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The Effect of Air Quality and Income Inequality on Health Status in Nigeria (1980 - 2020)

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Abstract: The World Health Organization (WHO) has implemented numerous economic policies to increase life expectancy, but the results have been disheartening in developing nations, particularly Nigeria. Thus, using Auto regressive distributed lag (ARDL) technique, this study investigated the effect of air quality and income inequality on health status in Nigeria. Annual data over the period of 1980 to 2020 sourced from the World Bank Development Indicators (WDI) were used for the study. The results showed that income inequality and carbon dioxide emissions in Nigeria had significantly influenced life expectancy in Nigeria. Furthermore, income inequality and CO2 emissions lead to significant health loss, particularly in Nigeria. However, improved air quality and reduced income inequality alone are insufficient for sustained good health status. Employment, improved Gross Domestic Product, strong macroeconomic policies, and an efficient institutional setup are equally significant. The study therefore advocates for policy that aid the redistributing income thus improving access to clean household energy by transitioning to cleaner cook-stoves and solar lighting, and improving municipal solid waste management should be put in place.

Keywords: Air Quality; Income Inequality; Health Status; ARDL

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1. Introduction

Good health cannot be compromised, because the productivity of any nation largely depends on the health of its populace. A way to invest in human capital is through health, and it is very significant to the development of any economy. Citizens' health is a factor in a country's wealth. It implies that active participation in economically productive sectors such as manufacturing, agriculture, mining, and informal sectors by healthy people can positively contribute to economic development (Fayissa & Gautema, 2005). Thus, it is apt to note that most less developed nations have faced numerous deprivations regarding quality health and health status (Peters et al., 2008; Oxley, 2009). However, there are claims that, in comparison to its neighbors, such as Ghana and Kenya, Nigeria's general health among the worst scourges of our era is air pollution because of its impact on climate change and individual health. Today, socio-economic advancement and the rise in human activities have been identified in the literature as two of the leading causes of air pollution and environmental degradation. These have resulted in a more strained connection between humans and nature (Dean and Green, 2018). According to data from the United Nations Environment Programme (UNEP, 2018), the ozone hole's area has been growing in recent years, which has caused the ozone layer to deplete and accelerated climate change. And this raises the danger of skin cancer exposure by allowing the sun's UV radiation to directly permeate people's skin. According to World Health Organization data, more than 90% of the population globally is exposed to environmental deterioration and air pollution, which lowers the average life expectancy by two years (WHO, 2018).

In Nigeria, the major significant forms of air pollution include diesel generators, road dust, diesel exhaust from trucks and automobiles, smoke from the open burning of household garbage, soot from indoor usage of biomass cookware, and tailpipe exhaust from these vehicles. Nigeria was classified as the tenth-most polluted nation in the world with an estimated average PM2.5 record of 44.8 g/m3 in the 2018 World Air Quality Report Region and City PM2.5 Ranking by IQ Air and Greenpeace. Nigeria's Kano is the most polluted city on the African continent, according to the assessment.

Updated data from the Health Effects Institute (HEI) and the Institute for Health Metrics and Evaluation (IHME) show that over 64,000 people died in Nigeria in 2017 due to household air pollution, primarily due to the use of leaky stoves and open flames to cook with solid fuels like charcoal and wood. The yearly PM2.5 mean concentration in Nigeria is extremely large. More than four times as many dangerous PM2.5 particles as the WHO's yearly recommendation for outdoor air quality are present in the country's air (46.3 g/m3 versus 10 g/m3). Nigeria has the second-worst air pollution mortality rate in Africa, at 307.4 deaths per 100,000 residents. Nigeria has more air pollution-related fatalities than South Africa, Kenya, and Angola put together. In 2017, well over 114,000 deaths in Nigeria were attributed to air pollution, the greatest number in the whole of Africa continent, according to recently revised figures by the HEI and the IHME.

