, the five models can thus be asymptotically distributed as thus:

$$\frac{X_{N,T}\mu\sqrt{N}}{\sqrt{v}} \Rightarrow N(0,1), \tag{9}$$

Given that $X_{N,T}$ is the replica of the test statistics, while μ v and respectively represent the mean and the variance of each test. The estimates for these statistics can be accessed in Table 2 of Pedroni (1999). Likewise, giving the deviation of the alternative hypothesis of panel v statistics to positive infinity, inferences can be said that the statistics is a narrow test where large positive values reject the null of no co-integration. The analogous statistics deviate from negative infinity implying the impacts of large negative values in the rejection of the null hypothesis.

In a piece of separate evidence on the computation of the long-run relationship, the Kao (1999) tests of co-integration, which specifically utilizes both DF and ADF are adopted Kao (19) is based on the conventional approach of the EG-step procedures of the panel regression model stated as:

$$Y_{it} = W_{it} + Z_{it} + e_{it} \quad (10)$$

Such that Y W and are unconditionally non-stationary.

3.3 Model

The empirical model gauging the impacts of nonrenewable energy on life expectancy in the paper aligns well with the extant studies on the energy-health nexus. More so, relying on the features of a panel dataset, the model adopted in this study is specified by integrating *t*(time) and *i*(individual units) to depict the attributes of cross-sections and time-series data. Consequently, the model is specified following the stated features thus:

$$lep_{it} = \sigma_0 + \sigma_1 nonre_{it} + \sigma_2 gdppc_{it} + \sigma_3 (gdppc \times nonre)_{it} + \sigma_4 co2_{it} + \varpi_{it}$$

(11)

Lep denotes life expectancy, which is further decomposed to capture life expectancy for female (lebf), male (lebm), and total (lebt). *Nonre* represents non-renewable energy measured by a vector of variables comprising fuel, gas, coal, and fossil fuel. *gdppc d*enotes gross domestic product per capita as a proxy for income. The interaction of both nonrenewable energy and life expectancy is denoted by *gdppc*×nonre. *co2* represents carbon emission; σ_0, $\sigma_0 + \sigma_{1-4}$ denote parameters, ϖ is disturbance term, t = 1, . . . , T denotes time, i = 1, . . . , N symbolizes country.

It is pertinent to mention that the stochastic term comprises two components i.e. the idiosyncratic stochastic (*ui,t*) which varies from cross-section to time, and unobserved individual-specific effect (*vi,t*) which accounts for unobserved country effect in the model. The model can be rewritten to include both decomposed nonrenewable energy indicators and the components of the stochastic term as

$$\begin{aligned} lep_{it} &= \sigma_0 + \sigma_1 fuel_{it} + \sigma_2 gas_{it} + \sigma_3 coal_{it} + \sigma_4 biofuel_{it} + \sigma_2 gdppc_{it} \\ &+ \sigma_3 (gdppc \times nonre)_{it} + \sigma_4 co2_{it} + \nu_i + \mu_{it} \end{aligned} \quad (12)$$

$$y_{it} = \alpha_i + x'_{it}\beta + e_{it}, \quad x_{it} = x_{i,t1} + \varepsilon_{it}. \quad (13)$$

The estimation technique that will be employed includes the Fully Modified OLS (FMOLS) and Dynamic OLS (DOLS). The model can be stated such that:

$$y_{it} = \partial_i + x'_{it}\theta + \pi_{it}, x_{it} = x_{i,t1} + \omega_{it}. \quad (14)$$

where $\omega_{it} = \left[\pi_{it}, \omega'_{it}\right]$ is the stationary series comprising covariance matrix Ω_i with an estimator θ which is assumed to be specifically persistent given that the assumption of co-integration between y_{it} x_{it} and is fulfilled by this error process $\omega_{it} + [\pi_{it}, \varepsilon'_{it}]'$. It is important to note that the OLS estimator may become inconsistent in estimating the stated model because of the parameters of the disturbance terms. Nevertheless, a semi-parametric modification to the constrained OLS estimator, which spontaneously reduces the presence of second-order bias, has been proposed. Leveraging on these preceding narratives and following Pedroni (1996, 2000) as exposited in Ajide and Ridwan (2018), the FMOLS estimator is specified thus:

