ENERGY CONSUMPTION, CO_2 EMISSION AND POPULATION HEALTH IN SUB-SAHARAN AFRICA

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ABSTRACT
This study examined the relationship between energy consumption, CO_2 emission and population health in 13 SSA countries from 1982 to 2014 based on data availability. Two health measures including under five mortality rate and life expectancy at birth were employed. A granger causality test was conducted after estimating a panel VAR model. Variance decomposition analysis and the impulse response function were used to examine the dynamic interactions among the variables and the effect of shocks. The neutrality hypothesis was found between under five mortality and total energy consumption. However, decomposing energy, a unidirectional causality was found from under five mortality to electricity consumption. There was a unidirectional causality from life expectancy to fossil fuel consumption based on a joint significance. Fossil fuel consumption shocks had a negative impact on life expectancy and greatest impact on CO_2 emission. Thus, policies towards improving life expectancy should target a reduction in fossil fuel demand through empowerment strategies and incentives to encourage a substantial transition to electricity consumption.
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JEL Classification: I10, N50

1. INTRODUCTION

Population is a critical resource for development, however, poor population is a challenge in SSA. An economically active population must make decisions but there should be caution as to what implications these decisions have on the environment and health. The importance of energy for several consumption activities cannot be overemphasized. It is necessary for cooking, lightning, driving vehicles, cooling or heating the home depending on the weather. Most appliances at home depend on electricity to power them. Around 2.4 billion people worldwide (around a third of the global population) cook using open fires or inefficient stoves fuelled by kerosene, biomass (wood, animal dung and crop waste) and coal, which generate harmful household air pollution. Despite the importance of energy, Africa is still characterized by low energy use especially for the case of clean or renewable energy. The main human activity that emits CO_2 is the combustion of fossil fuels (coal, natural gas, and oil) for energy and transportation (US EPA, 2020).

The growing level of CO_2 emission is a source of concern and Africa has been called to join in the energy transition agenda towards reducing global climate change. Despite the fact that Africa contributes only two to three percent of the world's CO_2 emission from energy and industrial sources, it is the most vulnerable continent and is already bearing a significant portion of the climate change impact on the environment and health as shown by the United Nations fact sheet on climate change. Two major reasons for environmental threats are climate change and global warming and they are seriously linked to the growing green house gas emissions (Nejat *et al.* 2015). CO_2 is a major contributor to total greenhouse gas emissions. CO_2 emissions has increased by about 90 percent since 1970 with emissions from fossil fuel combustion and industrial processes contributing about 78 percent of total GHG emission increase from 1970 to 2011 (US EPA, 2023). There are about 3.2 million deaths every year as a result of household exposure to smoke from dirty cook stoves and fuels (WHO, 2022).

Global carbon emission has significantly increased since 1900 and energy consumption, precisely from fossil fuel combustion is the major contributor. Greenhouse gas emissions from fossil fuels are also the major contributors to both climate change and air pollution (WHO, 2023). The second largest contributors are agriculture and changes in land use including deforestation (United States Environmental Protection Agency, 2023). The burning of coal, natural gas, and oil for electricity and heat is the largest single source of global greenhouse gas emissions (United States Environmental Protection Agency, 2023).
CO_2 emissions from energy combustion and industrial process accounted for 89 percent of energy related greenhouse gas emissions in 2022 (IEA, 2023).

Despite the fact that SSA is characterized by poor health outcomes, a greater proportion of the energy mix is made up of fossil fuel, which is environmentally unfriendly. Based on the World Development Indicator (2021), life expectancy at birth in SSA has fluctuated largely in favour of a decline. Children in sub-Saharan Africa are more than 14 times more likely to die before they get to the age of 5 than children in developed regions (WHO, 2021). Compared with developed countries, there is a relatively poor population health in SSA countries with life expectancy being below 60 years in most of the periods and countries since 1980. For instance, SSA countries such as Nigeria, Cameroon, Chad and Cote D'Ivoire had 125, 84.5, 125.6, 88, under five mortality rates and life expectancy at birth of 53.5, 58, 53, and 56.6 respectively in 2016 (WDI, 2022).

Energy consumption has been shown to increase CO_2 emission especially with the high consumption of fossil fuels for example, Sharma (2011), confirmed it for 69 countries while Shabaz *et al*. (2017) found it to hold in China precisely for coal consumption. However, high CO_2 emission levels could propel serious calls for changes in energy consumption behavior and policy efforts to divert household consumption choice to clean energy or renewable energy. Thus, there is the possibility of an interrelationship, which remains to be adequately confirmed empirically in the literature. Several studies have shown that energy use by household improve health outcomes because it raises the level of comfort as well as the sanitary conditions of homes. Other studies have also shown that increasing CO_2 emission worsen health outcomes. Few studies have considered the fact that prevailing health outcomes in an economy could also determine changes in the level of environmental degradation as well as the quantity of energy consumed. The poor health conditions of the population of various countries have raised global concerns and there are increasing efforts towards improving environmental quality and preventing energy consumption consequences. Chaabouni and Saidi (2017) examined the link between health spending and CO_2 emission for 51 countries while Ben Jebli (2016) considered the relationship between health indicators and, combustible renewables and CO_2 emission for the case of Tunisia. Could poor health outcomes be explained by energy consumption? Are energy consumption decisions also explained by health experiences and health consideration of individuals and households in developing countries, particularly SSA? Few studies such as Apergis *et al*. (2018), have considered the SSA situation, however, their data was limited to 2011 and only considered health expenditures and not health outcomes. Hanif (2018), which considered the effect of energy consumption on health, did not consider the U5MR (which specifically captures the health situation for children who are more vulnerable to the health hazards from energy use) and life expectancy at birth. In addition, its data was limited to 2015. Household air pollution was responsible for an estimated 3.2 million deaths per year in 2020, including over 237 000 deaths of children under the age of 5 (WHO, 2022). Thus, child health is a critical health indicator to examine when considering energy consumption.

Youssef *et al.* (2015) considered U5MR and life expectancy at birth and examined the effect of energy consumption but did not decompose energy into fossil fuel and solid fuel despite their heavy dominance in the energy mix in Africa. The study also did not provide a specific argument for SSA since it used only 16 countries from the African continent. The studies highlighted above confirm the possible interrelationship among energy consumption and health, however the dynamics of this relationship remains to be considered especially for SSA. This study therefore examined the relationship between energy consumption, CO_2 emission and population health in SSA. It used two measures of population health including the U5MR and life expectancy at birth. The study employed both aggregate and decomposed energy consumption (fossil fuel and solid fuel). It also examined the dynamic interactions among the variables and considered the effect of shocks. The rest of the study is structured from section 2 to 5. Section 2 presents the review of related studies, section 3 is the methodology and section 4 presents the results of the study and discusses the findings. Section 5 is the conclusion and policy recommendations.

2. LITERATURE REVIEW

2.1 Theoretical Review

Theories of health demand and health status show the relationship between health and other factors. For instance, the Grossman (1972) theory of health demand which posits the demand for health as a function of income, education and prices among other health production inputs. The theory explains the demand for health as a derived demand such that individuals seek good health towards being able to increase their participation in the labour force, increase their work hours and earn more income.

Schultz (1984) emphasized on the determinants of a child's health. Schultz (1984) child health production function presents child mortality or morbidity for the ith mother, Y_i as assumed to be a linear function of a vector of proximate biological inputs to child health. It also posits that child health status depends on either genetic or environmental conditions, which cannot be influenced by the family's behavior.

Bartel and Taubman (1979) explained that the relationship between labour force participation and health is such that previous period health status can determine the current level of labour supply and labour market wages. Therefore if a population suffered from poor health in the previous year, a fall in labour force participation is expected in the current year.