Nigeria is also bedeviled by the high-income inequality. The poor people in Nigeria usually has limited access to clean air, clean drinking water, appropriate shelter, food, sanitation, education, professional health care, a stable job, and health information. Nigeria's life expectancy is 55.12 years, below the world's average of 73.4 years (WDI, 2021). It is crucial to bring up the question of what role income disparity and air quality play in Nigeria's health. Therefore, from the foregoing, it is important to examine the influence of income inequality, air quality on Nigeria's health status.

Extant studies have found a connection between health outcomes (mortality, morbidity, etc.) and income inequality at the country level (Waldmann, 1992; Wennemo, 1993), as well as between states and cities within countries (Ben-Shlomo et al., 1996; Kaplan et al., 1996; Kennedy et al., 1996; Kawachi & Kennedy; 1997; Kawachi et al., 1997). Additionally, some research discovered a connection between income distribution and consumption of alcohol (Marmot et al., 1997), smoking statistics at the state level (Kaplan et al., 1996), and firearm crimes (Kennedy et al., 1998).

Numerous studies reveal that health status is indeed negatively impacted by income inequality. For instance, some studies all demonstrated a strong correlation between inequality (at the state or county level) and self-rated health conditions (Kennedy et al., 1998; Soobader & LeClere, 1999; Fiscella & Franks, 2000; Blakely et al., 2002). Daly et al. (1998) used various methods of measuring income disparity at the state level to examine its effects on individual mortality. They found evidence in favor of the theory of income disparity in a specific time frame. LeClere and Soobade (2000) also find corroborating findings using country-level inequality data, but only for selected categories in high-inequality counties.

On the contrary, some studies show no linkage between income disparity and health status. Fiscella and Franks (1997) found no impact of county-level inequality on mortality when measuring inequality by the percentage of income obtained by the population's bottom 50%. Meara (1999) looked at the connection between birth outcomes and state-level inequality but found no real connection. It is demonstrated by Mellor and Milyo (2002) that after individual income and locale impacts are taken into account, the effects of a number of inequality measures on self-rated health conditions are abolished, both at the state level and metropolises. Blakely et al., (2002), using the same data as Mellor and Milyo (2002), came to the same conclusion after accounting for income: that little correlation exists between health status and income disparity. A few studies (Osler et al., 2002; Shibuya et al., 2002; Gerdtham and Johannesson, 2004) offer more proof against income inequality.

Founded on Grossman's 1972 health model, Fayissa and Gutema (2005) developed for Sub-Saharan Africa a production function for health. The production system took into account social, economic, and environmental issues, and the estimated function took into account elements like illiteracy rate, income per capita, and ratio of health spending to GDP, urbanization rate, food availability, and carbon emissions per worker. Using a panel data analysis one-way and two-way fixed and random effects model, the production function was estimated. This study only included 31 sub-Saharan African nations, and it spanned from 1990 to 2000.

However, numerous environmental factors that are inputs into the creation of health, according to Fayissa and Gutema (2005) and Fayissa and Traian (2013), were not supported, further popularizing the discussion on the link between health and environment. The investigations discovered a high correlation between an improvement in birth weight and life expectancy and income per capita, an increase in food availability, and a decline in the illiteracy rate. However, statistical tests of significance did not support the impacts of increased urbanization rates, decreased alcohol use, decreased carbon dioxide, and decreased population growth rates on health outcomes.

There are various reviews on whether the consequences of exposure to air pollution are distributed differently by socio-economic status (SES). Some studies concluded that results differ depending on the socio-economic factors' level (individual-level or contextual-level). Most studies that examined factors at the individual level discovered some effect modification by SES, with an air pollution effect that was more pronounced among individuals with lower SES (Krewski et al., 2000; Pope et al., 2002). Studies employing contextual-level SES (e.g., percentage of those in poverty, unemployment rate, or minority status) have produced conflicting findings (Samet et al., 2000; Schwartz, 2000; Zanobetti et al., 2000; Jerrett et al., 2004; O'Neill et al., 2004). These contextual level studies have investigated how different aggregate socioeconomic characteristics within a selected research area can modify an effect.

