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An Econometric Analysis of the Long-Run Relationship Among Environmental Quality, Income Inequality, and Economic Indicators in Nigeria

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ABSTRACT

Purpose – The research employs annual time series data covering several decades and applies the Autoregressive Distributed Lag (ARDL) bounds testing approach to examine cointegration among variables such as carbon emissions, Gini coefficient, GDP per capita, inflation, and energy consumption.
Methodology/approach The ARDL bounds testing approach was used due to its ability to handle I(0) and I(1) variables. Diagnostic tests such as unit root (ADF and PP), multicollinearity, and residual diagnostics ensured model robustness. Stationarity was tested to prevent biased results, with decisions based on comparing test statistics to critical values. Analyses were performed in EViews 10.
Findings – The unit root tests using ADF and Phillips-Perron methods show a mixed order of integration: some variables are stationary at level [1(0)] such as CO_2, GCE, LER, and IFMR, while others—EC, GINI, PGDP, PST, and DFT—are stationary at first difference [1(1)]. This mix validates the use of the ARDL Bounds Test. Correlation analysis reveals no serious multicollinearity issues among the variables. In the ARDL Bounds Test for Model 1, the F-statistic is (10.04213), which exceeds the upper bound at the (1%) level (3.9), confirming the presence of a long-run relationship among the variables. These findings support further model estimations. The study highlights the need for policies that promote inclusive economic growth while ensuring environmental sustainability. Targeted strategies addressing both economic inequality and environmental protection are recommended to achieve balanced development outcomes.

INTRODUCTION

The growing concern over environmental degradation, coupled with persistent income inequality and fluctuating economic indicators, has intensified scholarly interest in understanding their long-run interrelationship. Despite significant economic growth in many countries, environmental quality continues to deteriorate, and income inequality persists. Traditional economic models have often treated these variables in isolation, failing to account for their dynamic and interdependent nature. The challenge lies in understanding whether economic indicators such as GDP, inflation, and unemployment can coexist with equitable income distribution and sustainable environmental practices over the long run. Furthermore, there is limited empirical consensus on the direction and strength of these relationships, particularly in developing economies where institutional weaknesses may amplify inequalities and environmental stress (Smith et al, 2022).

In exploring the long-run relationship, econometric models like the Autoregressive Distributed Lag (ARDL) approach and Vector Error Correction Models (VECM) have been employed to test for cointegration and causality among the variables. For instance, studies have found evidence of the Environmental Kuznets Curve (EKC), suggesting that environmental degradation initially worsens with economic growth but improves after a certain income threshold is reached (Al-Mulali et al, 2015). However, critics argue that this model may not fully capture the influence of income inequality, which can exacerbate environmental degradation by limiting access to clean technology and sustainable infrastructure for poorer populations (Pata et al, 2022).

Income inequality itself interacts with economic indicators in a feedback loop. Econometric findings often reveal that rising inequality can hinder economic growth by reducing human capital accumulation and lowering aggregate demand (Lima et al, 2021). Additionally, when inequality is high, environmental policies may become harder to implement due to political resistance from powerful elites who benefit from lax regulations. These dynamics underline the importance of integrating income inequality into environmental-economic models. Environmental quality, measured through proxies such as carbon emissions, air and water pollution, and deforestation rates, also affects economic productivity. Poor environmental conditions can reduce agricultural output, raise health expenditures, and lower labor productivity, thereby negatively influencing economic indicators (Nkalu & Edeme, 2019). Thus, the long-run sustainability of economic development depends on policies that simultaneously address inequality and environmental concerns.

LITERATURE REVIEW

Globally, the state of health outcomes is characterized by significant inequalities between and within countries (McCartney et al., 2019). Health outcomes are the results of a country's healthcare system's planned treatment and interventions (Khezrian et al., 2020). Achieving better health outcomes globally requires a multifaceted approach that addresses the root causes of health inequalities (McCartney et al., 2019). This includes providing universal access to quality health care, improving living conditions, and empowering individuals and communities to take charge of their own health and well-being (Smith et al., 2016), therefore, making clear that health status outcomes are affected by vectors of factors such as economic variables, social variables and environmental factors.