2.2 Empirical Review

2.2.1 Relationship between Energy Consumption and CO_2 Emission

Energy use especially from fossil fuel and solid fuel has been shown in the literature to contribute to green house gas emissions including CO_2 in both developed and developing countries. This has resulted in the energy transition effort, which has increasingly become more prominent in the current fight against climate change. Thus, the level of CO_2 emission determines not only the level but the type of energy people are encouraged to use. Using a dynamic panel data model and the GMM estimator, electric power consumption per capita and total primary energy consumption per capita were found to have an insignificant effect on CO_2 emission in a global panel of 69 countries by Sharma (2011). A further categorization of the countries into high, middle and low income panels revealed that electric power consumption per capita and total primary energy consumption per capita had a positive significant effect on CO_2 emission in high income countries while they were insignificant in both middle and low income countries. This is not surprising since countries with high income have a greater production level which would require a higher intensity of energy use. This is evidenced in Shahbaz *et al*. (2022) which found a positive relationship between energy use and economic growth. Employing the dynamic ordinary least square, Leon and Smyth (2010) found that electricity consumption per capita significantly increased CO_2 emission in five ASEAN countries. A granger causality test based on a panel VAR model showed that there was also short run causality running from CO_2 emission to electricity consumption. Al-Mulali *et al.* (2015) found that fossil fuel energy consumption increased CO_2 emission in Vietnam although; renewable energy consumption did not significantly reduce it. This was not surprising since renewable energy only accounted for one percent of total energy consumption in Vietnam. Coal consumption was found by Shabaz *et al.* (2017) to have a bidirectional causality or feedback effect with CO_2 emissions in China in the long run. In the short run, coal consumption and globalization granger caused CO_2 emission. The study employed the Bayer and Hanck cointegration approach and established the presence of a long run relationship among the variables. The VECM causality framework was used to determine the causal relationships. Anwar *et al.* (2022) found that renewable energy consumption decreased CO_2 emission in 15 Asian countries using the impulse response function and the variance decomposition techniques. Apergis *et al.* (2018) found a short run bidirectional causality between renewable energy consumption and CO_2 emission in SSA using the VECM causality framework. A short run unidirectional causality from the real GDP to CO_2 emission was also found. They also found renewable energy consumption and health expenditures to be significantly CO_2 decreasing while the real GDP had an increasing effect on CO_2 after employing the fully modified ordinary least squares and the dynamic ordinary least squares estimators. It is therefore not surprising that WHO (2022) would proffer that it is essential to expand the use of clean fuels and technologies such as solar, electricity, biogas, liquefied petroleum gas (LPG), natural gas, alcohol fuels, as well as biomass stoves that meet the emission targets in the WHO Guidelines inorder to reduce household air pollution and protect health. Other determinants of CO_2 emissions are female to male labour participation (Ogbeide-Osaretin & Efe, (2022)), environmental taxes (Bashir *et al*. (2022)),

2.2.2 Effect of Energy Consumption on Health

Studies have also revealed that energy use determine health outcomes. Nadimi and Tokimatsu (2018) showed that one of the incentives apart from poverty reduction that could cause pre-developing countries to collaborate towards improving human development using a suitable global energy strategy was the need to improve the quality of life. Markandya *et al*. (2009) estimated the effects of electricity generation on health using the Greenhouse Gas and Air Pollution Interactions and Synergies (GAINS) model was used to estimate the potential effect of changes in energy policies on carbon dioxide emissions, air pollution concentrations, and the resulting effects on health. The study also employed the Prospective Outlook on Long-term Energy Systems (POLES) model. The study found that changes in the method of electricity generation would reduce both CO_2 emissions and particulate air pollution and consequently reduce mortality in China, India and the European Union. Renewable energy consumption was found to granger cause health expenditures in SSA as shown by Apergis *et al.* (2018). Employing the one step system GMM approach, Hanif (2018) found that high mortality rate and the occurrence of tuberculosis are explained by increases in fossil and solid fuel consumption for cooking purposes in SSA. The study considered a sample of 34 middle and low income SSA countries for the period 1995 to 2015. However, renewable energy consumption had a negative effect on the incidence of tuberculosis and mortality. Transition to renewable energy sources and investments in clean energy infrastructures was thus suggested. Yilmaz and Şensoy (2023) however obtained no granger causality from renewable energy consumption to life expectancy. The study however did not consider the under five mortality rate as a health measure inorder to specifically capture the health situation for children who are more of the time at home with their mothers and thus exposed to the heath hazards from cooking fuel. The use of traditional energy consumption such as biomass was found to increasingly degenerate health status in China (Wang, 2010). The study also showed that increasing population contributed to environmental degradation and the worsening of public health. Health damages were also attributable to pollutions such as sulphur dioxide (SO2) emission and inhalable particulate matter (PM-10) in China (Wang, 2010). The study used emission parameters and expose-response functions to calculate the emission caused by energy consumption. A total transition from fossil fuel to renewable energy sources is still a global challenge and could still be so for sometime in the future since many developing and developed countries still depend heavily on fossil fuel. Assessing the level of energy dependence and the share of renewable energy in gross final energy consumption, Martins *et al.* (2018) concluded that many European countries still heavily depend on fossil fuel for energy.

Women and children disproportionately bear the greatest health burden from polluting fuels and technologies in homes as they typically labour over household chores such as cooking and collecting firewood as well as spending more time exposed to harmful smoke from polluting stoves and fuels. Gathering fuel increases the risk of musculoskeletal injuries and consumes considerable time for women and children – limiting education and other productive activities. Thus, there is the need for more evidences that consider the effect on child health since few studies have employed child health measures. For instance, employing the seemingly unrelated regression and a panel VAR model, the interrelationship between energy consumption and health outcomes were examined in 16 African countries by Youssef *et al.* (2015). They found a unidirectional causality from energy consumption to life expectancy at birth for some countries. A bidirectional causality was found for only Tanzania and a unidirectional causality from life expectancy to energy consumption only for Mozambique. A unidirectional causality was found from energy consumption to U5MR for seven countries, a bidirectional causality was found for Ghana and Cameroon while a unidirectional causality was found from U5MR to energy consumption for the case of Kenya, Mozambique and Tanzania. Hence, although there was uniformity in the causal relationships for some countries, it also differed for some specific or group of countries they considered.

2.2.3 Effect of CO_2 Emission on Health

Several studies including Oduntan *et al.* (2022) have explained the importance of preventing climate change for instance, using agricultural strategies while Samuel *et al.* (2022) showed that climate change affects output. This study goes beyond establishing the output effect to also considering the health effect. The state of the environment has significantly explained health outcomes in both developed and developing countries. For instance, Oyedele (2022) found CO_2 emission to significantly increase both infant and under five mortality rates in Nigeria.

Employing the GMM estimator, Chaabouni and Saidi (2017) found CO2 emission to have a positive and significant effect on health spending in lower middle income group and higher middle income group of countries but this was not obtained among the low income group. Estimating a dynamic simultaneous equation model, they also found a unidirectional causality from CO_2 emission to health spending in 51 countries except in the low-income group countries. It however did not consider the role of energy consumption.

Wilkinson (2009) emphasized the need to reduce GHG emissions inorder to improve public health and that a major area of focus in achieving this is to target the type of energy used by households. Solid fuel is mostly depended on for energy by the poorest half of the world's household and SSA contributes a greater fraction of such households (Wilkinson, 2009). Zou *et al.* (2015) employed the VECM to examine the impact of environmental and air pollution on the health and wealth of low income countries. The study found that arable land and fossil fuel energy consumption increased health expenditures. The variance decomposition analysis showed that arable land would have the greatest influence on both health and wealth in the future while CO_2 emission would have the least. Saleem *et al.* (2022) found a positive bidirectional relationship between CO_2 emission and healthcare spending. A long run bidirectional causality was also found between CO_2 emission and health expenditures in SSA by Apergis *et al.* (2018) based on a VECM causality framework. An increase in greenhouse gas emissions increased the prevalence of respiratory diseases and mortality rate in emerging Asian economies from 1995 to 2018 as shown by Anser *et al*. (2020). Employing a panel ARDL model, access to clean energy sources significantly reduces mortality rate and the prevalence of respiratory diseases. The U5MR was not captured neither was any effort made to specifically capture child health. The incidence of respiratory diseases or the number of reported cases of respiratory diseases increased with an increase in the combustion of fossil fuels. This study goes beyond other literature to also capture the effect of energy consumption and it does not only use an adult health measure (life expectancy at birth) but also considers child health (using the under five mortality rate).

2.2.4 Effect of Population Health on Energy Consumption and CO_2 Emission

Worsening health conditions especially due to environmental pollution-related diseases could determine individual and household decision on the type of energy to use and the quantity of each type of energy used. A deliberate public decision to prioritize the health of individuals would cause both public and private effort towards reductions in CO_2 emission and influencing the energy use decisions of households towards cleaner energy sources.

However, few studies have considered the possible effect of population health changes on energy use and CO_2 emission. Chaabouni and Saidi (2017) found health spending to significantly increase CO_2 emissions among the low-income countries and the higher middle-income countries out of a total of 51 countries considered. This was however not the case for the lower middle-income group. A healthy working population contributes to economic growth and Shamwill *et al.* (2023) has shown that changes in economic growth explain changes in energy consumption precisely for natural gas.