Thus, in the literature, the linkage between health status and income inequality, health status, and environmental quality is documented differently (Cropper & Griffiths, 1994; Elo & Preston, 1996; Samet al., 2000; Schwartz, 2000; Zanobetti et al., 2000; Krewski et al., 2000; Pope et al., 2002; Jerrett et al., 2004; O'Neill et al., 2004; Akintunde, 2012; Saka, 2014; Rahman, Saidi, & Mbarek, 2017).

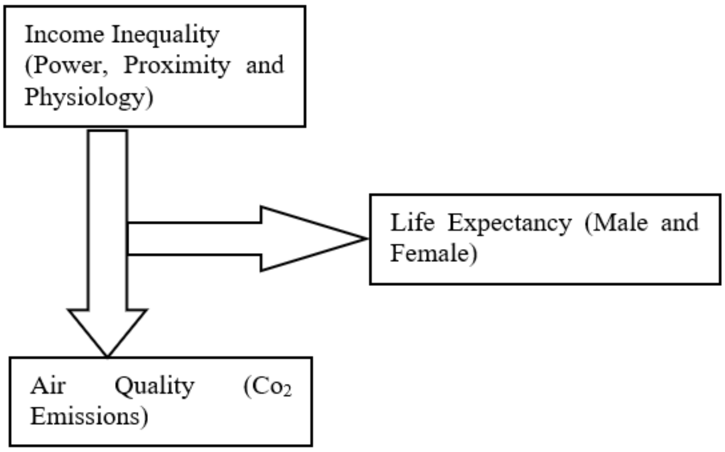
Also, in more recent studies, the linkages between air quality and economic growth, economic and social welfare, technological innovation, and urbanization are established (Ai et al., 2022; Abban et al., 2022; Abban et al., 2023; Khan et al., 2023; Ai et al., 2023; Nuta et al., 2024; Andrei et al., 2024). But studies on the effect of air quality, and income inequality on health status, which constitutes the central thrust of this study, were few and scanty, especially in Nigeria.

2. Research Methods

Power, proximity, and physiology serve as the three theoretical pillars that support the analytical framework for this study. According to the power principle, wealth concentration and political power could undermine environmental laws and protections (such as public discussions and working conditions, living standards, warnings, and other resources), making populations more vulnerable to the air pollution level specified. According to the proximity principle, wealth disparity may make people more susceptible to a particular amount of air pollution by causing vulnerable populations to be geographically segregated. Numerous studies demonstrate a link between higher levels of racial and class residential segregation and economic disparity (Jargowsky, 1996; Lobmayer & Wilkinson, 2002; Cheshire et al., 2003; Reardon & Bischoff, 2011).

Finally, the physiological principle postulates that, by compromising human populations' physiological health, wealth inequality may make people more susceptible to a given degree of air pollution. (Charafeddine and Boden, 2008). (Kawachi and Kennedy, 1999; Wilkinson, 1996; Lynch et al., 2000; Wilkinson, 2005; Wilkinson and Pickett, 2009; Truesdale and Jencks, 2016).

The above relationship among air quality, income inequality, and health status can be better explained with the diagram depicted below;



Source: Author's Compilation, 2024

From the above framework, we can deduce that there is a linkage between air quality, income inequality, and health status. Hence, the health production function can be defined as follows:

$$logY(t) = \beta logE(t) + \delta logH(t) + \alpha logK(t) + \gamma logL(t) \quad (3.1)$$

Where, Y = f (H, E, L, K) is the expected health output proxy by health status indicators (life expectancy rate). E represents environment proxy by carbon dioxide emissions, H represents human capital proxy by income per capita, and government expenditure on health. L represents labour proxy by unemployment rate and income inequality. K represents physical capital proxy by gross capital formation. The linear form of the equation of the model is presented as;

$$\ln LIFEX_t = \beta_0 + \beta_1 ln(GDPC_t) + \beta_2 ln(CO_{2t}) + \beta_3 ln(INC_t) + \beta_4 \ln(GEXH_t) + \beta_5 \ln(UNEM_t) + \beta_6 \ln(GCF_t) + \varepsilon_t. \quad (3.2)$$