$$\hat{\beta}_{FM}\beta = \sum_{i=1}^{N}\hat{\Omega}_{22i}^{2}\sum_{t=1}^{T}\left(x_{it}x_{t}\right)^{2\;1}\sum_{i=1}^{N}\hat{\Omega}_{11i}^{1}\hat{\Omega}_{22i}^{1}\sum_{i=1}^{T}\left(x_{it}\bar{x}_{t}\right)\ell_{it}Ty_{i} \tag{15}$$

$$\hat{\ell}_{it} = \ell_{it}\hat{\Omega}_{22i}^{1}\hat{\Omega}_{21i}\;\hat{y}_{t} = \Gamma_{21i} + \hat{\Omega}_{21i}^{0}\;\hat{\Omega}_{22i}^{1}\hat{\Omega}_{21i}\left(\hat{\Gamma}_{22i} + \Omega_{22i}^{0}\right) \tag{16}$$

In Equation (16), the covariance matrix is disintegrated as $\Omega_i = \Omega_i^0 + \Gamma_i\Gamma_i'$ giving that Ω_i^0 is the contemporaneous covariance matrix, and Γ_i is a weighted sum of autocovariances. Further, $\hat{\Omega}_i^0$ represents a significant estimator of Ω_i^0. An alternative to the FMOLS estimator is the DOLS, which is equally based on the between-dimension group means. This is further adopted to investigate the functional relationship between non-renewable energy consumption and life expectancy.

3.4 Data, Source and Preliminary Analyses

The present study employs annual panel dataset for the five chosen oil-producing African economies (Nigeria, Angola, Algeria, Egypt, and Libya) between1980 and 2017. Table 1 entails sources of the variables and equally presents their descriptive statistics. A careful glance at the Table reveals the mean values of 63.8, 0.1, and 61.8 for female, male and total life expectancy respectively. Among the cluster of selected oil-producing countries, in female life expectancy, Libya records the highest years with 71.81, 68, and 69.61 for female, male, and total in that order. Contra-wise, Nigeria ranks lowest in terms of the life expectancy indicators with 48.86, 46.87, and 47.85 for female, male, and total accordingly. Another insight from the Table can be noticed from the divergence in female and male life expectancy where the former is higher than the latter for the panel and equally from the individual country.

An ample of empirical studies equally found evidence for the chances of female having higher life expectancy than males (Regan& Partridge, 2013; Beltrán-Sánchez, Finch, and Crimmins, 2015); Goldin and Lleras-Muney, 2019). Regarding the attributes of the dataset and going by the values from both skewness (asymmetry) and kurtosis (leptokurtic), it can be concluded that all the variables employed are not normally distributed. This is particularly evident from the positive signs, which portrays the dataset as not being too far from symmetric. Likewise, the coefficient of the kurtosis, which is greater than one across board, indicates that the distribution is more clustered to the mean than in a platykurticor mesokurtic distribution.

Table 1: Descriptive Statistics

Variables	**Description/measurement**	**Mean**	**S.D**	**Maximum**	**Minimum**	**Skewness**	**Kurtosis**	**Source**
LEBF	Life expectancy at birth, female (years)	63.8	11.16	77.10	43.85	-0.57	1.63	WDI
LEBM	Life expectancy at birth, male (years)	60.1	10.87	74.67	39.59	-0.53	1.69	WDI
LGBT	Life expectancy at birth, total (years)	61.8	10.97	75.86	41.70	-0.55	1.65	WDI
COAL	coal consumption (Mst)	464	712.59	2214.54	0.00	1.29	3.14	EIA
FUEL	petroleum (Mb/d)	295	202.21	874.31	24.30	1.03	3.66	EIA
GAS	Natural gas (bcf)	481	480.79	1876.89	8.16	1.19	3.57	EIA
FFUEL	Fossil fuel(% of total)	68.6	36.22	99.98	15.85	-0.44	1.27	WDI
GDPPC	GDP per capita (constant 2010 US$)	359	2547	12120	1347	1.95	6.12	WDI
CO2	CO2 emissions (kt)	681	48153	217163	3890	1.06	4.18	WDI

Note: S.D= standard deviation. WDI= world development indicators. EIA=energy information agency

Source: Authors Computation, 2022

The results of the correlation presented in Table 2 reveal the presence of a high correlation of 75% between fuel and coal, 81% gas and fuel. In addition, the result of VIF-test indicates that the model is free from the issue of multicollinearity in the dataset employed. This is evident from the mean VIF of the variables (2.61) which is below the benchmark of 5.