Examining the dynamic interaction between health indicator, economic growth, combustible renewables and waste consumption, rail transport, and carbon dioxide (CO_2) emissions, Ben Jebli (2016) found that in the short run, there was a unidirectional causality running from health to combustible renewables and waste consumption in Tunisia. A unidirectional causality was also found from health to CO_2 emission. Thus, health experiences and outcomes influenced energy decisions and energy related behavioural changes. A bidirectional causality was however obtained in the long run. Yilmaz and Şensoy (2023) found a one way causality from renewable life expectancy to renewable energy consumption in Turkey.

This study however goes beyond the existing literature to consider the possible effect of population health changes on both energy use and CO_2 emission. It also does not only examine causality issues as is mostly found in literature but also examines the effect of shocks.

3. METHODOLOGY

3.1 The Model

The model of the study is based on the Grossman (1972) theory of health demand, which posits the demand for health as a function of income among other health production inputs. We measure income using the percentage growth of gross domestic product (GDP). We captured the effect of energy consumption in the model by including total energy consumption. The model is thus presented as:

$$HO = f\,(GRGDP, ENC, CO_2) \qquad (1)$$

Controlling for environmental conditions using the level of CO_2 emission, the functional form of the model is presented in equation (2) as:

$$HO_{it} = \beta_0 + \beta_1 GRGDP_{it} + \beta_2 ENC_{it} + \beta_3 CO_{2it} + e_{it} \qquad (2)$$

Using the two health outcome measures considered in this study we have equations (3) and (4) as:

$$U5MR_{it} = \beta_0 + \beta_1 GRGDP_{it} + \beta_2 \log(ENC_{it}) + \beta_3 \log(CO_{2it}) + e_{it} \qquad (3)$$

$$LEB_{it} = \beta_0 + \beta_1 GRGDP_{it} + \beta_2 \log(ENC_{it}) + \beta_3 \log(CO_{2it}) + e_{it} \qquad (4)$$

Examining the causal relationship among the variables, we employed the panel vector auto regression (VAR) model specification where each variable, beginning with the health outcome measure is presented as a function of its lag and the lag of other explanatory variables. The panel VAR model for under five mortality rate is presented in equations (5), (6), (7) and (8) below.

$$U5MR_{it} = a_1 + \beta_1 U5MR_{it-1} + \dots + \beta_1 U5MR_{it-p} + d_1 GRGDP_{it} + \dots + d_1 GRGDP_{it-p} + v_1 \log(ENC_{it}) + \dots + v_1 \log(ENC_{it-p}) + w_1 \log(CO_{2it}) + \dots + w_1 \log(CO_{2it-p}) + e_{it} \qquad (5)$$

$$GRGDP_{it} = a_1 + d_1 GRGDP_{it-1} + \dots + d_1 GRGDP_{it-p} + \beta_1 U5MR_{it} + \dots + \beta_1 U5MR_{it-p} + v_1 \log(ENC_{it}) + \dots + v_1 \log(ENC_{it-p}) + w_1 \log(CO_{2it}) + \dots + w_1 \log(CO_{2it-p}) + e_{it} \qquad (6)$$

$$\mathrm{Log}(ENC_{it}) = a_1 + v_1 \log(ENC_{it-1}) + \dots + v_1 \log(ENC_{it-p}) + d_1 GRGDP_{it} + \dots + d_1 GRGDP_{it-p} + \beta_1 U5MR_{it} + \dots + \beta_1 U5MR_{it-p} + w_1 \log(CO_{2it}) + \dots + w_1 \log(CO_{2it-p}) + e_{it} \qquad (7)$$

$\log(CO_{2it}) = a_1 + w_1\log(CO_{2it-1}) + \ldots + w_1\log(CO_{2it-p}) + d_1GRGDP_{it} + \ldots + d_1GRGDP_{it-p} + v_1\log(ENC_{it}) + \ldots + v_1\log(ENC_{it-p}) + \beta_1U5MR_{it} + \ldots + \beta_1U5MR_{it-p} + e_{it}$ (8)

The panel VAR model for life expectancy at birth is presented in equations (9), (10), (11) and (12) below.

$LEB_{it} = a_2 + \beta_2LEB_{it-1} + \ldots + \beta_2LEB_{it-p} + d_2GRGDP_{it} + \ldots + d_2GRGDP_{it-p} + v_2\log(ENC_{it}) + \ldots + v_2\log(ENC_{it-p}) + w_2\log(CO_{2it}) + \ldots + w_2\log(CO_{2it-p}) + e_{it}$ (9)

$GRGDP_{it} = a_2 + d_2GRGDP_{it-1} + \ldots + d_2GRGDP_{it-p} + \beta_2LEB_{it} + \ldots + \beta_2LEB_{it-p} + v_2\log(ENC_{it}) + \ldots + v_2\log(ENC_{it-p}) + w_2\log(CO_{2it}) + \ldots + w_2\log(CO_{2it-p}) + e_{it}$ (10)

$\log(ENC_{it}) = a_2 + v_2\log(ENC_{it-1}) + \ldots + v_2\log(ENC_{it-p}) + d_2GRGDP_{it} + \ldots + d_2GRGDP_{it-p} + \beta_2LEB_{it} + \ldots + \beta_2LEB_{it-p} + w_2\log(CO_{2it}) + \ldots + w_2\log(CO_{2it-p}) + e_{it}$ (11)

$\log(CO_{2it}) = a_2 + w_2\log(CO_{2it-1}) + \ldots + w_2\log(CO_{2it-p}) + d_2GRGDP_{it} + \ldots + d_2GRGDP_{it-p} + v_2\log(ENC_{it}) + \ldots + v_2\log(ENC_{it-p}) + \beta_2LEB_{it} + \ldots + \beta_2LEB_{it-p} + e_{it}$ (12)

Where:
U5MR = under five mortality rate (per 1,000 live births)
LEB = life expectancy at birth (total years)
log(ENC) = log of total energy consumption per capita
GRGDP = GDP growth (annual percent)
$\log(CO_2)$ = log of carbon dioxide emission (metric tons per capita)
log(ELEC) = log of electricity consumption (kWh per capita)
FOSSIL = fossil fuel consumption (% of total)

We decompose energy consumption into electricity consumption and fossil fuel consumption, which capture both clean and polluting energy forms respectively. Thus panel VAR models for under five mortality rate and life expectancy at birth are also estimated using the two decomposed energy forms. Energy consumption is expected to have a positive and negative effect for the case of using clean and polluting energy respectively (Apergis *et al.* 2018; Hanif, 2018). An increase in CO_2 emission is expected to have a negative effect on health since it is an unhealthy greenhouse gas for humans (Oyedele, 2022; Anser *et al*. 2020). The estimation method involves estimating a panel vector autoregression model from which a granger causality or block endogeneity test is derived. The dynamic interactions among the variables and their response to shocks are also estimated using the variance decomposition analysis and the impulse response functions.

3.2 Data and Data Source

Data for this study covers the period from 1982 to 2014. The period was chosen based on data availability. The data include life expectancy at birth, under five mortality rate, growth of the GDP, total energy consumption, electricity consumption, fossil fuel consumption and carbon dioxide emission per capita. The study focuses on sub-Saharan African, a region characterized by high child mortality rate, relatively low life expectancy rate, relatively low energy

consumption and a growing level of carbon dioxide emission. Thirteen countries were considered including Nigeria, Benin, Cameroon, Ghana, Botswana, Congo Democratic Republic, Cote D'ivoire, Kenya, Senegal, Zambia, Zimbabwe, Ethiopia and Mozambique.
The data was obtained from the World Development Indicators (2021) published by the World Bank.

4. RESULTS AND DISCUSSION OF FINDINGS

4.1 Descriptive Statistics

The descriptive statistics of the variables presented in Table 1 show that the mean under five mortality rate was 129.79 revealing a high level of child deaths in the region with a maximum value of 264.7 deaths per 1,000 live births. The average live expectancy at birth was 53 years. Therefore, the poor population health challenge in SSA is glaring. The mean energy consumption per capita was 511.85. The mean growth rate of the GDP was low at 0.895 percent.

Table 1 Descriptive Statistics

Variable	Mean	Std. Dev.	Minimum	Maximum
U5MR	129.79	49.80	35.1	264.7
GRGDP	0.895	5.074	-18.491	18.066
Log(CO_2)	0.494	0.559	0.016	3.414
LEB	53.23	5.33	43.07	66.37
Log(ELEC)	319.83	362.81	17.57	2126.49
Log(ENC)	511.85	220.84	208.12	1300.63
FOSSIL	23.82	17.56	1.64	74.69
Observations	429	429	429	429

Source: Computed by Author (2023)

4.2 Unit Root Test

The estimation process of the panel VAR models began with a unit root test conducted using the Levin, Lin & Chu unit root method and the Im, Pesaran and Shin method. The results showed a mixed order of integration among the variables as presented in Table 2. Hence, we employed the Kao residual cointegration test and the Pedroni residual cointegration test.