Where $LIFEX_t$= is the life expectancy rate and the proxy for health status, CO_{2t}= carbon dioxide emissions the proxy for air and environmental qualities, INC_t = Gini coefficient on income inequality, $UNEM_t$ = represents the unemployment rate, $GEXH_t$ = is the total government expenditure on health, GCF_t = is the gross fixed capital formation, ε_t= is the error term and $GDPC_t$ is the gross domestic product per capita.

2.1 Definitions and Measurement of variables

From the literature, the measurements of the different variables of the model for the study are described briefly and stated as follows.

Table 2.1. Definitions and Measurement of Variables

Variable	Descriptions	Symbol	Data Source
Environmental Degradation & Air Quality	Environmental degradation is measured using CO_2 emissions (metric tons per capita). This variable is the dependent variable in this study	CO_2	WDI
Economic Development	GDP per capita, which is the value of all goods and services generated by a nation divided by its total population, is used in this study to measure economic development.	GDPC	WDI
Income Inequality	This is measured by Gini and is referred to as the household disposable income for a specific year.	INC	WDI
Unemployment Rate	This is the proportion of the labor force that is unemployed.	UNEM	WDI
Gross fixed capital formation	Outlays on additions to *fixed assets*, plus the net change in inventories.	GCF	WDI

Life Expectancy Rate	This is total life expectancy for both male and female. Thus, it is defined the number of years a newborn is expected to live and it is used as the proxy for health status.	LIFEX	WDI
Government Expenditure on Health	This refers to the spending of the public sector on health	GEXH	WDI

Source: Author's Compilation, 2024

2.2. Estimation Technique

The autoregressive distributed lag (ARDL) technique is employed in order to examine the influence of income inequality and air quality on health status in Nigeria. Adoption of this estimation technique was based on the result of the stationarity test, which revealed that the series used in the study are a mix of variables integrated either of order zero [stationary at level, I(0)] or order one [stationary at first difference I(1)]. The ARDL estimation technique enables the estimation of long-run effects. Specifically, the ARDL technique began with the specification and estimation of the explicit unrestricted ARDL version of equation (3.2)

$$\Delta LIFEX_t = \beta_0 + \sum_{j=1}^{n} \partial_j \Delta LIFEX_{t-1} + \sum_{J=1}^{P} \alpha_j \Delta GDPC_{t-1} + \sum_{J=1}^{p} \varphi_j \Delta CO2_{t-1} + \sum_{J=1}^{p} \Phi_j \Delta INC_{t-1} + \sum_{j=1}^{P} \theta_j \Delta GEXH_{t-1} + \sum_{j=1}^{P} \Upsilon_j \Delta GCF_{t-1} + \beta_1 GDPC_{t-1} + \beta_2 \mathrm{CO2}_{t-1} + \beta_3 INC_{t-1} + \beta_4 GEXH_{t-1} + \beta_5 GCF_{t-1} + \tau ECM_{t-1} + \mu_t \quad (3.3)$$

The estimation of the unrestricted ARDL model in the equation enabled the performance of the bounds test and the derivation of the long-run coefficients of health status proxied by life expectancy, the explanatory variables, and the control variables. The bounds test is used to ascertain evidence of a long-run relationship among the variables, and the long-run coefficients measure the long-run effect of air quality and income inequality on health status in Nigeria.