Table 2: Descriptive Statistics

LEBF	LEBM	LEBT	COAL	FUEL	GAS	FFUEL	GDPPC	CO2	VAR.
1	0.99	0.99	0.41	0.45	0.53	0.94	0.52	0.51	LEBF
	1	0.50	0.39	0.46	0.56	0.93	0.50	0.53	LEBM
		1	0.40	0.46	0.55	0.94	0.51	0.52	LEBT
			1	0.75	0.61	0.48	-0.30	0.61	COAL
				1	0.81	0.42	-0.12	0.68	FUEL
					1	0.47	-0.11	0.69	GAS
						1	0.45	0.42	FFUEL
							1	0.51	GDPPC
								1	CO2
n.a.	n.a.	n.a.	1.48	3.18	1.4	2.69	4.74	1.28	VIF
n.a.	n.a.	n.a.	0.58	0.21	0.72	0.37	0.21	0.78	1/VIF
								2.61	MEAN VIF

Note: LEBF= Life expectancy at birth, female (years). LEBM= Life expectancy at birth, male (years). LEBT= Life expectancy at birth, total (years). COAL= coal consumption (Mst). FUEL= petroleum (Mb/d). GAS= Natural gas (bcf).FFUEL= Fossil fuel(% of total). GDPPC= GDP per capita (constant 2010 US$). CO2= CO2 emissions (kt). VIF=Variance inflation factor

Source: Authors Computation, 2022

3.5 Panel Cross-Section Dependence Test

At times, many panel models are built on the assumption that stochastic terms do exhibit cross-sectional dependence (CSD hereafter) among series in the dataset, which in facts concur with the reality of economic phenomenon. Consequently, not accounting for the possible presence of CSD in panel model could thus not only make the model to be bias but the statistical test also unreliable. To resolve this possible estimation problem, several tests have been proposed in the literature for investigating the presence of CSD in a panel model. The conventional standard in the literature has always been to conduct a CSD test to determine whether it is the first generation or the second generation of the panel unit root test that is most suitable in a given situation. This present study employs two categories of cross-sectional dependence tests, which are: the Breusch–Pagan (1980) and Pesaran (2004) CSD test.

Breusch–Pagan LM: The Breusch–Pagan LM test statistic is based on the assumption of no cross-section dependence among the disturbance in the cross-section units. The mathematical form of the test can be stated as thus:

$$LM = \sqrt{\frac{1}{N(N-1)}} \cdot \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} (T\tilde{\rho}_{ij}^2 - 1) \quad (17)$$

Such that $\tilde{\rho}_{ij}$ are the correlation coefficients derived from the residuals in the model as previously exposited.

Pesaran CD: The Pesaran CD is based on the average of the pairwise correlation coefficients $\tilde{\rho}_{ij}$ and can be stated as follows:

$$CD = \sqrt{\frac{2}{N(N-1)}} \cdot \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} T_{ij} \rho_{ij}^{\sim 2} \Rightarrow N(1,0) \quad (18)$$

Which assumes $T_{ij} \to \infty$ and $N \to \infty$ are asymptotically standard normal for in any order. Table 3 presents the empirical results for the test conducted.

Table 3: Cross-Sectional Dependence Test

Test	Statistic	Probability
Breusch-Pagan LM	42.32	0.52
Pesaran CD	3.45	1.23

Source: Authors Computation, 2022

The result of CSD presented in Table 3 suggests that the null hypothesis of cross-sectional dependence can be rejected implying no presence of CSD among series. This is consistent with recent studies based on oil-rich economies in Africa (Eregha & Mesagan, 2020, 2017) and G7 countries (Ajide & Ridwan, 2018). In essence, the first-generation unit root tests become sufficient and reliable.