Table 2 Unit Root Test

Variable	Levin, Lin & Chu Statistic	Order of Integration	Im, Pesaran and Shin W-Statistic	Order of Integration
U5MR	(-6.918)*	I(0)	(-3.359)*	I(0)
GRGDP	(-5.790)*	I(0)	(-7.370)*	I(0)
Log(CO_2)	(-1.679)**	I(0)	(-9.887)*	I(1)
LEB	(-19.468)*	I(0)	(-18.044)*	I(0)
Log(ELEC)	(-7.171)*	I(1)	(-12.532)*	I(1)
Log(ENC)	(-5.679)*	I(1)	(-9.129)*	I(1)
FOSSIL	(-5.486)*	I(1)	(-9.811)*	I(1)

* and ** denote significance at 1% and 5% level respectively

4.3 Cointegration Test

The cointegration test was conducted using two methods - the Kao residual cointegration test and the Pedroni residual cointegration test for robustness.

4.3.1 Kao Residual Cointegration Test

This test is Engel Granger based and the null hypothesis states that there is no cointegration. This hypothesis was not rejected since the t-statistic value of -0.863 was not significant at 5 percent as shown in Table 3. Thus, there was no cointegration among the variables (under five mortality rate, real GDP per capita growth rate, electricity consumption, fossil fuel consumption and CO2 emission).

Table 3 Kao Residual Cointegration Test

Variables	t-statistic	Probability
Under Five Mortality Rate		
U5MR, GRGDP, ENC CO_2	-0.721	0.2356
U5MR, GRGDP, ELEC, FOSSIL, CO_2	-1.492	0.0679
Life Expectancy at Birth		
LEB, GRGDP, ENC CO_2	-0.600	0.2743
LEB, GRGDP, ELEC, FOSSIL, CO_2	-0.541	0.2944

Source: Computed by Author (2023)

4.3.2 Pedroni Residual Cointegration Test

Population Health Measured by Under Five Mortality Rate

Model 1

Testing for cointegration among under five mortality rate, real GDP per capita growth rate, energy consumption and CO2 emission, we also employed the Pedroni Residual Cointegration Test. The result is presented in Table 4. The null hypothesis of no cointegration was not rejected since all of the 4 test statistics including the panel and group PP and ADF statistics were not significant at 5%. This is similar to the Kao Residual Cointegration Test that also found no cointegration.

Table 4 Pedroni Residual Cointegration Test

	Statistic	**Probability**	**Weighted Statistic**	**Probability**
Panel PP-Statistic	3.249	0.9994	3.923	1.0000
Panel ADF-Statistic	3.578	0.9998	3.934	1.0000
Group PP-Statistic	3.908	1.0000	-	-
Group ADF-Statistic	4.630	1.0000	-	-

Source: Computed by Author (2023)

Model 2

Testing for cointegration among under five mortality rate, real GDP per capita growth rate, electricity consumption, fossil fuel consumption and CO2 emission, we also employed the Pedroni residual cointegration test. The result is presented in Table 5. The null hypothesis of no cointegration was not rejected since all of the statistics including the panel and group PP and ADF statistics were not significant at 5%. This is similar to the Kao residual cointegration test that also found no cointegration.

Table 5 Pedroni Residual Cointegration Test

	Statistic	**Probability**	**Weighted Statistic**	**Probability**
Panel PP-Statistic	3.580	0.9998	3.505	0.9998
Panel ADF-Statistic	3.846	0.9999	3.539	0.9998
Group PP-Statistic	3.738	0.9999		
Group ADF-Statistic	4.423	1.0000		

Source: Computed by Author (2023)

Population Health Measured by Life Expectancy at Birth

Model 3

Testing for cointegration among life expectancy at birth, real GDP per capita growth rate, energy consumption and CO2 emission, we also employed the Pedroni residual cointegration Test. The result is presented in Table 6. The null hypothesis of no cointegration was not rejected since almost all of the statistics including the panel and group PP and ADF statistics were not significant at 5%. This is similar to the Kao residual cointegration test that also found no cointegration.

Table 6 Pedroni Residual Cointegration Test

	Statistic	Probability	Weighted Statistic	Probability
Panel PP-Statistic	6.690	1.0000	5.717	1.0000
Panel ADF-Statistic	7.673	1.0000	5.947	1.0000
Group PP-Statistic	6.195	1.0000		
Group ADF-Statistic	5.665	1.0000		

Source: Computed by Author (2023)

Model 4

Testing for cointegration among life expectancy at birth, real GDP per capita growth rate, electricity consumption, fossil fuel consumption and CO2 emission, we also employed the Pedroni Residual Cointegration Test. The result is presented in Table 7. The null hypothesis of no cointegration was not rejected since almost all of the statistics including the panel and group PP and ADF statistics were not significant at 5%. This is similar to the Kao Residual Cointegration Test that also found no cointegration.

Table 7 Pedroni Residual Cointegration Test

	Statistic	Probability	Weighted Statistic	Probability
Panel PP-Statistic	4.993	1.0000	3.816	0.9999
Panel ADF-Statistic	6.805	1.0000	5.623	1.0000
Group PP-Statistic	4.134	1.0000)		
Group ADF-Statistic	5.082	1.0000		

Source: Computed by Author (2023)

4.4 Relationship between the Under Five Mortality Rate and Total Energy Consumption

Based on an estimated panel VAR model, a granger causality test or block exogeneity wald test was conducted to examine the relationship between the under five mortality rate and total energy consumption. Control variables were also included in the model including the GDP per capita growth and CO_2 emission. The optimal lag applied in the panel VAR model estimation was determined as 4 based on the Akaike information criterion.

4.4.1 Granger Causality Test

Since there was no cointegration, a panel VAR model was estimated using the first difference values of all the variables. The error correction term was therefore not included. The panel granger causality test was conducted based on the estimated panel VAR model. The results in Table 8 reveal that the GDP per capita growth did not significantly granger cause the under five mortality rate. Total energy consumption and CO_2 emission did not individually and significantly granger cause under five mortality and vice versa. The neutrality hypothesis was therefore found to hold between under five mortality and total energy consumption since they had no causal relationship. This is contrary to Ben (2016) that found a unidirectional causality from health to CO_2 emission although it was for the case of China. It is also contrary to Youssef *et al.* (2015) examined the case for 16 African countries and found a unidirectional causality from energy consumption to U5MR for seven countries while a bidirectional causality was found for Ghana and Cameroon.

Table 8 VAR Granger Causality/Block Exogeneity Wald Tests

Dependent variable: U5MR		
Excluded	Chi-sq	Prob.
GRGDPPC	6.067925	0.1941
LOG(ENC)	1.709872	0.7889
LOG(CO_2)	1.909085	0.7525
All	9.285144	0.6784
Dependent variable: GRGDPPC		
Excluded	Chi-sq	Prob.
D(SER04)	13.48312	0.0091
LOG(ENC)	1.885891	0.7567
LOG(CO_2)	5.348121	0.2534
All	24.84484	0.0156
Dependent variable: LOG(ENC)		
Excluded	Chi-sq	Prob.
D(SER04)	1.716823	0.7877
GRGDPPC	4.442434	0.3494
LOG(CO_2)	2.200168	0.6990
All	8.501219	0.7448
Dependent variable: LOG(CO_2)		
Excluded	Chi-sq	Prob.
D(SER04)	4.722239	0.3170
GRGDPPC	8.124866	0.0871
LOG(ENC)	4.012262	0.4043
All	17.88234	0.1193

Source: Computed by Author (2023)

There was also no joint significant causality from all the variables to the under five mortality rate. There was however a significant unidirectional causality running from under five mortality rate to GDP per capita growth while other variables had no individual significance. All the variables had a joint significant causal effect on GDP growth. For the case of CO_2 emission, no causality was found running from under five mortality and other variables to CO_2 emission. This is also contrary to Ben (2016) that found a unidirectional causality from health to CO_2 emission. The post estimation test showed no serial correlation at the fifth lag but the null hypothesis for normality was rejected.