3. Results and Discussion

3.1 Descriptive Statistics

The results presented in Table 3.1 show that the average logarithmic value of life expectancy between 1980 and 2020 is 49.48, with a maximum of 54.81 and a minimum of 43.40. In addition, the average logarithmic value of the Gini coefficient of income inequality (INC) in Nigeria during the study period is about 41.74, ranging from 32.30 to 48.10. Concerning the gross domestic product per capita (GDPC), the study revealed that the average logarithmic value is 1316.9, and it varies between the range of 3098.9 and 270.2. However, on carbon dioxide emissions (CO2), the table shows that this ranges from 0.46 and 0.93 (minimum and maximum respectively), with an average logarithmic value of 0.69.

Furthermore, the average value of total government expenditure on health (GEXH) is 1312.6, with a maximum value of 518.5 and a minimum of 9.64. In contrast, the mean logarithmic value of unemployment is 11.04 percent, ranging from 27.10 percent to 1.90 percent. The gross fixed capital formation (GFC) average logarithmic value is -1.61, with a maximum of 40.4 and a minimum of-33.8.

Table 3.1. Descriptive Statistics of the Variables

	CO2	LIFEX	GCF	GDPC	GEXH	INC	UNEM
Mean	0.69	49.48	-1.61	1316.9	1312.6	41.74	11.04
Median	0.67	49.55	0.61	902.2	947.7	42.84	11.90
Maximum	0.93	54.81	40.4	3098.9	5185.3	48.10	27.10
Minimum	0.46	43.40	-33.8	270.2	9.64	32.30	1.90
Std. Dev.	0.11	3.27	14.7	866.9	113.47	4.48	6.84
Skewness	0.17	0.08	0.08	0.49	1.16	0.78	0.31
Kurtosis	2.56	1.86	3.62	1.79	3.19	2.73	1.91
Jarque-Bera	0.52	2.25	0.70	4.10	9.18	4.32	2.68
Probability	0.77	0.33	0.70	0.13	0.01	0.13	0.26
Sum	8.56	228.75	65.90	593.95	516.28	1711.4	452.59
SumSq. Dev.	0.47	428.9	814.2	325.0	917.0	803.9	871.32
Observations	41	41	41	41	41	41	41

Source: Author's Computation 2024

The series is widely dispersed from the mean values, as captured by the values of their standard deviations in Table 3.1. The rule of thumb states that every variable's standard deviation should be zero or very close to zero, which implies that for a reduced volatility to be desirable for our chosen series, the deviation from the mean must be a little larger. All the standard deviations are not different from zero over time. The skewness shows how spread the data is from their means. It measures the asymmetry of the series distribution around the mean. The statistics in table 3.1 reveal that all variables (CO2, LIFEX, GCF, GDPC, GEXH, INC, UNEM) are positively skewed, implying that these distributions have long right tails. In addition, the kurtosis measures the peakedness (height) or flatness of the series distribution. Distributions with kurtosis values of less than three are said to be platykurtic.

Hence, CO2, LIFEX, GDPC, INC, and UNEM are all platykurtic with 2.56, 1.86, 1.79, 2.73, and 1.91, respectively, indicating that the distributions are flat relative to normal. However, distributions with kurtosis values greater than three are said to be leptokurtic (GCF and GEXH with values of 3.62 and 3.19, respectively), indicating that they produce more outliers than the normal distribution, and this suggests that, when compared to other variables in the distributions, they have heavier tails or a larger risk of extreme outlier values.

Lastly, the Jarque-Bera (JB) statistic measures whether the series is normally distributed or not. The p values of all variables except GEXH, with a p value of 0.01, are greater than 0.05. Other variables showed p values of 0.77, 0.33, 0.70, 0.13, 0.13, and 0.26. Hence, the null hypothesis of normal distribution at 5% was accepted for CO2, LEB, GCF, GDPC, INC, and UNEM, while it was rejected for GEXH.

3.2. The Unit Root (Stationarity) and Bounds Tests Results

It became necessary to ascertain the stationarity or non-stationarity of the variables using augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests. By comparing the ADF and PP test statistics with the critical values, it was found that most of the variables were non-stationary at levels (LIFEX, LGDPC, LGEXH, LINC, and UNEM). However, it became stationary at first, differencing I(1) except for CO2 and LGCF, which were stationary at level I(0). Having established that all variables were integrated at orders of one and zero, we applied the bounds test for cointegration analysis in the model.