4. Results and Discussion

4.1 Panel Unit Root Test Results

The results of the first-generation unit root tests are presented in Table 4for the set of different categories of tests such as Breitung, (2000), Levin et al., (2002), Im et al. (2003), Fisher-ADF test, and Fisher-PP test. From the Table, it is apparent that we cannot reject the null hypothesis of unit roots at level. This is grounded on the fact that virtually all the series are non-stationary at levels thus validating the presence of a unit root at level. In a situation like this, the standard practice has always been to conduct the tests further at the first difference level, which in the case of our study appears to be stationary for all the variables. Hence, the feedbacks from both level and first difference lead us to the empirical conclusion that the variables are stationary at their first differences specifically at the 1% statistical significance level.

Table 4: First Generation Panel Unit Root

	LEBF	LEBM	LEBT	FUEL	COAL	GAS	FFUEL	GDPPC	CO2
LLC	-18.09	-18.36	-19.00	0.14	-0.50	-0.97	0.33	-0.68	-0.09
UB	-1.17	-0.82	-0.19	2.45	-0.21	-1.77	2.51	-0.26	0.68
IPS	-12.16	-12.52	-12.62	0.85	-1.51	-1.25	0.73	0.70	-0.06
Fisher-ADF	30.93	32.01	31.42	5.06	19.84	18.26*	9.11	5.21	11.94
Fisher-PP	22.69	16.05	21.02	5.42	11.03	18.99**	11.10	12.45	21.01
First Difference									
LLC	-17.95***	-15.71***	-17.81***	-3.44***	-5.56***	-5.79***	-4.06***	-0.86	-2.84***
UB	-3.50***	-3.67***	-3.64***	-0.01***	-2.40***	-2.17***	-4.01***	-0.43	-2.64***
IPS	-16.50***	-16.15***	-16.76***	-5.36***	-5.54***	-10.09***	-7.04***	-2.08**	-6.65***
Fisher-ADF	34.16***	36.55***	35.03***	51.15***	44.09***	-95.53***	61.49***	19.07**	58.57***
Fisher-PP	65.34***	4.71***	5.11*	31.47***	68.17***	43.27***	35.73***	41.49***	36.81***

Note: ***, **, * indicate the level of statistical significance at 1, 5, and 10%, in that order. (#) Null hypothesis: the series are stationary.

Source: Authors Computation, 2022

4.2 Panel Co-integration Result

Having confirmed the stationary status of the series at first difference, we proceed further to conducting the test on panel co-integration. The Kao residual test of co-integration is employed to investigate whether or not, there exist a long-run relationship between non-renewable energy, life expectancy, and income level.

Table 5: Kao Residual Co-Integration Test

ADF	**-2.988962*** **

Note: *** indicates the level of statistical significance at 1%. (#) Null hypothesis: co-integration does not exist

Source: Authors computation, 2022

The outcome of Kao co-integration test in Table 5 confirms the existence of co-integration among the series going by statistical significance at 1%. By implication, the above panel co-integration result leaves us with no confusion that life expectancy appears to depend on non-renewable energy consumption and income level.

4.4 Panel Co-integration Result

The confirmation of the presence of long-run relationship among stated variables avails us the opportunity to further proceed to estimate the functional relationship among the variables using the residual-based panel Fully Modified OLS (FMOLS) and Dynamic OLS (DOLS) estimators. These estimators are based on Phillips and Moon (1999), Pedroni (2000, 2001); and

Kao and Chiang, (2000). The choice of adopting these estimators is anchored on the proficiency in producing normally distributed coefficient and asymptotically unbiased estimates.

Before dwelling on the empirical results in the subsequent sub-sections, it is pertinent to shed more light on two significant approaches adopted in the presentation of the results. First, the results are presented in two categories namely: the panel and country-specific results. In the panel results, aggregated empirical findings for all the five oil-producing economies are presented while the country-specific results present the empirical findings for the individual countries (i.e. Algeria, Angola, Egypt, Libya, and Nigeria). While this approach will avail the study to deduce robust policy implications applicable for the group of countries, the African region as a whole, and individual countries, the outcome of the cross-sectional dependence tests further makes this approach more demanding.