4.4.2 Variance Decomposition Analysis

The variance decomposition analysis showed the dynamic interactions among the variables in terms of their contributions to changes in U5MR and life expectancy. The results as presented in Table 9 and 10 revealed that variations in the u5mr were due to 100 percent of its own forecast error variance. There was a consistent increase in the forecast error variance of GDP growth from zero percent in the first year to 0.303 in the tenth year, which explained changes in u5mr. There was also a steady increase in the forecast error variance of energy consumption from the first year to the tenth year thus besides its own shock, energy consumption had the greatest forecast error variance of 0.47 percent, which caused variations in the u5mr by the tenth year.

Table 9 Variance Decomposition of U5MR

Period	SE	U5MR	GRGDPPC	LOG(ENC)	LOG(CO_2)
1	0.749526	100.0000	0.000000	0.000000	0.000000
2	1.285066	99.91451	0.062558	0.010652	0.012276
3	1.700894	99.62093	0.258221	0.109791	0.011058
4	2.010116	99.47171	0.286803	0.221426	0.020062
5	2.232262	99.37520	0.285635	0.310735	0.028425
6	2.388992	99.30026	0.294706	0.370857	0.034175
7	2.498344	99.25058	0.298921	0.412414	0.038090
8	2.573904	99.21722	0.300345	0.441459	0.040972
9	2.625781	99.19391	0.301881	0.461238	0.042975
10	2.661240	99.17806	0.302852	0.474752	0.044336

Source: Computed by Author (2023)

Table 10 Variance Decomposition of Energy Consumption

Period	SE	U5MR	GRGDPPC	LOG(ENC)	LOG(CO_2)
1	0.041944	0.209430	1.432280	98.35829	0.000000
2	0.042079	0.222731	1.894995	97.74464	0.137634
3	0.042188	0.237382	2.144022	97.30488	0.313720
4	0.042247	0.271592	2.377391	97.03812	0.312893
5	0.042249	0.279672	2.378878	97.02855	0.312903
6	0.042255	0.289385	2.393720	97.00393	0.312969
7	0.042257	0.298370	2.396636	96.99206	0.312937
8	0.042258	0.303346	2.396515	96.98716	0.312976
9	0.042259	0.307125	2.396866	96.98305	0.312963
10	0.042260	0.309929	2.396817	96.98030	0.312955

Source: Computed by Author (2023)

Although in the first year, zero percent of the variance in the forecast error of GDP growth, energy consumption and CO_2 emission explained changes in U5MR, by the tenth year it had increased to 0.30, 0.47 and 0.04 percent respectively. Thus the greatest contribution to variations in the under five mortality rate over the ten year period was from energy consumption. This is similar to Hanif (2018) and Wang (2010), which found energy consumption to degenerate health status, increase mortality rate and tuberculosis incidence. Innovations from total energy consumption also had the greatest variation in GDP growth by the tenth year. CO_2 emission had the greatest variance in forecast error of 0.313 that explained variations in energy consumption over the ten year period apart from its own shocks. The second highest cause of variations in energy consumption was the under five mortality which had a forecast error variance that increased consistently from the first year to the tenth year.

4.4.3 Impulse Response Function

Impulse response functions were generated to trace the temporal responses of a variable to its own shock and shocks from other variables. Long term and short term responses were captured using the Cholesky decomposition for responses on u5mr to shocks from energy consumption and other variables including GDP per capita growth and CO_2 emission were examined. Table 11 and 12 contain the results.

Table 11 Response of U5MR

Period	U5MR	GRGDPPC	LOG(ENC)	LOG(CO_2)
1	0.733196	0.000000	0.000000	0.000000
2	0.882569	-0.040874	0.026525	-0.030056
3	0.997746	-0.070477	0.050818	-0.026024
4	1.089752	-0.070338	0.086871	-0.030644
5	1.040209	-0.010884	0.066471	-0.064036
6	0.936364	-0.027259	0.061138	-0.072609
7	0.814004	-0.026959	0.053444	-0.068216
8	0.656015	-0.019242	0.031271	-0.069734
9	0.488952	-0.028330	0.018098	-0.070456
10	0.330772	-0.016163	0.009555	-0.060305

Source: Computed by Author (2023)

Table 12 Response of Energy Consumption

Period	U5MR	GRGDPPC	LOG(ENC)	LOG(CO_2)
1	0.001782	0.005540	0.042211	0.000000
2	0.000979	0.003151	-0.000382	0.001658
3	-0.002941	0.003109	-0.000391	-0.002412
4	0.000697	-0.000852	0.002647	0.000382
5	-6.49E-05	-0.000869	-0.005249	-0.000320
6	-0.000791	-0.000735	-0.000377	-0.000111
7	0.000321	-0.001048	0.000181	-0.000167
8	-0.000340	0.000830	-0.000548	0.000189
9	-0.000452	5.96E-06	0.000576	1.02E-06
10	-0.000128	3.62E-06	0.000184	0.000238

Source: Computed by Author (2023)

A one standard deviation shock in GDP growth had negative impacts on U5MR and this negative impact was maintained over the ten years at values less than zero. On the otherhand, a one standard deviation shock from energy consumption caused positive responses in U5MR so that it rose from zero in the first year to 0.010 by the tenth year. This is however a minimal response to energy consumption shocks and little wonder that the granger causality test results showed no causality between them. A one standard deviation shock in U5MR caused energy consumption to increase minimally in the first and second period but later declined towards the tenth year.

4.5 Relationship between the Under Five Mortality Rate and Decomposed Energy Consumption (Electricity consumption and Fossil fuel consumption)

Inorder to examine the differentials in the causality when we consider a relatively clean energy and a polluting fuel, we further examined the causal relationship between U5MR and energy consumption decomposed into electricity and fossil fuel consumption. A VAR model was estimated using the optimal lag of 4 based on the Akaike information criterion.

4.5.1 Granger Causality Test

The granger causality test thereafter conducted showed that electricity consumption did not granger cause under five mortality but under five mortality granger caused electricity consumption as shown in Table 13. Hence, there was a unidirectional causality running from under five mortality to electricity consumption. This implies that as the number of child death increase, energy consumption decisions of individuals and households begin to change probably towards the use of cleaner energy forms.

Table 13 VAR Granger Causality/Block Exogeneity Wald Tests

Dependent variable: U5MR		
Excluded	Chi-sq	Prob.
GRGDPPC	5.309415	0.2570
LOG(ELEC)	0.329146	0.9879
FOSSIL	3.540475	0.4718
LOG(CO_2)	2.506766	0.6434
All	11.37765	0.7856
Dependent variable: GRGDPPC		
Excluded	Chi-sq	Prob.
U5MR	12.61413	0.0133
LOG(ELEC))	5.005694	0.2867
FOSSIL	2.516295	0.6417
LOG(CO_2)	3.045333	0.5503
All	30.19157	0.0170
Dependent variable: LOG(ELEC)		
Excluded	Chi-sq	Prob.
U5MR	14.82163	0.0051
GRGDPPC)	2.738390	0.6025
FOSSIL	1.265267	0.8672
LOG(CO_2)	3.020467	0.5544

All	22.62531	0.1241
Dependent variable: D(FOSSIL)		
Excluded	Chi-sq	Prob.
U5MR	1.114807	0.8919
GRGDPPC	7.808107	0.0989
LOG(ELEC)	15.35936	0.0040
LOG(CO_2)	6.071385	0.1939
All	33.42955	0.0065
Dependent variable: LOG(CO_2)		
Excluded	Chi-sq	Prob.
U5MR	4.090461	0.3939
GRGDPPC	8.201747	0.0845
LOG(ELEC)	5.391195	0.2495
FOSSIL	16.73504	0.0022
All	35.75561	0.0031

Source: Computed by Author (2023)

Fossil fuel consumption did not granger cause under five mortality and vice versa. Thus, the neutrality hypothesis holds in this case as no causal relationship was found between them. The neutrality hypothesis also holds in the relationship between GDP growth and both electricity and fossil fuel consumption since there was no granger causality between each per of them. Thus, despite the increase in GDP, it did not translate to increased energy consumption probably because the growth was too marginal to affect energy consumption. However, all the variables had a joint significant causality on GDP growth.

Although individually, only electricity consumption granger caused fossil fuel consumption, there was however a joint significant causality from all the variables to fossil fuel consumption. Thus, the under five mortality rate granger caused fossil fuel consumption when we controlled for other variables including GDP growth, CO_2 emission and electricity consumption. Ben Jebli (2016) also found a unidirectional causality from health indicator to combustible renewables but in the short run.