Table 3.2. Results of Unit Root Tests

Variable	**Augmented Dickey-Fuller (ADF)**				**Phillip Perron (PP)**				**Decision**
	Level	First Difference	I(d)	Prob Value	Level	First Difference	I(d)	Prob Value	
CO2	-3.3641**	None	I(0)	0.0184	-3.2683**	None	I(0)	0.0232	I(0)
LIFEX	-1.3395	-8.4189*	I(1)	0.0000	-0.2171	-12.2176*	I(1)	0.0000	I(1)
LGCF	-4.7221*	None	I(0)	0.0005	-5.2243*	None	I(0)	0.0001	I(0)
LGDPC	-1.1858	-7.0389*	I(1)	0.0000	-1.0155	-6.6452*	I(1)	0.0000	I(1)

LGEXH	-1.4522	-7.0389*	I(1)	0.0000	-1.4760	-6.9856*	I(1)	0.0000	I(1)
LINC	-2.7449	-4.8625*	I(1)	0.0003	-1.9458	-3.9608*	I(1)	0.0040	I(1)
UNEM	-0.7048	-6.5860*	I(1)	0.0000	-0.3177	-6.7055***	I(1)	0.0748	I(1)

*Source: Authors' computation; Note: *, ** and *** imply statistical significance at 1%, 5% and 10% levels respectively, while all variables are estimated at intercept.*

Table 3.3. ARDL Bounds Test for Co-integration Relationship

Model	Computed F-Statistic	
LIFEX	67.344	
Bounds Level	I(0)	I(1)
1% critical Value	3.15	4.43
5% critical Value	2.45	3.61
10% critical Value	2.12	3.23

Source: Author's computation: Notes: computed Bounds is the ARDL co-integration test and asymptotic critical value bounds are automatically generated from Eviews 9.0 for k=6.

The Bounds test for cointegration relationships states that cointegration exists if computed F-statistics exceed the upper bound I(1). Otherwise, no cointegration if it is below the lower bounds of I(0). In accordance with this principle, Table 3.3 bounds test outcome indicated cointegration since the computed F-statistics (67.344) is higher than the upper bound (3.61) at a 5% level of significance. Hence, analysis of the long-run estimates of the variables is necessitated.

Since the cointegration has been established, the long run estimate of the variables is presented in the Table 3.4 below.

3.3 Long-run Analysis of the Variables

Table 3.4. Estimated Long Run Coefficients for Health Status

Variables	Coefficient	Standard Error	T-Ratio	Prob. Value
Constant	0.2143*	0.0417	5.1345	0.0143
LGCF	0.0023	0.0014	1.6729	0.1929
LGDPC	0.0027***	0.0010	2.5401	0.0847
LGEXH	-0.0789**	0.0947	-0.8332	0.0659
LINC	-0.1946**	0.0495	-3.9300	0.0293

UNEM	-9.4608***	3.3820	-2.7974	0.0680
CO2	-45.0359**	6.6596	-6.7626	0.0066

*Source: Author's Computation: Notes: *, **, *** denotes statistical significance at 1%, 5% and 10% levels. Dependent variable is LEB (log of life expectancy at birth).*

The long-run result revealed that income inequality and carbon dioxide emissions significantly decreased life expectancy by 0.1946 and 45.03359 respectively. Similarly, in line with apriori expectation, both income inequality and carbon dioxide emissions contributed to the decrease in health status in Nigeria, which is proxied by life expectancy. From the results obtained for the estimated long-run elasticities, the statistically significant variables are the Gini coefficient on income inequality (INC) and carbon dioxide emissions (CO2).