Second, for each panel and country-specific empirical findings, the results are presented in four models namely Model 1 (fuel), Model 2 (coal), Model 3 (gas), and Model 4 (fossil fuel). While the first three models represent the individual effects of non-renewable energy consumption, the fourth model represents the aggregated impacts of the components. We embark on this approach to enable us to derive policy suggestions relating to individual component without missing the areas of concerns regarding their aggregate impacts. More importantly, the results of the correlation matrix which reveals the existence of high correlation between some of the non-renewable energy indicators (Table 2) further accentuates the choice of the models.

4.5 Fully Modified OLS Results

The subsequent tables present and elucidate how non-renewable energy impacts life expectancy while factoring in the conditional role of income level. The panel results for the selected five oil producing countries as presented in Table 6 reveal fuel, coal, gas, and fossil fuel impede life expectancy. This is evident from the negative signs and statistically significant impacts associated with all the highlighted indicators of non-renewable energy. By implication, a percentage increase in the consumption of non-renewable energy reduces the expected years of living for the females, males, and the total for both genders. This result is in tandem with the findings of Nkalu and Edeme (2019) who found environmental hazards associated with solid fuel consumption to reduce life expectancy specifically for 7 weeks (1 month and 3 weeks). In essence, the consumption of non-renewable energy can lead to several forms of fatal diseases, which would reduce the expected years of living.

Empirical findings from Asghar et al. (2019) support this view by concluding that non-renewable energy (oil, coal, and gas) increases air pollutants, measles, cases of Tuberculosis, and mortality rate. The impacts of income are noted to enhance life expectancy for the models with statistical significance. More so, the interaction of income with each of the individual and aggregated components came out to be equally enhancing to life expectancy. Intuitively, the impacts of non-renewable energy with the presence of increasing income enhance the transition from dirty to clean and more improve energy consumption. These results are consistent with the notion proposed by energy ladder and some empirical studies which have used different surrogate of income like natural resource rents, Shobande, (2020); real GDP per capita Akinlo and Sulola (2019) and health expenditure (Becchetti et al. 2017).

The impacts of income from both marginal and conditional angles remain positive and enhancing respectively which leads us to infer that, an increasing level of income, which raises the standard of living, is a key factor in achieving the transition to cleaner energy consumption and subsequently improves life expectancy. More so, the impacts of carbon emission on life expectancy further compound the deteriorating state of life expectancy across the panel and individual countries. By implication, continuous increase in the volume of carbon emission implies a corresponding marginal decrease in life expectancy. This submission is consistent with Alimi and Ajide (2020) and Ajide and Alimi (2020).Overall, the impacts of non-renewable energy have constituted a drag down on life expectancy, which is further by the deleterious environmental impacts captured by CO2. That notwithstanding, the role of income appears to salvage the situation all things being equal.

Table 6: Panel Estimation of the Non-renewable energy, Income, and Life Expectancy Nexuses

Var	Dependent Variable: Life Expectancy Female				Dependent Variable: Life Expectancy Male				Dependent Variable: Life Expectancy Total			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Fuel	-0.062*** (0.018)				-0.039*** (0.007)				-0.038*** (0.007)			
Coal		-0.006* (0.002)				-0.005 (0.002)				-0.005** (0.002)		
Gas			-0.005** (0.002)				-0.002 (0.004)				0.002 (0.004)	
Ffuel				-0.221*** (0.059)				-0.215*** (0.061)				-0.219*** (0.059)
Gdppc	0.004*** (0.001)	0.001 (0.002)	0.850 (0.001)	0.007*** (0.007)	0.004*** (0.004)	0.811 (0.000)	0.006* (0.002)	0.006*** (0.007)	0.003*** (0.004)	0.927 (0.002)	0.001* (0.000)	0.006*** (0.001)
INTR	0.121*** (0.442)	0.105 (0.744)	0.555** (0.276)	0.662*** (0.742)	1.271*** (1.506)	0.883 (0.759)	0.191* (0.001)	0.649*** (0.764)	0.125*** (0.152)	0.967 (0.750)	0.198* (0.103)	0.657*** (0.746)
co2	0.204 (0.313)	0.162 (0.166)	0.293 (0.189)	-1.680* (0.934)	-0.372*** (0.115)	0.223 (0.169)	-0.447*** (0.165)	-0.901 (0.961)	0.338*** (0.116)***	0.194 (0.167)	-0.420** (0.163)	-1.290 (0.938)

Note: Var=variables. ***, ** and * denotes statistical significant levels at 1%, 5% and 10%. INTR=interaction income with the respective components of nonrenewable energy. The values in the brackets represent standard deviation. Bolded values represent significant impacts of the stated variable.