Fossil fuel consumption had an individual significant causal effect on CO_2 emission. This shows the significant contribution that fossil fuel combustion makes to the high CO_2 emission level and the negative consequences such as climate change and global warming. This finding is similar to Al-Mulali *et al.* (2015), which found that fossil fuel energy consumption increased CO_2 emission in Vietnam. Sharma (2011) also found that energy consumption explained CO_2 emissions. There was also a joint significant causality running from all the variables including electricity consumption to CO_2 emission. Thus, electricity consumption caused changes in CO_2 emission when we controlled for other variables. This is not surprising since most of the electricity consumed is based on burning fossil fuels in generators inorder to produce electricity for households and firms.

The post estimation tests revealed the absence of serial correlation at the second and fifth lags. The null hypothesis of normality presence was however rejected.

4.5.2 Variance Decomposition Analysis

The variance decomposition analysis for U5MR, electricity consumption and fossil fuel consumption are presented in Table 14, 15 and 16. The forecast error variance of both electricity and fossil fuel consumption explained changes in the under five mortality rate. The variance in their forecast errors increased consistently from zero percent to 0.174 and 2.254 respectively. Thus, innovations in the consumption levels of electricity and fossil fuel caused changes in the number of child deaths. This is similar to Hanif (2018) and Wang (2010), which found energy consumption to degenerate health status and increase mortality rate.

Table 14 Variance Decomposition of U5MR

Period	SE	LEB	GRGDPPC	LOG(ELEC)	FOSSIL	D(LOG(CO_2))
1	0.735167	100.0000	0.000000	0.000000	0.000000	0.000000
2	1.147215	99.80600	0.104058	0.001876	0.005394	0.082676
3	1.520517	99.43718	0.230714	0.019458	0.174699	0.137953
4	1.873409	98.99359	0.244027	0.031308	0.518157	0.212920
5	2.145534	98.52496	0.187533	0.054965	0.793694	0.438850
6	2.346506	97.96190	0.156898	0.088700	1.145548	0.646957
7	2.489399	97.44703	0.139518	0.109721	1.496178	0.807554
8	2.579959	96.99722	0.131990	0.131105	1.784641	0.955039
9	2.631895	96.56941	0.126900	0.157411	2.043024	1.103252
10	2.657481	96.23068	0.127143	0.173593	2.253737	1.214849

Source: Computed by Author (2023)

Table 15 Variance Decomposition of Electricity Consumption

Period	SE	LEB	GRGDPPC	LOG(ELEC)	FOSSIL	D(LOG(CO_2))
1	0.097879	0.012668	1.432032	98.55530	0.000000	0.000000
2	0.098096	0.019549	1.493056	98.30588	0.038699	0.142812
3	0.098847	0.063288	2.097534	97.61409	0.079189	0.145900
4	0.099803	1.411002	2.119822	95.77553	0.130257	0.563386
5	0.100436	2.011908	2.346361	94.65557	0.218924	0.767233
6	0.100878	2.787091	2.327269	93.85115	0.250918	0.783574
7	0.101301	3.535465	2.309809	93.06966	0.300150	0.784915
8	0.101599	4.062373	2.297559	92.52514	0.314729	0.800199
9	0.101870	4.481060	2.286092	92.03586	0.355560	0.841427
10	0.102031	4.743469	2.278880	91.74485	0.373501	0.859303

Source: Computed by Author (2023)

Table 16 Variance Decomposition of FOSSIL

Period	SE	LEB	GRGDPPC	LOG(ELEC)	FOSSIL	D(LOG(CO_2))
1	2.086936	0.035487	1.678889	0.005715	98.27991	0.000000
2	2.148299	0.034995	3.197514	3.537006	92.75783	0.472652
3	2.175788	0.451331	3.897785	4.171122	90.65041	0.829348
4	2.227776	0.439641	3.909796	4.046376	90.77617	0.828013
5	2.240827	0.481046	3.864964	4.690781	89.85181	1.111400
6	2.242789	0.496064	3.858244	4.817623	89.71616	1.111907
7	2.245105	0.498845	3.855693	4.810771	89.69089	1.143802
8	2.246321	0.516621	3.868862	4.843378	89.62820	1.142941
9	2.246707	0.522003	3.875430	4.848278	89.60271	1.151581
10	2.246838	0.522115	3.878027	4.847910	89.59741	1.154539

Source: Computed by Author (2023)

Fossil fuel consumption had the greatest contribution to variations in under five mortality amongst GDP growth, electricity consumption and CO_2 emission. CO_2 emission had the next highest contribution to variations in under five mortality with a forecast error variance increasing from zero percent in the first year to 1.215 by the tenth year. This emphasizes the important implication of CO_2 emission in the environment on worsening health outcomes. Oyedele (2022) also confirmed the increasing effect of CO_2 emission on infant and under five mortality in Nigeria.

Over the ten year period, variations in fossil fuel consumption was explained by 4.848, 3.878 and 0.522 percent of forecast error variance in electricity consumption, GDP growth and under five mortality respectively. Therefore an increase in the use of electricity by households would reduce the amount of fossil fuel consumed. An increase in the growth of the GDP empowers individuals and households to afford the consumption of electricity rather than the use of fossil fuel for most of their energy needs. As households experience more child deaths, they become more willing to take necessary precautions to avoid more health hazards including using clean energy forms.

4.5.3 Impulse Response Function

The impulse response function generated to examine the response of variables to its own shock and shocks from other variables is presented in Table 17, 18 and 19. The results show that under five mortality had a zero response to shocks from electricity consumption in the first year and thereafter there was a negative impact which was maintained over the ten year period. However, a one standard deviation shock in fossil fuel consumption had a positive impact on under five mortality. This further confirmed the increasing or worsening effect of fossil fuel use on child and population health.

Table 17 Response of U5MR

Period	U5MR	GRGDPPC	LOG(ELEC)	FOSSIL	LOG(CO_2)
1	0.735167	0.000000	0.000000	0.000000	0.000000
2	0.879249	-0.037007	-0.004969	0.008426	-0.032986
3	0.992678	-0.062965	-0.020620	0.062992	-0.045840
4	1.084150	-0.056837	-0.025475	0.118939	-0.065447
5	1.030086	0.008261	-0.037834	0.135465	-0.112822
6	0.926528	-0.002488	-0.048514	0.162907	-0.124179
7	0.803137	0.002677	-0.043768	0.172177	-0.120096
8	0.646079	0.011807	-0.043899	0.161460	-0.116293
9	0.482621	0.002163	-0.046659	0.150760	-0.113365
10	0.326752	0.013744	-0.036821	0.132838	-0.096821

Source: Computed by Author (2023)

Table 18 Response of Electricity Consumption

Period	U5MR	GRGDPPC	LOG(ELEC)	FOSSIL	LOG(CO_2)
1	-0.001102	0.011713	0.097169	0.000000	0.000000
2	-0.000817	-0.002546	0.004238	0.001930	0.003707
3	-0.002074	0.007828	0.008819	-0.002003	0.000716
4	-0.011591	0.002491	0.001513	-0.002288	0.006470
5	-0.007900	0.005053	0.002891	0.003018	0.004613
6	-0.008982	-0.000382	0.001548	-0.001858	0.001532

7	-0.008898	-0.000444	-8.80E-05	-0.002295	-0.000898
8	-0.007518	0.000362	0.000102	-0.001299	0.001432
9	-0.006759	-0.000278	0.000498	-0.002100	0.002172
10	-0.005366	4.97E-05	0.000184	-0.001409	0.001462

Source: Computed by Author (2023)

Table 19 Response of FOSSIL

Period	U5MR	GRGDPPC	LOG(ELEC)	FOSSIL	LOG(CO_2)
1	0.039314	0.270408	-0.015777	2.068910	0.000000
2	-0.008337	0.272856	0.403721	0.023638	0.147695
3	-0.140539	0.192229	-0.184996	0.102420	-0.132091
4	0.021285	0.097568	-0.057948	0.462354	-0.042807
5	-0.048327	0.005389	0.186326	-0.080777	0.121296
6	-0.028244	-0.001424	-0.082419	0.032904	0.011104
7	0.013846	-0.016503	-0.012461	0.089716	-0.041512
8	-0.030401	0.029582	0.043681	-0.041649	0.004356
9	-0.016751	0.019968	-0.018206	0.016430	0.021354
10	-0.002956	-0.012406	0.003156	0.016128	0.012495

Source: Computed by Author (2023)

Although shocks from under five mortality had a consistently negative impact on electricity consumption over the ten year period, and shocks from GDP growth did not maintain a steady increasing effect on electricity consumption, a one standard deviation shock in CO_2 emission had a majorly positive impact on electricity consumption. This implies that as the emission levels increase and have become a global concern, more environmental hazards enlightenment efforts begin to take place causing households to consider transition to clean energy such as electricity. However, the positive impact of CO_2 emission on electricity consumption was marginal.