The above findings showed that income inequality and carbon dioxide emissions had a significant detrimental effect by exacerbating health status in Nigeria. The result of the carbon dioxide emissions that show a negative sign is in tandem with the study of Sunday and Adofu (2021). They examined the connection between non-accidental, cardiovascular, and respiratory disease-related mortality in Nigeria from 1970 to 2019 and ambient air pollution, as measured by carbon dioxide.

Their study showed that carbon dioxide emissions have a negative effect on life expectancy in Nigeria. Similarly, in their study, Curtis et al. (2006) discovered that significant outdoor air pollutants such as carbon monoxide, sulfur, and nitrogen oxides cause health issues in bodily systems, including cardiovascular and respiratory disorders that lower life expectancy at birth. Also, Osabohien et al. (2020) found a significant negative effect of carbon emissions on life expectancy. Carbon dioxide emissions (CO2) and income inequality have a negative impact on health status. This may be due to the fact that air pollution in Nigeria is produced by generator fumes, which result in the deadly gas carbon monoxide, by older cars with potentially unhealthy fumes, and by the fact that most Nigerians opt to burn their trash in their neighborhoods rather than throw it away, which adds to the pollution in the atmosphere. A second issue contributing to Nigeria's air pollution crisis is the use of coal and firewood for cooking, which is found chiefly among low-income earners or the poor in Nigeria. The aforementioned air contaminants can cause lung damage and deterioration, as well as the onset of conditions like cancer, emphysema, asthma, and bronchitis.; accelerated lung aging; and, by implication, the shortened life span of people. The estimated long-run elasticities for gross fixed capital formation (GCF) and the measure of economic development proxied by the real gross domestic product per capita (GDPC) are 0.0023 and 0.0027, respectively. Both estimated elasticities have the expected signs but are not statistically significant at the 5% level. The positive effect of gross fixed capital formation on life expectancy is corroborated by Monsef and Mehrjardi (2015). Although, the results by these authors showed that gross fixed capital formation was significant, In addition, the estimated long-run elasticities for total government expenditure on health (GEXH) is-0.0789. Total government expenditure on health shows a non-statistically significant value greater than 5% (0.0659). Lastly, the estimated long-run elasticities for the unemployment rate (UNEM) is -9.4608. UNEM shows a negative sign, which conforms to the a priori expectation. However, it is not statistically significant at the 5% level due to its probability value of 0.0680 being more significant than 5%. In support of this, but with a significant sign, Monsef and Mehrjardi (2015), in their study, revealed unemployment as a leading economic factor influencing life expectancy negatively.

4. Conclusion

This study investigated the effect of air quality and income inequality on health status in Nigeria from 1980 to 2020. Six known variables, such as carbon dioxide emissions, Gini coefficient, real GDP, government expenditure on health, unemployment, and gross capital formation, are used as regressors to examine their significant effects on life expectancy, using ARDL. The results showed that income inequality and carbon dioxide emissions in Nigeria had significantly influenced life expectancy in Nigeria. The result specifically showed that income inequality and CO_2 emissions lead to significant health losses, particularly in Nigeria.

Meaning that poor air quality adversely impacts public health by fostering respiratory illnesses, cardiovascular diseases, and various other health concerns, and income inequality worsens the influence of inadequate air quality on health results. People from lower socio-economic backgrounds bear a disproportionate burden of air pollution due to factors like restricted healthcare access, substandard housing conditions, and heightened exposure to pollution sources. Consequently, this exacerbates prevailing health inequalities, resulting in an expanding disparity in health outcomes in Nigeria. However, improving air quality and reducing income inequality will improve health status. Nevertheless, improved air quality and reduced income inequality alone are insufficient for sustained good health status. Employment, improved Gross Domestic Product, strong macroeconomic policies, and an efficient institutional setup are equally significant.

Therefore, it is recommended that appropriate policy tools be put in place to strengthen laws to regulate and lessen emissions of air pollution from vehicles, industry, and other sources. This entails investing in pollution control technologies, encouraging the use of greener energy sources, and enacting stronger emission regulations, which would lengthen life expectancy by reducing income inequality and improving air quality.

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