Source: Authors Computation, 2022

4.6 Dynamic OLS Results

The results from DOLS Table (7) are not sufficiently different from those emanating from FMOLS results. For instance, the panel result in Table 7 reveals a negative and significant impact of non-renewable energy consumption on life expectancy, while contrary signs are noted in the case of income captured by gdppc. This further highlights the conditional role of income in mitigating the deleterious effects of non-renewable energy on life expectancy.

Table 7: Panel Estimation of the Non-renewable energy, Income, and Life Expectancy Nexuses

Var	Dependent Variable: Life Expectancy Female				Dependent Variable: Life Expectancy Male				Dependent Variable: Life Expectancy Total			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Fuel	-0.029*** (0.008)				-0.033*** (0.009)				-0.032*** (0.009)			
Coal		-0.009*** (0.002)				-0.008*** (0.002)				-0.009*** (0.002)		
Gas			-0.004*** (0.001)				0.006 (0.001)				0.005 (0.007)	
Ffuel				-0.119 (0.077)				0.120 (0.084)				0.120 (0.079)
Gdppc	0.003*** (0.005)	0.334** (0.001)	0.619** (0.907)	0.008*** (0.001)	0.004*** (0.001)	0.923 (0.001)	0.009** (0.004)	0.008*** (0.001)	0.004*** (0.001)	0.667 (0.001)	0.001** (0.004)	**0.008*** (0.009)**
INTR	0.139*** (0.442)	0.184*** (0.509)	0.320 (0.145)	0.783*** (0.923)	0.147*** (0.225)	1.631*** (0.570)	0.384* (0.202)	0.774*** (0.101)	0.143*** (0.219)	0.173*** (0.529)	0.384* (0.197)	**0.781*** (0.956)**
co2	-0.305*** (0.108)	-0.401*** (0.122)	-0.192** (0.787)	-1.881** (0.909)	-0.392 (0.113)	-0.453*** (0.137)	-0.400 (0.206)	-0.109 (0.995)	-0.350*** (0.110)	-0.429*** (0.127)	0.366* (0.210)	-1.481 (0.941)

Note: Var=variables. ***, ** and * denotes statistical significant levels at 1%, 5% and 10%. INTR=interaction income with the respective components of nonrenewable energy. The values in the bracket represent standard deviation. Bolded values represent significant impacts of the stated variable.

Source: Authors Computation, 2022

Summarily, the two sets of empirical results, which emanate from both Fully Modified OLS and Dynamic OLS jointly attest to the significant impacts of non-renewable energy and income as impediment and enhancement to life expectancy in the oil-producing countries in Africa. Following the reported results, it becomes pertinent to test for causality among the variables through the estimation of a panel-based error correction model. This is needed to examine the existence of short-run and long-run causality between non-renewable energy, income, CO2, and life expectancy.

Table 8: **Analyses of Panel Causality For The Oil-producing African Economies**

No causality	Unidirectional	bidirectional
LEBF — LEBM	FUEL → LEBF	GDPPC ↔ CO2
LEBF — LEBT	FUEL → LEBM	
LEBM — LEBT	FUEL → LEBT	
COAL — LEBM	COAL → LEBF	
	COAL → LEBT	
	GAS → LEBF	
	GAS → LEBM	
	GAS → LEBT	
	FFUEL → LEBF	
	FFUEL → LEBM	
	FFUEL → LEBT	

Note. — denotes no causality, → denotes the direction of causality, ↔ denotes bidirectional causality.