A one standard deviation shock in the under five mortality rate had an initial positive impact on fossil fuel consumption but it declined by the second and third years. Further fluctuations continued until the eighth year when a steady negative impact was sustained. Fossil fuel is a major source of energy in SSA and many households may not substantially reduce their consumption unless other clean energy forms are made more available and affordable. It is therefore not surprising that the results show minimal responses to child health shocks.

4.6 Relationship between Life Expectancy at Birth and Energy Consumption

Inorder to ensure robustness as well as conduct a sensitivity analysis, we employed a second measure for population health, which captures both child and adult health. Conducting a block exogeneity wald test or a granger causality test after estimating a panel VAR model, we examined the causal relationship between life expectancy and energy consumption using both total energy consumption and decomposed energy consumption (electricity and fossil fuel consumption). The optimal lag applied in the VAR model estimation was 4 based on the Akaike information criterion.

4.6.1 Granger Causality Test

The granger causality test results presented in Table 20 showed that there was no causal relationship between life expectancy and total energy consumption. Thus the neutrality hypothesis was upheld. This is contrary to Youssef *et al.* (2015) that found a unidirectional causality from energy consumption to life expectancy at birth for some countries out of 16 African countries considered.

Table 20 VAR Granger Causality/Block Exogeneity Wald Tests Using Total Energy Consumption

Dependent variable: LEB		
Excluded	Chi-sq	Prob.
GRGDPPC	7.683462	0.1039
LOG(ENC)	4.368664	0.3584
LOG(CO_2)	4.081216	0.3951
All	14.47677	0.2713

Source: Computed by Author (2023)

Table 21 VAR Granger Causality/Block Exogeneity Wald Tests Using Decomposed Energy Consumption

Dependent variable: LEB		
Excluded	Chi-sq	Prob.
GRGDPPC	7.825346	0.0982
LOG(ELEC)	0.557015	0.9677
FOSSIL	2.920977	0.5711
LOG(CO_2)	3.688622	0.4498
All	13.48470	0.6370
Dependent variable: GRGDPPC		
Excluded	Chi-sq	Prob.
LEB	9.089330	0.0589
LOG(ELEC)	6.021071	0.1976
FOSSIL	2.301950	0.6804
LOG(CO_2)	3.642268	0.4566
All	26.49254	0.0475
Dependent variable: LOG(ELEC		
Excluded	Chi-sq	Prob.
LEB	2.742573	0.6018
GRGDPPC	3.771842	0.4378
FOSSIL	1.030674	0.9051
LOG(CO_2)	2.088486	0.7195
All	10.28283	0.8514
Dependent variable: FOSSIL		
Excluded	Chi-sq	Prob.
LEB	6.139356	0.1890
GRGDPPC	8.391539	0.0782
LOG(ELEC)	14.15272	0.0068
LOG(CO_2)	5.780172	0.2162
All	38.92594	0.0011
Dependent variable: LOG(CO_2)		
Excluded	Chi-sq	Prob.
LEB	6.031248	0.1968
GRGDPPC	7.167118	0.1273
LOG(ELEC)	5.317854	0.2562
FOSSIL	15.12116	0.0045
All	37.87346	0.0016

Source: Computed by Author (2023)

The results of this study also showed that there was also no granger causality amongst other variables when total energy consumption was used. However, when energy consumption was decomposed into electricity consumption and fossil fuel consumption, the results (in Table 21) showed that although electricity consumption and fossil fuel consumption did not granger cause life expectancy, life expectancy significantly granger caused fossil fuel consumption jointly with other variables including GDP growth, electricity consumption and CO_2 emission. Thus, as people begin to experience reduction in longevity they may begin to evaluate their energy consumption decisions that are environmentally unfriendly and reduce the use of fossil fuel. This is however possible when clear efforts and incentives towards achieving reductions in CO_2 emission are made and when the GDP growth is such that economically empowers households to afford clean energy sources including the use of more electricity. Thus, there was no granger causality between life expectancy and electricity consumption showing that the neutrality hypothesis holds in this case. However, there was a unidirectional causality running from life expectancy to fossil fuel consumption based on a joint significance. This is similar to Youssef *et al.* (2015) that found a unidirectional causality from life expectancy to energy consumption for Mozambique. However, the study did not decompose energy consumption.
Electricity consumption had an individual significant causal effect on fossil fuel consumption but not vice versa. Hence there was a unidirectional causality running from electricity use to fossil fuel use. This implies that as individuals increase their use of electricity, their demand for fossil fuel will consequently decline. However, if they have to generate their electricity using fossil fuel sources (for example, using a generator powered by petrol motor spirit), their demand for fossil fuel will also increase.

Life expectancy also did not have an individual significant causal effect on CO_2 emission but it had a joint significant causality on CO_2 emission together with GDP growth, electricity consumption and fossil fuel consumption. Therefore, just as we see in the fossil fuel case above, life expectancy significantly caused changes in CO_2 emission levels only when GDP growth, electricity consumption and fossil fuel consumption were controlled for. There was a significant unidirectional causality running from fossil fuel consumption to CO_2 emission. A similar finding was obtained by Al-Mulali *et al.* (2015) that found fossil fuel energy consumption to increase CO_2 emission in Vietnam. A continuous increase in the combustion of fossil fuel when carrying out consumption and production activities significantly contribute to increasing the amount of CO_2 emission in the environment.
The post estimation tests showed the absence of serial correlation at the second, fourth and fifth lags. The null hypothesis of normality was however rejected.

4.6.2 Variance Decomposition Analysis

Examining the contribution of each variable to changes in other variables, the variance decomposition analysis of each variable was conducted. The results presented in Tables 22, 23 and 24 showed that 100 percent of its own shock explained changes in life expectancy in the first year but by the tenth year, own shocks had declined to 98.13 percent.

Table 22 Variance Decomposition of Life Expectancy at Birth

Period	SE	LEB	GRGDPPC	LOG(ELEC)	FOSSIL	D(LOG(CO_2)
1	0.011439	100.0000	0.000000	0.000000	0.000000	0.000000
2	0.038624	99.93851	0.055138	0.000620	0.004334	0.001403
3	0.082088	99.86306	0.131639	0.001304	0.003187	0.000807
4	0.138387	99.71306	0.276802	0.004152	0.001947	0.004040
5	0.201891	99.49264	0.465208	0.008962	0.013166	0.020028

6	0.266495	99.23236	0.653728	0.016241	0.039816	0.057853
7	0.327024	98.95016	0.824894	0.026458	0.080467	0.118018
8	0.379899	98.66668	0.964792	0.040305	0.131528	0.196690
9	0.423297	98.39166	1.072857	0.057761	0.189546	0.288172
10	0.456867	98.12994	1.154221	0.077883	0.251406	0.386553

Source: Computed by Author (2023)

Table 23 Variance Decomposition of Electricity Consumption

Period	SE	LEB	GRGDPPC	LOG(ELEC)	FOSSIL	D(LOG(CO_2)
1	0.099574	0.365602	1.205129	98.42927	0.000000	0.000000
2	0.100021	0.581521	1.221735	98.12434	0.021205	0.051204
3	0.101134	0.569606	2.017453	97.29722	0.062374	0.053352
4	0.101442	0.566156	2.095977	96.90821	0.092999	0.336659
5	0.101852	0.563067	2.292060	96.42732	0.234251	0.483298
6	0.101897	0.564565	2.301641	96.39295	0.245295	0.495553
7	0.101920	0.571544	2.301493	96.35040	0.251464	0.525100
8	0.101939	0.594797	2.312419	96.31572	0.251771	0.525296
9	0.101981	0.655547	2.312007	96.23703	0.254353	0.541062
10	0.102031	0.747803	2.309882	96.14348	0.254110	0.544725

Source: Computed by Author (2023)

Table 24 Variance Decomposition of FOSSIL

Period	SE	LEB	GRGDPPC	LOG(ELEC)	FOSSIL	D(LOG(CO_2)
1	2.071865	0.423337	1.959870	0.023901	97.59289	0.000000
2	2.130130	0.429503	3.603079	3.191933	92.33528	0.440203
3	2.152802	0.420746	4.227459	3.998808	90.51155	0.841438
4	2.200499	0.406683	4.190212	3.959238	90.59329	0.850574
5	2.212249	0.411648	4.147797	4.466429	89.83435	1.139774
6	2.214235	0.410983	4.141949	4.625280	89.68395	1.137841
7	2.216389	0.411278	4.135554	4.631603	89.63431	1.187258
8	2.217143	0.411861	4.140117	4.655219	89.60617	1.186637
9	2.217599	0.426780	4.145982	4.660096	89.57549	1.191652
10	2.218448	0.492110	4.147937	4.656584	89.51160	1.191766

Source: Computed by Author (2023)

The results on Table 22 show that a zero percent of forecast error variance in both electricity consumption and fossil fuel consumption explained life expectancy in the first year but it increased to 0.078 and 0.251 respectively by the tenth year. Thus, innovations in fossil fuel consumption explained greater variations in life expectancy than innovations in electricity consumption. This is not surprising as it is common to find more households and firms consuming fossil fuel than electricity. Even when electricity is produced, it is based on fossil fuel combustion for example, using petrol or diesel in a generator. Life expectancy variations was also explained by variance in the forecast error of CO_2 emission which increased from zero percent in the first year to 0.387 in the tenth year. We can see that CO_2 emission had the greatest contribution to changes in life expectancy at birth over the ten year period apart from its own shock.

