Effect of Energy Consumption on Health Outcome in Nigeria and South Africa: The ARDL Bound Testing Approach

Uche Abamba OSAKEDE[1] and Gbenga Peter SANUSI[2]

[1] Bowen University, P.M.B. 284, Iwo Osun State, Nigeria

Email: uche.osakede@bowenuniversity.edu.ng; ucheabamba@gmail.com

[2]Anchor University, Lagos, Nigeria

Email:gsanusi@aul.edu.ng; petersbanks1@gmail.com

Abstract

This paper examines the effect of fossil fuel and electricity consumption on life expectancy and infant mortality in Nigeria and South Africa. Both countries are leading economies in the sub-Saharan Africa (SSA) region with large differences in the amounts of energy consumed and health outcome measures. The aim is to determine whether the energy type consumed has contributed to the existing gap in health outcome given its role on developmental indices. The Autoregressive Distributed Lag (ARDL) model with data from the World Development Indicators (WDI) was employed. Findings from the study showed negative effects of fossil fuel use on life expectancy and infant mortality rates for both countries. The effect of fossil fuel use on life expectancy is only noticeable in the short run. In Nigeria, negative effect of fossil fuel consumption on infant deaths is observed both in the short and long run with indications of stronger long run effects. Findings for South Africa, however,

[1]Corresponding author.

showed negative effect of fossil fuel consumption on infant deaths only in the short run with higher magnitude than short run effects in Nigeria. Negative effects of electricity consumption on health outcome was observed in both countries, but in South Africa the effect was only in the short run. This could be due to health hazards associated with the mining of coal from which electricity is produced in South Africa. In particular, there are evidences of water and air pollution associated with coal mining that can be detrimental to health status. Policy actions geared towards improvements in health outcome in Nigeria and South Africa should consider measures that discourage the use of fossil fuel for electricity generation.

Key words: Electricity Consumption; Fossil fuel, Health Outcome; ARDL model.

Introduction

General consideration of energy use, particularly electricity, portrays some vital benefits such as welfare improvements, comfort and ease of economic activities for individuals. Other benefits are noticeable in the attraction and retaining of skilled workers, particularly in the health sector, fast emergency response, refrigeration for blood and vaccines, sterilization facilities, quicker and accurate diagnosis and comfortable environment for health care delivery (WHO, 2015). This suggests that electricity use enhances health status as well as smoothens economic progress. The effect is shown to be more pronounced on reduction in infant mortality (Gohike et al., 2011). However, when energy consumption results in emission of toxic substances such as carbon monoxide and particulate matter, adverse effect on health status results (Duflo et al., 2008; Lelieveld et al., 2015). The emission of toxic substances from fossil fuel use, for instance, induces a rise in premature mortality (Lelieveld et al., 2015). It has been observed that fossil fuel use emits toxic substances that bring about a reduction in birth weight and increase the risk of still births (Amegah, 2014). Besides the harmful effect of fossil fuel use on infant health, negative impacts on life expectancy have also been observed (Yeh, 2004). These suggest that variation in energy type consumed could account for differences in health status across boundaries.

Not many studies have explored this relationship, particularly for sub-Saharan Africa (SSA) where health indices are low compared to global estimates (WHO, 2004; Gohike et al., 2011; World Bank, 2013). Thus, this study adds to knowledge by determining whether energy type consumed accounts for existing differences in health status, using Nigeria and South Africa as case study. Both countries are leading economies in the SSA region with a wide gap in health indices and energy use, particularly electricity and fossil fuel. The intent is to determine whether existing variations in health indices for these countries can be explained by current differences in the type and amount of energy consumed.

Trend Comparison of Energy Use and Health Status in Nigeria and South Africa

Electricity consumption is generally lower in Nigeria compared to South Africa. Figure 1 shows the distribution of electricity consumption in both countries in kilowatt consumption per capita (KW/cap) for the years 1970 to 2011.

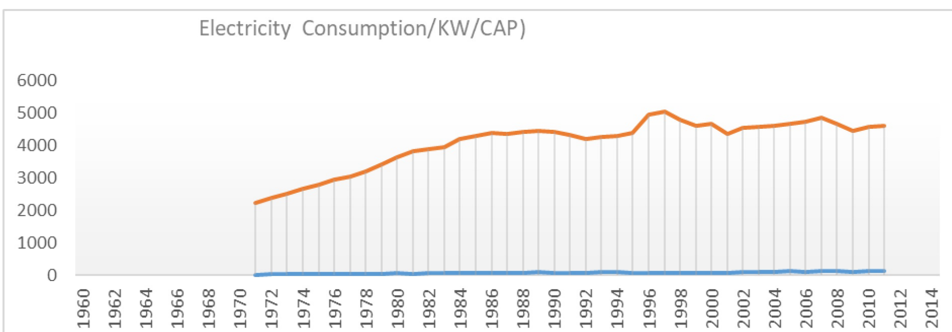

Figure 1: Electricity consumption in Nigeria and South Africa (Top Line representing South Africa, lower line Nigeria).

Source: Authors' computation from WDI, (2015).

The total amount of electricity consumed in Nigeria was near zero in 1972. The trend remained low with slight increase from 1974. The statistics for electricity consumption was however far less than 200 KW/cap in Nigeria, even as at 2011. In South Africa, total amount of electricity consumed was over 2,000 KW/cap from 1972 and rose substantially to over 4,000 KW/cap in 2011. Comparing the amounts of electricity produced in Nigeria to South Africa for the period 1971 to 2011, it can be observed that

South Africa had a steady rise in electricity consumption over time. The statistics denote low production and consumption of electricity in Nigeria relative to South Africa.

In Nigeria, electricity production is mainly from hydropower, fossil (gas) and thermal power sources and was initially the sole prerogative of the government. The production of electricity in Nigeria began with the establishment of the Nigerian Electric Supply Company (NESCO) in 1929. NESCO was taken over by the Electric Corporation of Nigeria (ECN) in 1951. The ECN and Nigeria Dam Authority were merged to form the National Electric Power Authority (NEPA) in 1972. These initiatives were unarguably meant to address insufficient power supply in the country and enable better management of power generation and distribution (Usman and Abbasoglu, 2014). Regardless of these attempts, power shortages persisted. Low electricity generation is mainly attributed to under-capacity production of installed power plants, especially for government-owned power plants. The lack of maintenance, existing neglect and underfunding by government are major causes of under-capacity production and low output of electricity in Nigeria (Nkiruka, 2011; Aliyu et al. 2013). Reforms instituted by government to increase power distribution informed the commercialization of power in 1988 and thereafter the creation of the independent Power Holding Company of Nigeria (PHCN) in 2004. In spite of these reforms, the amount of electricity output remain generally low. (Usman and Abbasoglu, 2014).

In South Africa on the other hand, electricity is mainly generated from indigenous production of coal. More than 90% of electricity generation in South Africa is obtained from coal (Fisher and Downes, 2016). The South African economy is listed among the top ten global producers of coal. Concentration of hard coal in South Africa is still high with estimated reserve deposits of about 66.7 billion tons as at 2014 (Department of Mineral Resources (DMR), 2015). The huge coal deposit in the country informs electricity generation using this natural resource.