Source: Authors Computation, 2022

The panel causality explicating the direction of impacts among the variables in the selected oil-producing countries is presented in Table 8. As depicted from the Table, no causality is noted between life expectancy female and life expectancy male; life expectancy female and life expectancy total; life expectancy male and life expectancy total; coal and life expectancy male. Further, unidirectional causality is evident running from fuel to the three components of life expectancy (female, male, and total). Similar unidirectional causality is observed running from coal to both life expectancy male and total. More so, both gas and fossil fuel are observed to independently cause the three components of life expectancy (female, male, and total). This implies that non-renewable energy is very significant in dictating the extent of longevity in the selected countries, a situation that could be linked to their over-dependence on nonrenewable energy for both economic and domestic activities. The two-directional causality between nonrenewable (fuel, coal, gas, and ffuel) and GDPCC is a clear indication of how the economies of the selected oil-producing countries are inseparable from energy consumption. Similar causality of bidirectional relationship is observed between GDPPC and CO2 explication of the intermingling roles of economic growth and environmental quality.

Table 9: Results on Diagnostic Tests

	χ^2-statistic	Probability
White heteroskedasticity test	5.15	0.39
Wald test	54.77	**0.00*** **
Jarque–Bera test	1.51	0.47

Source: Authors Computation, 2022

The extent to which the models and the functional relationship among the variables of interest to this study can be sufficiently relied upon depends on whether or not they fulfil the standard diagnostic tests. For this reason, in Table 9, three diagnostic tests are conducted and the outcomes showed the empirical models of this study meet the stated criteria. First, the White heteroscedasticity test conducted revealed that the stochastic term is homoscedastic. Second, the Jarque–Bera (JB) test, which hypothesizes normal distribution of residuals in the models, cannot be rejected. Third, the outcome of Wald test did not only complements the joint significance of the variables employed in the model but also reinforces our general conviction regarding the validity and correctness of the results obtained.

5. Conclusion

This study examines the impact of non-renewable energy consumption on life expectancy in selected oil-producing countries in Africa with focus on the conditional role of income level. Before embarking on the analyses, the selected variables were subjected to stationarity tests and were found to be stationary only at the first differences. In addition, panel unit root tests based on the first-generation tests under the assumption of cross-sectional independence were conducted. The panel co-integration was anchored on Kao (1999) to examine the existence of a long-run relationship in the selected variables. The results indicated the existence of long-run co-integration among the variables. This paves way for the study to examine the causal nexuses among the series using both Fully Modified and Dynamic OLS estimators. Furthermore, causality running among the variables was stated.

To ensure more precision of the impacts of non-renewable energy on life expectancy in the study areas, the measures of non-renewable energy were disintegrated into four namely: fuel, coal, gas, and fossil fuel. Life expectancy was equally decomposed into three entailing life expectancy female, life expectancy male, and life expectancy total. Based on this segregation, the empirical analyses were analyzed and the following findings emanated. First, the impacts of non-renewable energy (fuel, coal, gas, and fossil fuel) were found to be negative and statistically significant on life expectancy. Second, income exerted a positive and statistically significant influence on life expectancy. Third, the impacts of non-renewable energy when the conditional role of income was taken into consideration were found to be positive for the most significant models. Fourth, environmental degradation captured by CO2 emission negatively and significantly influenced life expectancy. These aforementioned results are closely related to both Fully Modified OLS and Dynamic OLS estimators. Fifth, the causal relationships among the variables were noted to be divergent, ranging from no causality to unidirectional and bidirectional

Policy inferences, which are deductible from the study, are but not limited to: first, since non-renewable energy consumption negatively influences life expectancy in the oil-producing countries in Africa, it is therefore suggested that policies, initiatives, and efforts be geared towards discouraging its consumption. This can be done by subsidizing cleaner energy sources, intensifying on educating the populace regarding the dangers inherent in consuming non-renewable energy, and embarking on capital projects that will empower people to have increased income that will enable them to sufficiently transit from non-renewable to renewable energy. In addition, governments and private bodies in the African oil-producing countries and the region at large should come up with more pragmatic measures of abating environmental contaminants in order to complement the conditioning role of income in the strides towards raising the bar of life expectancy.

While the study is of high pertinence to addressing the longevity issues embattling the African region as a whole, the role of renewable energy in mitigating the negative impacts of non-renewable energy and equally improving life expectancy remains a major lacuna, which future research studies could consider. This is particularly sacrosanct at this time when the world is advocating the need to embrace cleaner energy as one of the key targets of achieving sustainable development by 2030.

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