Table 23 shows that GDP growth had the greatest contribution to changes in electricity consumption with a forecast error variance of 1.205 in the first year increasing over the ten year period to 2.312. This shows the importance of household income in determining their ability to consume electricity and the quantity consumed. The forecast error variance in electricity consumption had the greatest contribution to changes in fossil fuel consumption with a forecast error variance of 0.024 explaining variations in fossil fuel consumption in the first year and increasing to 4.656 by the tenth year as shown in Table 24. Therefore as more individuals move to the use of electricity, less of fossil fuel would be consumed. The next variable with a high forecast error variance that explained fossil fuel consumption was GDP growth increasing from 1.960 to 4.148 over the ten year period. Life expectancy had the lowest contribution to changes in fossil fuel use. This shows that individuals, households and firms pay less attention to health considerations when demanding for fossil fuel.

4.6.3 Impulse Response Function

A one standard deviation shock in electricity consumption had zero impact on life expectancy in the first year but by the tenth year it had increased to 0.008 maintaining a positive impact over the ten year period as shown in Table 25. On the other hand, fossil fuel consumption shocks had a negative impact on life expectancy over the ten year period declining from zero percent in the first year to -0.014 by the tenth year. Thus we see a negative response of life expectancy to fossil fuel shocks while a positive response was found for electricity use. This emphasizes the need for energy transition from fossil fuel use to cleaner energy sources such as electricity.

Table 25 Response of Life Expectancy at Birth

Period	LEB	GRGDPPC	LOG(ELEC)	FOSSIL	D(LOG(CO_2))
1	0.011439	0.000000	0.000000	0.000000	0.000000
2	0.036879	-0.000907	9.62E-05	0.000254	0.000145
3	0.072376	-0.002837	0.000280	0.000387	0.000183
4	0.111206	-0.006644	0.000841	-0.000398	0.000848
5	0.146483	-0.011688	0.001690	-0.002235	0.002718
6	0.172978	-0.016573	0.002807	-0.004787	0.005738
7	0.188009	-0.020443	0.004094	-0.007601	0.009226
8	0.191250	-0.022588	0.005466	-0.010187	0.012556
9	0.184118	-0.023020	0.006732	-0.012239	0.015247
10	0.168897	-0.022064	0.007686	-0.013606	0.017044

Source: Computed by Author (2023)

Table 26 Response of Electricity Consumption

Period	LEB	GRGDPPC	LOG(ELEC)	FOSSIL	D(LOG(CO_2))
1	-0.006021	0.010931	0.098789	0.000000	0.000000
2	0.004683	-0.001654	0.007574	0.001457	0.002263
3	-0.000288	0.009172	0.011622	-0.002064	-0.000578
4	1.81E-06	0.003056	0.004540	-0.001786	0.005402
5	-0.000389	0.004700	0.005555	0.003838	0.003936
6	0.000456	-0.001099	0.002316	-0.001081	0.001148
7	0.000867	-0.000303	0.000244	-0.000808	-0.001759
8	0.001561	0.001106	0.000195	0.000203	0.000201
9	0.002524	-0.000398	0.000460	-0.000539	0.001298
10	0.003110	-0.000113	4.97E-05	-2.11E-05	0.000660

Source: Computed by Author (2023)

Table 27 Response of FOSSIL

Period	LEB	GRGDPPC	LOG(ELEC)	FOSSIL	D(LOG(CO_2))
1	0.134805	0.290052	-0.032031	2.046777	0.000000
2	-0.036280	0.281706	0.379218	-0.019362	0.141329
3	-0.003348	0.180100	-0.201233	0.071683	-0.137924
4	0.013882	0.083512	-0.079919	0.438058	-0.046792
5	-0.021303	-0.009838	0.163936	-0.099144	0.120808
6	-0.001896	-0.008823	-0.090447	0.022833	-0.002319
7	-0.007331	-0.009011	-0.027424	0.078243	-0.050361
8	-0.006510	0.019038	0.036272	-0.040136	0.003016
9	0.027240	0.019295	-0.018280	0.017512	0.016453
10	0.056845	-0.015883	-0.001597	0.015085	0.007104

Source: Computed by Author (2023)

A one standard deviation shock in life expectancy had a negative impact on electricity consumption in the first year and despite some fluctuations, it maintained a positive impact from the sixth to the tenth year as shown in Table 26. A one standard deviation shock in CO_2 emission had positive impact on electricity consumption for most of the periods during the ten years. This implies that the growing environmental degradation due to CO_2 emission actually stimulated an increase in the use of more of electricity. This is because people may have become more aware of the negative consequences of exposure to CO_2. Table 27 shows that fossil fuel consumption had both positive and negative responses to shocks from life expectancy and CO2 emission showing that little attention is being paid to the need to reduce fossil fuel use because of health considerations and environmental hazards.

5. CONCLUSION AND POLICY RECOMMENDATIONS

The population of a country is a critical resource for development, however, poor population health is a challenge in SSA. An economically active population must make economic decisions concerning energy use but there should be caution as to what implications these decisions would have on the environment and health. This study examined the relationship between energy consumption, CO_2 emission and population health in SSA. The study considered 13 SSA countries for the period 1980 to 2014 based on data availability. Two health measures including under five mortality rate and life expectancy at birth were employed. The study made use of total energy consumption and also decomposed it into electricity consumption and fossil fuel consumption. The study employed the panel VAR approach. A granger causality test was conducted after estimating a VAR model. The study also employed the variance decomposition analysis and the impulse response function to examine the dynamic interactions among the variables and the effect of shocks.

The findings revealed that the neutrality hypothesis holds between under five mortality and total energy consumption since they had no causal relationship. Decomposing energy into electricity and fossil fuel, the neutrality hypothesis was also confirmed between under five mortality and fossil fuel consumption.

However, the study found a unidirectional causality running from under five mortality to electricity consumption. This implies that as child deaths increase, households begin to see the need to transit to clean energy use such as electricity. Therefore, the study recommends that health considerations should be emphasized when determining energy policies and transition strategies.

The study also found that although there was no granger causality between life expectancy and total energy consumption, the causality between them became significant when energy consumption was decomposed. There was no granger causality between life expectancy and electricity consumption showing that the neutrality hypothesis holds in this case.
However, there was a unidirectional causality running from life expectancy to fossil fuel consumption based on a joint significance. This implies that as individuals live longer, the level of fossil fuel consumption would also increase due to their economic activities. Therefore policies towards improving population health should also target strategies that help reduce fossil fuel consumption such as organizing greater public health awareness programmes.

Fossil fuel consumption shocks had a negative impact on life expectancy over the ten year period. Thus, policies geared towards improving life expectancy should target a reduction in fossil fuel demand.

Findings from the variance decomposition analysis showed that the forecast error variance in electricity consumption had the greatest contribution to changes in fossil fuel consumption. Thus policies towards reducing fossil fuel consumption should seek to implement empowerment strategies and incentives that encourage a substantial transition to electricity consumption. Such strategies should also discourage the production of electricity using fossil fuel inorder not to defeat the purpose of increasing electricity consumption.

Fossil fuel consumption had the greatest contribution to variations in CO_2 emission levels just as expected, followed by the forecast error variance in GDP growth. This study therefore recommends that policy strategies towards CO_2 emission reduction should focus on developing transition strategies from fossil fuel to the use of cleaner energy sources.

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