Fossil fuel consumption is higher in Nigerian relative to South Africa. The comparison of fossil fuel use between Nigeria and South Africa is shown in figure 2.

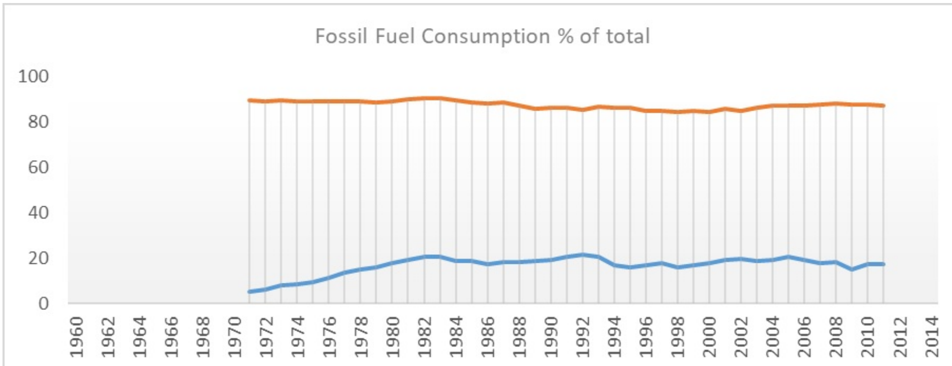

Figure 2: Fossil fuel consumption in Nigeria and South Africa (Top Line representing Nigeria, lower line South Africa).

Source: Authors' computation from WDI, 2015.

Considering the period 1971 to 2011, fossil fuel consumption in Nigeria was higher than that of South Africa. This contrast with South Africa shows a huge margin of more than 50% difference. Fossil fuel exists in different forms such as coal, crude oil and natural gas. They are used as energy sources for transportation, electricity, and sometimes for cooking and other manufacturing activities. In Africa, Nigeria is one of the leading producers of oil and has the largest natural gas reserves on the continent. It was the world's fourth leading exporter of liquefied natural gas (LNG) as at 2012 (Usman and Abbasoglu, 2014). This endowment likely accounts for the huge consumption of fossil fuel in Nigeria relative to South Africa. Extraction processes of fossil fuel can generate air and water pollution which are hazardous to public health and the environment.

In terms of health indices, the figures for Nigeria are shown to be lower relative to South Africa. Differences in health status measured using life expectancy and mortality rates reflect poor public health status in the former relative to the latter. The trend of life expectancy and infant mortality for instance show poorer figures for Nigeria relative to South Africa. Figure 3 shows the trend of life expectancy for both countries.

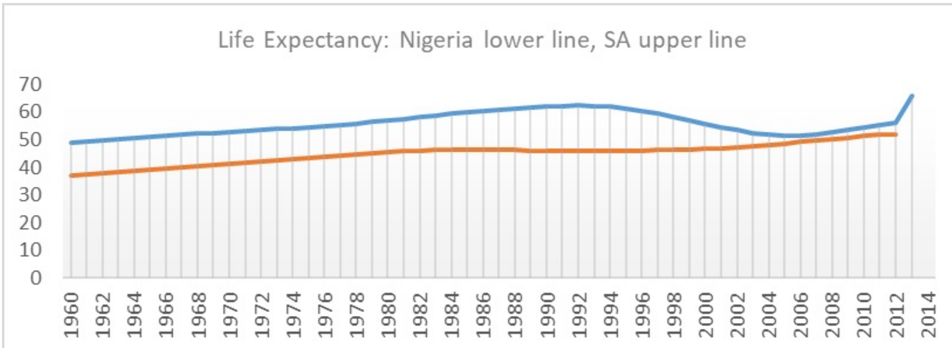

Figure 3: Life Expectancy at birth: Nigeria and South Africa for the periods 1960-2013.

Source: Authors' computation from WDI, (2015).

In figure 3, the trend for life expectancy in Nigeria is below that of South Africa all through the period 1960 to 2014. Life expectancy in Nigeria over the period remained less than 50 years on average. On the contrary, South Africa's life expectancy had not dropped below 50 years since 1962. In terms of health status measured using infant mortality/1000 live births, again, the figures are remarkably higher in Nigeria relative to South Africa. Graphical illustration for infant mortality rates in both countries are shown in figure 4.

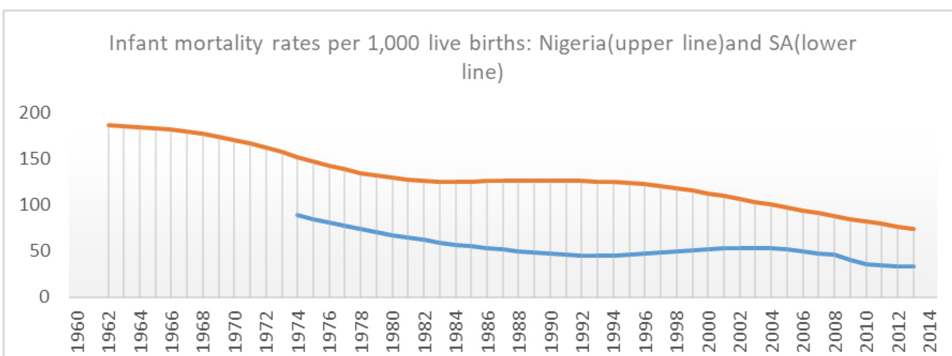

Figure 4: Infant mortality rates: Nigeria and South Africa, for the periods 1962-2013.

Source: Authors' computation from WDI, (2015).

Figures for infant mortality/1000 live births were more than a 100 times higher in Nigeria than South Africa, specifically in 1974. Although both countries had appreciable drop in infant mortality over time, differences remain significantly high. In 2014, the infant mortality rate in Nigeria was estimated at about 74/1000 live births while the estimate for South Africa was about 33/1000 live births. The difference in health indicators between both countries projects South Africa with better public health indices than Nigeria.

Literature Evidence

Studies examining the impact of energy use on health have focused mainly on pollution effects and how they affect health status. For example, in India and China, it has been shown that emissions from the use of solid fuel and traditional cooking stoves constitute indoor air pollution (IAP) and promote premature mortality (Lelieveld et al., 2015). Estimates from WHO (2002) showed that IAP is responsible for about 2.7% of the loss of disability adjusted life years (DALYs) worldwide and 3.7% in high-mortality developing countries.

Energy use, from sources such as power generating plants and cars (outdoor pollution), is also problematic for health status. In developed economies, pollution from power generating plants and cars are highest and contain huge amounts of particulate matter ($PM_{2.5}$). Estimates of global premature deaths associated with $PM_{2.5}$ are as high as approximately 3.3 million per year (Duflo et al., 2008).

Exposure to air pollution commonly from energy consumption can lead to a rise in the burden of illness, especially for non-communicable diseases. Health problems such as cardiopulmonary illnesses, lung cancer and asthma have been noted as common in areas with air pollution, ozone and nitrogen (Pope et al. 2009; Shah et al. 2013; Giles and Koehle 2014; Chatzidiakou et al. 2014; Li et al. 2015). Sow (2006) showed that particulate matter specifically increases infant mortality in the United States. There are also indications of detrimental effects of particulate matter and nitrogen oxides on birth weight and gestation. Similarly, a study by Amegah (2014) showed that household combustion of solid fuels emits toxic chemicals that have adverse effects on pregnancy outcomes, such as reduction in birth weight and increase in the risk of still births.

An earlier study by Yeh (2004), using country case studies from OECD countries, showed that energy consumption, specifically from biomass fuel, impairs health status by increasing infant mortality rates and reducing life expectancy. Findings are indicative of a fall in child mortality rate by about 7 deaths per 1,000 live births with a 10 percentage point decrease in the share of energy consumption from biomass fuel. Where there is a rise in bio-mass fuel consumption by the same amount, life expectancy will fall by as much as about 8.7 years with larger effects on males than females.

Further findings on adverse effects of energy consumption on health status are shown by Rahut et al. (2017). Using a propensity score-matching approach, the findings indicate that households using dirty fuels, particularly fuelwood, charcoal, cow dung and kerosene, have a higher incidence of respiratory disease. Such households also stand higher chances of contracting tuberculosis.

In examining the effect of energy consumption on health status, Gohike et al. (2011) took a different approach by categorizing countries as low, middle and high infant mortality and life expectancy using 1965 values of health status as benchmark figures. Findings from Gohike et al. (2011) support the argument of significant positive effects of electricity consumption on health status particularly for infant mortality. This result was obtained only for countries with poor health status; high infant mortality and low life expectancy. Countries with mid- infant mortality and life expectancy also showed significant positive effects of electricity consumption on health status. Electricity consumption was shown to have no significant effect on health conditions of countries with existing high health indices. On the other hand, an increase in coal consumption raised infant mortality both for countries with low and high health status.

In a more recent study, Youssef et al. (2016) provide findings for the effect of electricity consumption on health, specifically for African countries. Findings showed negative unidirectional causality from electricity consumption to life expectancy for South Africa, Nigeria, Ghana, Morocco, and Egypt. This result is seemingly not conventional given that electricity generation should ordinarily improve health.

Apart from the health effects of air pollution from energy use, there are observed impacts on economic activities such as labour supply and productivity. The identified pathway of pollution to labour supply and productivity follows mainly from workers absence due to ill health. While salaried workers are still considered as employed and receive income, persons who are self-employed may not be able to get income from employment when suffering from air pollution-related illnesses. In Mexico, Hanna and Olivia (2015) showed that work hours dropped by about 0.61% with an approximate 1% rise in air pollution basically from sulphur-related substances. Another study by Graff and Neidell (2012), showed that a 10 parts per billion (ppb) decrease in ozone concentrations increases worker productivity by 5.5 percent in California. This finding is indicative of an extension of health effects of energy consumption from unclean sources on the economic well-being of the populace. In view of this, an assessment of the effect of energy consumption on health status is imperative and vital in any economic developmental processes.

Methodology

This study adopted the Auto Distributed Lag (ARDL) model specification in the analysis of health impact of energy use. The ARDL model is adopted in this study following several advantages, one of which is its appropriateness where there is insufficient data for most of the explanatory variables (Levine et al. 2001; Antunes and Waldman 2002; El-Zein et al. 2004; Kale et al. 2004; Kovats et al. 2004). Given the sample period of the study (1960 to 2014), some of the variables do not have data for some of the time periods, making the ARDL model a preferred choice. The model efficiently determines the co-integrating relation even in small sample cases (Ghatak and Siddiki, 2001; Tang, 2003). It is also preferred for scientific determination of the parsimonious equation from the over-parameterized specification. The time reaction of variables may be dissimilar, an indication of non-uniform optimal lags for different variables. Such instances of diverse number of optimal lags for different variables are permitted by the ARDL model. In addition, it does not necessarily require a restrictive assumption that all variables should be integrated of the same order. It can be applied irrespective of whether the regressors are integrated of order 1 that is I (1) or order zero I(0) or even mutually co-integrated. It is however necessary that the integration order of the variables is at most 1 (Pesaran et al. 2001; Acaravci and Ozturk, 2012; Orhunbilge, 2014). If the nature of the stationarity of the data is unclear, then the use of the ARDL bounds test is appropriate (Pesaran et al. 2001; Fuinhas and Marques, 2012; Hoque and Yusop, 2010).

The variables used in this study are similar to those by Gohike et al. (2011). Rather than compare countries based on low, middle and high infant mortality and/or low life expectancy, this study simply considered one country with low health status –Nigeria and one country with high health status – South Africa (Gohike et al. 2011). The study slightly adjusts the model used by Gohike by introducing gross domestic product (GDP) per capita to fossil fuel use and electricity generation. The inclusion of GDP is to further determine whether income variation in both countries contribute to differences in health status. The ARDL model follows an ordinary least squares (OLS) estimation technique and hence must satisfy critical assumptions of the OLS for best linear unbiased estimated results. We therefore checked for assumptions of normality, homoscadasticity, linearity and serial dependence (Gujarati, 2004).

The study considers the effect of energy consumption basically on life expectancy at birth and infant mortality as measures of health status. Both measures of health are used mainly because long-term improvements in the health status of a population are best reflected in infant mortality and life expectancy rates (Gupta and Mitra, 2004). In addition, improvements in health are commonly deciphered in longer years of life and fall in infant death.

According to Pesaran and Pesaran (1997) and Pesaran et al. (2001)[2] the ARDL model specification is given as:

$$\emptyset(L,p)y_t = c_0 + \sum_{i=1}^{k} \beta_i (L,q_i)x_{it} + \delta w_t + u_t; t = 1, \ldots, n \qquad (1)$$

where, y_t is the dependent variable, c_0 is the constant term, x_{it} are the independent variables, L is the lag operator, and w_t is the s x 1 vector of deterministic variables including intercept terms, dummy variables, time trends and other exogenous variables with fixed lags.

[2] Cited in Hoque and Yusop, 2010, Nkoro and Uko, 2016

Using the variables of interest in this study, let HE_t be health status measured using average life expectancy at birth at time *t*, HE_t be infant mortality per 1,000 live births, E_t be electricity consumption (in kw/cap) at time *t*, and F_t be fossil fuel consumption (% of total) at time *t*. The general form of the model specification used in the study is stated as:

$$LnHE_t = \beta_0 + \beta_1 t + \beta_2 LnE_t + \beta_3 LnF_t + \beta_4 LnGDP_t + \in_t \quad (2)$$

$$LnHI_t = \emptyset_0 + \emptyset_1 t + \emptyset_2 LnLE_t + \emptyset_3 LnLF_t + \emptyset_4 LnGDP_t + \cup_t \quad (3)$$

where β_0 and $\emptyset_0$ are the intercepts, *t* the trends, *Ln* is the natural logarithm, $\in_t$ and $\cup_t$ are the disturbance terms assuming white noise and normal distribution.

The natural logarithm specification enables interpretation of findings as percentages or elasticities of the variables by their associated coefficients. Equations 2 and 3 can be converted into an unrestricted ARDL form as;

$$\Delta LnHE_t = \beta_0 + \beta_1 t + \sum_{i=1}^{p-1} \beta_{2i} \Delta LnHE_{t-i} + \sum_{i=0}^{p-1} \beta_{3i} \Delta LnE_{t-i} + \sum_{i=0}^{p-1} \beta_{4i} \Delta LnF_{t-i} + \sum_{i=0}^{p-1} \beta_{5i} LnGDP_{t-i} + \beta_6 LnE_t + \beta_7 LnF_t + \beta_8 LnGDP_t + \omega_t LnHI \quad (4)$$

$$\Delta LnHI_t = \emptyset_0 + \emptyset_1 t + \sum_{i=1}^{p-1} \emptyset_{2i} \Delta LnHI_{t-i} + \sum_{i=0}^{p-1} \emptyset_{3i} \Delta LnE_{t-i} + \sum_{i=0}^{p-1} \emptyset_{4i} \Delta LnF_{t-i} + \sum_{i=0}^{p-1} \emptyset_{5i} LnGDP_{t-i} + \emptyset_6 LnE_t + \emptyset_7 LnF_t + \emptyset_8 LnGDP_t + \sigma_t \quad (5)$$

where: Δ denotes the first difference operator and p is the maximum lag length. The parameters β_2 to β_5 and $\emptyset_2$ to $\emptyset_5$ explain the short run dynamic coefficients, while β_6 to β_8 and $\emptyset_6$ to $\emptyset_8$ explain the long run multipliers of the equation when there is co-integration. With no co-integration, only the short run parameters of the variables are shown with the difference operator.

The existence of a co-integrating relationship indicates that the nexus between health status and the predictor variables is stable over the sample period and hence in such instance, results reported are for both the short and long run.

The expected signs of the parameters in equation 4 are:

$\beta_0 \neq 0; \beta_1 \neq 0; \beta_{2i} \neq 0; \beta_{3i} > 0; \beta_{4i} < 0; \beta_{5i} > 0;$

and in equation 5:

$\emptyset_0 \neq 0; \emptyset_1 \neq 0; \emptyset_{2i} \neq 0; \emptyset_{3i} < 0; \emptyset_{4i} > 0; \emptyset_{5i} < 0; \emptyset_{6i} < 0; \emptyset_{7i} > 0; \emptyset_{8i} < 0$

Equations 4 and 5 are estimated separately for Nigeria and South Africa. The models are applied to each country's data set for the years 1960-2014.

We begin by observing the statistical properties of the data and stationarity of the series. Two different unit root tests were used to enhance confidence in the results, particularly where such findings help to reinforce each other. Unit root test was examined using the Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP). The choice of these tests is simply based on their wide applicability in the literature, suggesting efficacy and reliability of results (Hoque and Yusop, 2010; Fuinhas and Marques, 2012; Orhunbilge, 2014). After that, the ARDL model was estimated taking into consideration[3] the optimal number of lags that yields the best outcome for statistical significance of variables and passes the diagnostic tests. The diagnostic tests considered are: Jarque-Bera normality test, Breusch-Godfrey serial correlation LM test, ARCH test for heteroscedasticity, and the Ramsey RESET test for model specification. The optimal model was achieved and the bounds test was then carried out to determine the presence of co-integration. Using the computed bounds F-test statistic, it can be concluded that the variables are not co-integrated when the F- statistic falls below the lower bound and hence the short run estimates are presented. When the bounds F-test statistic exceeds the upper bound, it is concluded that there is co-integration requiring use of the long run parameters. The short run can also be presented as well, given evidence of a stable relationship over the sample period. The test is inconclusive when the bounds F-test statistic lies between the bounds. In this case, both the short and long run results can be reported (Hoque and Yusop, 2010; Fuinhas and Marques, 2012; Orhunbilge, 2014).

[3] We did not consider time dummies in the analysis because the study did not involve issues related to structural breaks such as regime shifts.

Results

Empirical findings with analysis of the statistical properties of the data are shown in Table 1 for Nigeria and South Africa.

Table 1: Summary Statistics

		E	F	GDP	HI	HE
Nigeria	Mean	84.13227	16.72022	565.5749	129.5577	45.01204
	Median	85.52059	17.81408	318.2019	125.8000	46.08695
	Maximum	148.9285	21.55328	3005.514	186.4000	52.10902
	Minimum	28.49249	5.489419	92.81187	74.30000	37.18295
	Std. Dev.	29.92316	4.029389	663.8244	30.97828	3.732752
	Observations	41	41	54	52	53
South Africa	Mean	4085.862	87.46222	2883.207	53.61500	55.87768
	Median	4365.490	87.66347	2907.254	50.90000	55.13506
	Maximum	5061.200	90.50629	7830.505	88.80000	66.00000
	Minimum	2246.136	84.24644	423.2720	32.80000	49.03629
	Std. Dev.	760.6967	1.785997	1944.389	13.39450	4.219414
	Observations	41	41	54	40	54

Source: Authors' Computation from WDI (2015).

Overall, the summary statistics show small standard deviation of mean values from sample values except for GDP per capita for both Nigeria and South Africa and electricity consumption for South Africa. The standard deviation values suggest close representation of average figures with values in the overall data set for the respective variables. Following the requirement of applying the ARDL model to variables that are stationary at not more than first difference (I(1)), we proceeded to conduct unit root tests as shown in Table 2. The results are presented as Tables 2A and 2B for Nigeria and South Africa respectively.

In Table 2A, the result for the ADF and Phillips-Perron tests show stationary values for the variables both at level and first difference. Similarly, in Table2B, the results show that the variables used in the study are stationary at level except for fossil fuel that is stationary at first difference.

Table 2A: Unit Root Test Results (Nigeria)

Variable	Augmented Dickey-Fuller (ADF)			Phillip Peron (PP)		
	Constant	Constant and Trend	None	Constant	Constant and Trend	None
Level						
E	-0.069275	-0.380321***	0.038657*	-0.069275	-0.380321***	0.025521
F	-0.162469***	-0.143561**	0.007913	-0.162469***	-0.143561**	0.007913
GDP	0.110739**	0.064167	0.108493***	0.110739**	0.064167	0.108493***
HE	-0.000281	-0.003842***	6.21E-05***	-0.009830	-0.031845	0.006293***
HI	-0.000962	-0.025118***	-0.001199***	-0.003230	-0.020754	-0.016145***
First Difference						
E	-1.346680***	-1.346507***	-1.272619***	-1.346680***	-1.346507***	-1.272619***
F	-0.874362***	-0.980600***	-0.840989***	-0.874362***	-0.980600***	-0.840989***
GDP	-1.010984***	-1.130942***	-0.616430***	-1.010984***	-1.130942***	-0.939687***
HE	-0.011343**	-0.003310	-0.000695	-0.021307	-0.014572	-0.009726
HI	-0.074422***	-0.075520***	-0.017223	-0.030842	-0.031729	-0.003173

Source: Authors' computation (2017).

Note: *** Significant at 1%, ** Significant at 5% and * Significant at 10% level.

Table 2B: Unit Root Test Results (South Africa)

Variable	Augmented Dickey-Fuller (ADF)			Phillips- Perron (PP)		
	Constant	Constant and Trend	None	Constant	Constant and Trend	None
Level						
E	-0.090985***	-0.093169	0.010958*	-0.090985***	-0.093169	0.010958*
F	-0.097953	-0.112570	-0.000726	-0.097953	-0.112570	-0.000726
GDP	0.008031	-0.242902***	0.035590*	-0.002876	0.076443***	0.027893
HE	-0.001817	-1.640654***	0.011785***	-0.033615	-0.048104	0.005548
HI	-0.129255***	-0.062815	-0.005319	-0.072187***	-0.095727***	-0.028993***
First Difference						
E	-0.772703***	-0.897034***	-0.682649***	-0.772703***	-0.897034***	-0.897034***
F	-1.122001***	-1.140470***	-1.116528***	-1.122001***	-1.140470***	-1.116528***
GDP	-0.989582***	-1.033124***	-0.846500***	-0.680476***	-0.688456***	-0.624037***
HE	0.295904	0.545734*	0.345021	0.295904	0.545734*	0.345021
HI	-0.190721***	-1.334850***	-0.138876**	-0.190721***	-0.199054**	-0.138876**

Source: Authors' computation (2017).

Note: *** Significant at 1%, ** Significant at 5% and * Significant at 10% level.

Findings from the unit root test results suggest stationarity of the variables at level and first difference, indicating adaptability to the use of the ARDL model. Results of the ARDL model are shown in Tables 3 and 4 for Nigeria and in Tables 5 and 6 for South Africa.

Estimates for life expectancy in Nigeria are presented in Table 3. Close examination of the diagnostic test results for the model of life expectancy in Nigeria show that the Jarque-Bera statistic indicates normality behaviour of the estimated residuals. The Breusch–Godfrey LM test statistic rejects the null hypothesis for the existence of serial correlation and the ARCH test confirms that the residuals are homoscedastic. The RESET test also shows no misspecification of the model. The bounds test F-statistic suggests inconclusive results for the existence of any co-integrating relationship except at the 10% level of significance. Hence the short and long run results are presented.

Table 3: Estimates of the ARDL model result for Nigeria (equation 4: life expectancy)

Dependent Variable : Life expectancy	
Variable	Coefficient
Short run results	
	2.980153***
D(LnHE (-1))	(0.154673)
	-3.446007***
D(LnHE (-2))	(0.474065)
	2.216447***
D(LnHE (-3))	(0.666853)
	-1.538552**
D(LnHE (-4))	(0.660598)
	1.212861***
D(LnHE (-5))	(0.464863)
	-0.451268***
D(LnHE (-6))	(0.150839)
	-0.000022
D(LnE)	(0.000084)
	-0.000201**
D(LnF)	(0.000101)
	-0.000127*
D(GDP)	(0.000069)

Variable	Coefficient		
Long run results			
LnE	0.185399(0.691541)		
LnF	1.720846(1.370919)		
LnGDP	-0.502494(0.805218)		
Diagnostics			
Normality (Jarque-Bera) H0: Normal	2.660219 [0.264448]		
Serial dependence			
Breusch Godfrey Serial Correlation LM Test H0:No serial correlation	F-statistic : 0.157292 Prob F 1,29 0.6946		
Heteroskedasticity Test: ARCH	F-statistic 0.729742		
H0 Error term is homoscedastic	Prob F 1,38 [0.3983]		
Linearity (Ramsey-reset test)	F-statistic 0.774570		
H0: model is linear	1, 29 [0.3860]		
Bounds Test			
F-statistic	3.395927		
	K=3		
Critical Value Bounds Significance		I0 Bound	I1 Bound
	10%	2.01	3.1
	5%	2.45	3.63
	2.50%	2.87	4.16
	1%	3.42	4.84

Source: Authors' computation (2017).

Notes: Elasticity values reported with standard errors in brackets and P values in bracelets. Estimated method: least squares. *** Significant at 1%, ** Significant at 5% and * Significant at 10% level.

No significant effects of electricity consumption is seen on life expectancy. There are however significant effects of fossil fuel consumption. The effect is observed only in the short run showing an inverse relationship. The result suggests that a 100% rise in fossil fuel use reduces life expectancy by about 0.02%. This finding is suggestive of unhealthy effect of fossil fuel use in Nigeria particularly in the immediate period. The result is expected given that fossil fuel use constitutes some form of air pollution that is detrimental to health status (Amegah 2014). The results are similar to that obtained by earlier studies in the literature (Yeh, 2004; Gohike et al. 2011; Amegah, 2014; Rahut et al. 2017).

The finding for per capita income is indicative that an increase in economic output does not improve health status. This is contrary to a priori expectation that a rise in income would increase health outcome via its impact on welfare. However, where the rise in per capita income follows from increased environmental pollution, health indices will inevitably fall. It is also possible that the increase in income is for a small fraction of the population, reducing expected overall health impacts.

Estimates for the effect of energy consumption on infant mortality in Nigeria are presented in Table 4. Similar to the diagnostic test results in model 4, the results for model 5 in Nigeria show that the Jarque-Bera statistic indicates normality of the estimated residuals. The Breusch-Godfrey LM test statistic shows non-existence of serial correlation and the ARCH test confirms that the residuals are homoscedastic. The RESET test ratifies the correct functional form of the equation. The bounds test F-statistic suggests existence of a co-integrating relationship in the model. Hence we report findings for both the short and long-run specification of the model.

Table 4: Estimates of the ARDL model result for Nigeria (equation 5: Infant Mortality)

Dependent variable: Infant Mortality: Long run results

Variable	Coefficient
Short run	
	0.902676***
D(LnHI (-1))	(0.024818)
	-0.000723
D(LnE)	(0.001146)
	0.003473
D(LnF)	(0.002113)
	-0.004552**
D(LnF(-1))	(0.001846)
	-0.000987
D(LnGDP)	(0.000801)
	-0.000599***
D(@TREND())	(0.000062)
Long run	
	-0.023201
LnE	(0.035484)

Variable	Coefficient		
LnF	0.229463*** (0.058754)		
LnGDP	-0.031696 (0.020393)		
C	4.993624*** (0.229821)		
@TREND	-0.019218*** (0.002351)		
Diagnostics			
Normality (Jarque-Bera) H0: Normal	0.436711 (0.803840)		
Serial dependence			
Breusch Godfrey Serial Correlation LM Test H0:No serial correlation	F-statistic 0.248363 Prob. F(2,28) 0.7818		
Heteroskedasticity Test: ARCH H0 Error term is homoscedastic	F-statistic 2.605131 Prob. F 1,36 0.1153		
Linearity (Ramsey-reset test) H0: model is linear	F-statistic 2.190495 (1, 29) 0.1496		
Bounds Test			
F-statistic	67.95586 K=3		
Critical Value Bounds Significance		I0 Bound	I1 Bound
	10%	3.47	4.45
	5%	4.01	5.07
	2.50%	4.52	5.62
	1%	5.17	6.36

Source: Authors' computation (2017).

Notes: Elasticity values reported with standard errors in brackets and P values in bracelets. Estimated method: least squares. *** Significant at 1%, ** Significant at 5% and * Significant at 10% level.

The elasticities are correctly signed showing a rise in infant mortality with increase in fossil fuel use. This finding is observed both in the short and long run. Increase in output, as expected, reduces infant mortality in Nigeria. Findings do not show any significant effects of electricity use and output on infant mortality. Short run results suggest that a 100% increase in fossil fuel use is associated with about 0.001% rise in infant mortality. Results for the long-run elasticity show higher effect of fossil use on infant mortality. Findings suggest that a 100% rise in fossil fuel consumption induces approximately 22% increase in infant deaths. This finding supports literature arguments of poor health status in relation to fossil fuel consumption and further suggests worse effects over time. The results are similar to findings in the literature by Yeh (2004), Gohike et al. (2011), Amegah, (2014), and Rahut et al. (2017).

Findings for South Africa on health effect of energy consumption are not the same with Nigeria. The results for the effect of energy use on health outcome in South Africa are shown in tables 5 and 6.

Table 5: Estimates of ARDL model results for South Africa (equation 4: life expectancy)

Dependent variable: Life expectancy

Variable	Coefficient
Short-run results	
	43.541945***
D(LnHE (-1))	(11.347754)
	-67.424046**
D(LnHE (-2))	(25.66878)
	21.174084
D(LnHE (-3))	(18.327691)
	-0.40922*
D(LnE)	(0.181679)
	0.235989
D(LnE(-1))	(0.193446)
	0.391218*
D(LnE(-2))	(0.159704)
	0.088325
D(LnE(-3))	(0.125553)
	0.033552
D(LnE(-4))	(0.134162)
	-0.293185
D(LnE(-5))	(0.158799)
	-0.522865**
D(LnE(-6))	(0.130174)
	-0.072715
D(LnF)	(0.670806)
	0.519095
D(LnF(-1))	(0.394791)

Variable	Coefficient
	-1.95053*
D(LnF(-2))	(0.817446)
	-3.44268***
D(LnF(-3))	(0.77429)
	-1.652682**
D(LnF(-4))	(0.632507)
	-2.651937**
D(LnF(-5))	(0.65444)
	0.054495
D(LnGDP)	(0.047951)
	-0.069392
D(LnGDP(-1))	(0.065819)
	-0.128274*
D(LnGDP(-2))	(0.054663)
	0.004398
D(LnGDP(-3))	(0.057705)
	-0.062322
D(LnGDP(-4))	(0.049254)
	-0.093819*
D(LnGDP(-5))	(0.036175)
	0.103696
D(LnGDP(-6))	(0.06106)
Long-run Results	
	-1.095165
LnE	(1.118266)
	9.395744*
LnF	(3.819641)
	0.569792
LnGDP	(0.544054)
	-33.292114*
C	(12.240438)
Diagnostic	
Normality (Jarque-Bera) H0: Normal	2.090044 (0.351684)
Serial dependence	F-statistic 1.003206
Breusch Godfrey Serial Correlation LM Test H0:No serial correlation	Prob. F(1,3) 0.3903

Heteroskedasticity Test: ARCH	F-statistic 0.015513 Prob. F(1,29) 0.9017		
H0 Error term is homoscedastic			
Linearity (Ramsey-reset test)	F-statistic: 12.64415		
H0: model is linear	Degree of freedom (1, 3) Prob 0.0379		
Bounds Test			
F-statistic	15.53816		
	K=3		
Critical Value Bounds Significance		I0 Bound	I1 Bound
	10%	2.72	3.77
	5%	3.23	4.35
	2.z50%	3.69	4.89
	1%	4.29	5.61

Source: Authors' computation (2017).

Notes: Elasticity values reported with standard errors in brackets and P values in bracelets. Estimated method: least squares. *** Significant at 1%, ** Significant at 5% and * Significant at 10% level.

Similar to the diagnostic test results for models 3 and 4 in Nigeria, in model 5, the Jarque-Bera statistic indicates normality for the estimated residuals. The Breusch-Godfrey LM test statistic shows non-existence of serial correlation and the ARCH test confirms that the residuals are homoscedastic. The RESET test also confirms the correct functional form of the equation. The bounds F-statistic shows the existence of a long-run relationship between life expectancy and other variables in the model, hence, the short and long-run results are reported. The elasticities are correctly signed particularly for short-run values of electricity and fossil fuel consumption. Contrary to apriori expectation, short-run values for output growth are negatively signed.

These findings suggest negative effects of electricity consumption on life expectancy in South Africa. This result is particularly observed in the short run with the difference electricity variable at zero and sixth time lags. The result suggests that with a 100% increase in electricity consumption, life expectancy would fall by as much as between 41% and 52 % in the short run. Although for the second period lag, electricity consumption increases life expectancy, the magnitude of positive effect is however lower than the negative. Negative impacts of electricity consumption on life expectancy may be due to health hazards associated with the mining of coal from which electricity is produced. In particular, there are evidences of water and air pollution associated with coal mining that can be detrimental to health status (Lloyd, 2013; Munnik et al., 2010). This result is an indication that even though electricity consumption improves health status, the source of production could play a role in determining the final outcome. Findings of negative effect of electricity use on health status in South Africa validate arguments that the human toxicity impact (HTI) of electricity produced from coal is relatively high and can impact negatively on health status (Chen et al. 2017). This finding however validates arguments that the HTI of electricity produced from coal is relatively high and can impact negatively on health status (Chen et al., 2017). Negative effects of electricity consumption on life expectancy in South Africa contradicts literature findings by Gohike et al. (2011), but is similar to that of Youssef et al (2016).

The result for the impact of fossil fuel use on life expectancy in South Africa, is also negative. Negative effects of fossil fuel use are observed from the second to fifth time lags. With a 1% rise in fossil fuel consumption, life expectancy would fall from between 1.7% to about 3.4%. This shows that fossil fuel use slows down health improvements which is similar to existing results in the literature (Yeh, 2004; Gohike et al.2011; Amegah, 2014). In the same way, the result for output increases also suggest negative impacts on life expectancy. Although the parameter is not correctly signed, the result may be due to a concentration of income in the hands of a few persons arising from income inequality, hence dampening the welfare impacts of income rise on life expectancy or unhealthy working conditions of labour that generate the overall rise in income.

Table 6: Estimates of ARDL model results for South Africa (equation 5: Infant Mortality)

Dependent variable: Infant Mortality

Variable	Coefficient
Short run results	
D(LnHI (-1))	-0.045311 (0.239736)
D(LnHI (-2))	1.012625*** (0.251441)
D(LnHI (-3))	2.330591*** (0.819424)

Variable	Coefficient		
	-1.823545***		
D(LnHI (-4))	(0.604471)		
	0.061891		
D(LnE)	(0.043652)		
	0.747672***		
D(LnF)	(0.243208)		
	-0.037594**		
D(LnGDP)	(0.016454)		
	0.042892*		
D(LnGDP(-1))	(0.024341)		
	-0.020892		
D(LnGDP(-2))	(0.024223)		
	0.076787***		
D(LnGDP(-3))	(0.026263)		
	-0.032162		
D(LnGDP(-4))	(0.024216)		
	0.063325***		
D(LnGDP(-5))	(0.020524)		
Diagnostics			
Normality (Jarque-Bera) H0: Normal	0.484001 (0.785056)		
Breusch Godfrey Serial Correlation LM Test H0:No serial correlation	F-statistic 0.242858 Prob. F(2,15) 0.7874		
Heteroskedasticity Test: ARCH H0 Error term is homoscadastic	F-statistic 0.672404 Prob. F(1,29) 0.4189		
Linearity (Ramsey-reset test)	F-statistic: 1.959523		
H0: model is linear	Degree of freedom (1, 16) Prob 0.1807		
Bounds Test			
F-statistic	2.393184		
	K=3		
Critical value Bounds Significance		I0 Bound	I1 Bound
	10%	2.72	3.77
	5%	3.23	4.35
	2.50%	3.69	4.89
	1%	4.29	5.61

Source: Authors' computation (2017).

Notes: Elasticity values reported with standard errors in brackets and P values in bracelets. Estimated method: least squares. *** Significant at 1%, ** Significant at 5% and * Significant at 10% level.

The results for the long run show insignificant effects of electricity use on life expectancy. However fossil fuel use indicates a positive impact. This is a pointer of some welfare impacts of fossil fuel consumption that improves living conditions and hence health status. But such experience can only be noticed in the long run. This result however contradicts the findings of unhealthy impact of fossil fuel consumption on health status (Yeh, 2004; Gohike et al. 2011; Amegah, 2014; Rahut et al., 2017). Findings for the effect of energy consumption on life expectancy in South Africa differs from that obtained for Nigeria. In Nigeria, there are no significant effects of electricity use on life expectancy. Negative effects of fossil fuel use are also observed in Nigeria but only in the short run.

As observed in other estimated models, the diagnostic tests for the Jarque-Bera statistic indicates normality for the estimated residuals. The Breusch-Godfrey LM test statistic shows non-existence of serial correlation and the ARCH test confirms that the residuals are homoscedastic. The RESET test endorses the correct functional form of the equation specified for infant mortality in South Africa.

The bounds test F-statistic results show no existence of a long-run relationship, hence only the short-run results are reported. The elasticities are correctly signed except for first, third and fifth time lags of output showing a rise in infant deaths with increase in economic output. As earlier mentioned, this can be due to concentration of income increase in the hands of a few people dampening its expected positive effect on health status. Electricity consumption did not show any significant effects on infant mortality. However, a rise in fossil fuel use would induce increase in the rate of infant deaths. Where fossil fuel use rises by 100%, infant deaths would also increase by as much as about 75%. This result suggests higher magnitude of the effect of fossil fuel use on infant deaths in South Africa compared to that for Nigeria. The effects of fossil fuel use on infant death in South Africa is however noticeable only in the short run. Negative effects of fossil fuel use on infant mortality in Nigeria is observed both in the short and long run. Findings of adverse effect of fossil fuel use on infant deaths is similar to existing results in the literature (Yeh, 2004; Gohike et al. 2011; Amegah, 2014; Rahut et al. 2017).

Conclusion

Using the ARDL bound testing approach, this study examined the effect of energy consumption specifically electricity and fossil fuel on health outcome in Nigeria and South Africa. The main objective is to determine whether differences in sources of electricity generation for both countries has implication for health outcome. Health outcome measured used are life expectancy and infant mortality. Choice of these health indices is mainly because they are best considered as measures of long-term improvements in the health status of a population.

No significant effects of electricity consumption is seen on life expectancy and infant mortality in Nigeria. Surprisingly, electricity consumption reduces life expectancy in South Africa, but only in the short run. Use of electricity in South Africa does not have any noticeable effect on infant deaths. On the other hand, the use of fossil fuel in Nigeria reduces life expectancy particularly in the short run. Fossil fuel use also induces a rise in infant deaths with indications of stronger effects in the long run. Similarly, fossil fuel consumption in South Africa reduces life expectancy in the short run but reverse effects occur in the long run. The use of fossil fuel also promotes higher infant deaths in South Arica but only in the short run. Overall, electricity consumption does not have any effect on health outcome in both countries except in South Africa where it induces short-run negative effects on life expectancy. Fossil fuel use on the other hand has negative effects on health outcome in both countries with indications of higher magnitude on infant mortality in South Africa.

The findings imply that the differences in health outcome of both countries are explained by variations in the impact of energy use, particularly fossil fuel consumption. The result for the effect of electricity on life expectancy in South Africa suggests poor health effects of electricity when it is generated from non-clean energy sources. It also implies that higher electricity consumption in South Africa relative to Nigeria does not account for better health outcome in the latter relative to the former.

Policy actions geared towards improvements in health outcome for both countries should consider measures that promote energy generation through renewable sources. In South Africa, strategic actions to curb the use of coal in the generation of electricity would significantly raise existing life expectancy.

References

Acaravcı, A. and Ozturk, I. (2012). Foreign direct investment, export and economic growth: Empirical evidence from new EU countries. *Romanian Journal of Economic Forecasting*, 2: 52-67.

Aliyu, A.S., Ramli, A.T. and Saleh M.A. (2013). Nigeria electricity crisis: Power generation capacity expansion and environmental ramifications. *Energy* 61: 354 – 367.

Amegah, A.K., Quansah, R., and Jaakkola, J.J.K. (2014). Household air pollution from solid fuel use and risk of adverse pregnancy outcomes: a systematic review and meta-analysis of the empirical evidence. *PLoS ONE* 9(12): e113920. doi:10.1371/journal.pone.0113920

Antunes, J.L. and Waldman, E.A. (2002). Trends and spatial distribution of deaths of children aged 12-60 months in São Paulo, Brazil, 1980-98. *Bull World Health Organ,* 80(5): 391-8.

Chatzidiakou, L., Mumovic, D. and Dockrell, J. (2014). The effects of thermal conditions and indoor air quality on health, comfort and cognitive performance of students. The Bartlett, UCL Faculty of the Built Environment, UCL Institute for Environmental Design and Engineering, London.

Chen, L. Miller, S.A and Ellis, B.R. (2017). Comparative human toxicity impact of electricity produced from shale gas and coal. *Environ Sci Technol.* 7(5121): 13018-13027.

Department of Mineral Resources (DMR). (2015). *South Africa's Mineral Industry 2013/2014*. Pretoria: DMR.

Duflo, E., Greenstone, M. and Hanna R. (2008). Indoor air pollution, health and economic well-being. *Surv. Perspect. Integr. Envir. Soc.*, 1: 1–9.

El-Zein, A, Tewtel-Salem, M. and Nehme, G. (2004). A time-series analysis of mortality and air temperature in Greater Beirut. *Sci Total Environ,* 330(1–3): 71–80.

Fisher, N. and Downes, G. (2016). South Africa – International Energy Agency (IEA) Retrieved from www.iea.org/ciab/South_Africa_Role_Coal_Energy_Security.pdf

Fuinhas, J.A., and Marques, A.C. (2012). Energy consumption and economic growth nexus in Portugal, Italy, Greece, Spain and Turkey: An ARDL bounds test approach (1965–2009). *Energy Economics*, 34: 511–517.

Ghatak, S. and Siddiki, J. (2001). The use of ARDL approach in estimating virtual exchange rates in India. *Journal of Applied Statistics*, 11: 573–583.

Giles, L.V. and Koehle, M.S. (2014). The health effects of exercising in air pollution. *Sports Med*, 44: 223–49.

Gohike, J.M., Thomas, R., Woodward, A., Campbell-Lendrum, D., Prüss-üstün, A. Hales, S. and Portier, C.J. (2011). Estimating the global public health implications of electricity and coal consumption. *Environmental Health Perspectives*, 119(6): 821-826.

Graff, J.Z. and Neidell, M. (2012). The impact of pollution on worker productivity. *American Economic Review*, 102(7): 3652–3673.

Gujarati, D.N. (2004). *Basic Econometrics* (4th ed.). New York: Mc-Graw Hill Companies Inc.

Gupta, I. and Mitra, A. (2004). Economic growth, health and poverty: an exploratory study for India. *Development Policy Review*, 22: 193-206.

Hanna, R. and Olivia, P. (2015). The effect of pollution on labor supply: Evidence from a natural experiment in Mexico City. *Journal of Public Economics*, 122: 68-79.

Hoque, M.M. and Yusop, Z. (2010) Impacts of trade liberalization on aggregate import in Bangladesh: An ARDL bounds test approach. *Journal of Asian Economics* 21: 37–52.

Kale, P.L, Andreozzi, V.L., and Nobre, F.F. (2004). Time series analysis of deaths due to diarrhea in children in Rio de Janeiro, Brazil, 1980–1998. *J Health Popul Nutr*, 22(1): 27–33.

Kovats, R.S., Hajat, S. and Wilkinson, P. (2004). Contrasting patterns of mortality and hospital admissions during hot weather and heat waves in Greater London, UK. *Occup Environ Med*, 61(11): 893–898.

Lelieveld, J., Evans, J.S., Fnais, M., Giannadaki, D. and Pozzer A. (2015). The contribution of outdoor air pollution sources to premature mortality on a global scale. *Nature* 525: 367–371.

Levine, R.S., Foster, J.E., Fullilove, R.E., Fullilove, M.T., Briggs, N.C., Hull, P.C., et al. (2001). Black-white inequalities in mortality and life expectancy, 1933–1999: Implications for Healthy People 2010. *Public Health Rep*, 116(5): 474–483.

Li, F., Liu, Y., Lü, J., Liang, L., Harmer, P. (2015). Ambient air pollution in China poses a multifaceted health threat to outdoor physical activity. *J Epidemiol Community Health*, 69(3).

Lloyd, P.J. (2013). Coal mining and the environment. Energy Research Institute, University of Cape Town.

Munnik, V., Hochmann, G.M. and Law, S. (2010). The social and environmental consequences of coal mining in South Africa: A case study. A joint initiative of Environmental Monitoring Group, Cape Town, South Africa and Both ENDs, Amsterdam, The Netherlands.

Nkiruka, C. M., (2011). Unbundling privatization of the Nigerian electricity sector: reality or myth? Centre for Energy, Petroleum and Mineral Law Policy, University of Dundee, UK.

Nkoro, E. and Uko, A.K. (2016). Autoregressive Distributed Lag (ARDL) co-integration technique: Application and interpretation. *Journal of Statistical and Econometric Methods*, 5(4): 63-91.

Orhunbilge, A.N. (2014). Manufacturing output in Romania: An ARDL approach. *Mediterranean Journal of Social Sciences*, 5(22).

Pesaran, M.H. and Pesaran, B. (1997). *Microfit 4.0*. Oxford University Press.

Pesaran, M.H., Shin, Y. and Smith R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, 16: 289–326.

Pope C.A., Ezzati, M. and Dockery, D.W. (2009). Fine-particulate air pollution and life expectancy in the United States. *N Engl J Med* 360: 376–86.

Rahut, D.B., Ali, A. and Behera, B. (2017). Domestic use of dirty energy and its effects on human health: Empirical evidence from Bhutan. *International Journal of Sustainable Energy*, 36.

Shah, A.S.I., Langrish, J.P., Nair, H., McAllister, D.A., Hunter, A.L., Donaldson, K., Newby, D.E., and Mills, N.L. (2013). Global association of air pollution ad heart failure: A systematic review and meta-analysis. *Lancet*, 382: 1039–48.

Sow, M L. (2006). The effects of air pollution on infant health: An empirical evaluation Georgia. Dissertation, Georgia State University, http://scholarworks.gsu.edu/econ_diss/17

Tang, T.C. (2003). Japanese aggregate import demand function: reassessment from 'bound' testing approach. *Japan and the World Economy*, 15(4): 419–436.

Usman, Z.G. and Abbasoglu, S. (2014). An overview of power sector laws, policies and reforms in Nigeria. *Asian Transactions on Engineering*, 4(2) (ATE ISSN: 2221-4267).

World Bank. (2013). The Global Burden of Disease: Main findings for sub-Saharan Africa. Retrieved from http://www.worldbank.org/en/news/feature/2013/09/09/global-burden-of-disease-findings-for-sub-saharan-africa

World Health Organization (WHO). (2004). Mortality and burden of disease estimates for WHO member states. Geneva: WHO. Retrieved from www.who.int/...burden_disease/gbddeathdaly.

World Health Organization. (2002). Addressing the links between indoor air pollution, household energy and human health, based on the WHO-USAID global consultation on the health impact of indoor air pollution and household energy in developing countries (Meeting report), Washington, DC, 3-4 May 2000.

World Health Organization (2015) Access to modern energy services for health facilities in resource-constrained settings: A review of status, significance, challenges and measurement WHO Library Cataloguing-in-Publication Data:

Yeh, E. (2004) Indoor air pollution in developing countries: Household use of traditional biomass fuels and the impact on mortality. University of California, Berkeley. Retrieved from https://are.berkeley.edu/fields/erep/seminar/s2004/eyeh-swea.pdf

Youssef, A.B., Lannes J., Rault C. and Soucat A. (2016). Consumption and health outcomes in Africa. *IZA Discussion Paper* No. 10325.