Life expectancy as one of the components of health outcomes is the estimated average number of years a person is projected or likely to live before death (Nkalu & Edeme, 2019). This means that it is the number of years a new-born infant would live if existing patterns of mortality at the time of its birth were sustained throughout its life. It is argued that life expectancy is multidimensional which means that what affects one continent might not affect others and this can be attributable to environmental and socioeconomic factors (Nkalu & Edeme, 2019). A higher living standard, a healthy working environment, maternal and

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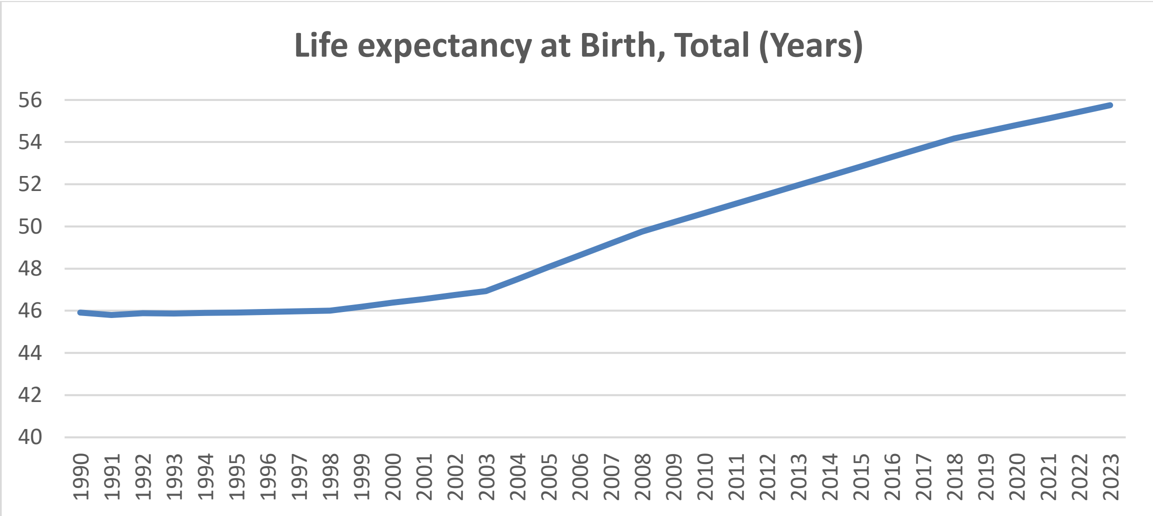
preventative care, an educated population, and high income are factors that improve life expectancy (Ranabhat et al., 2018). Recently, developed and developing countries has given much concern to population health through socio-economic policies, as it is important in the development process which decides investment in workforce and human capital.

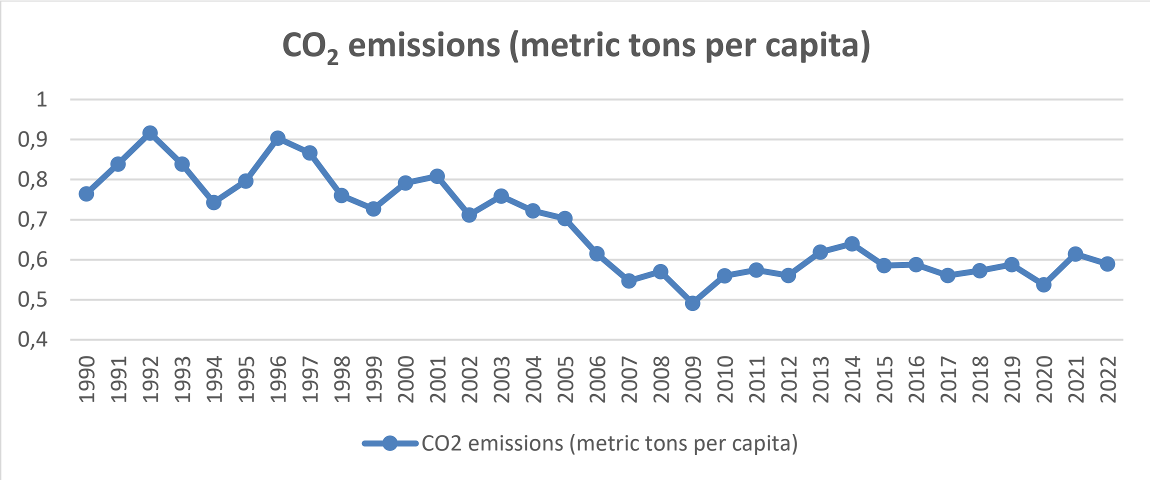


Source: Author's Computation from World Bank Database (2023)

Figure 1: Life Expectancy at Birth, Total (Years) in Nigeria

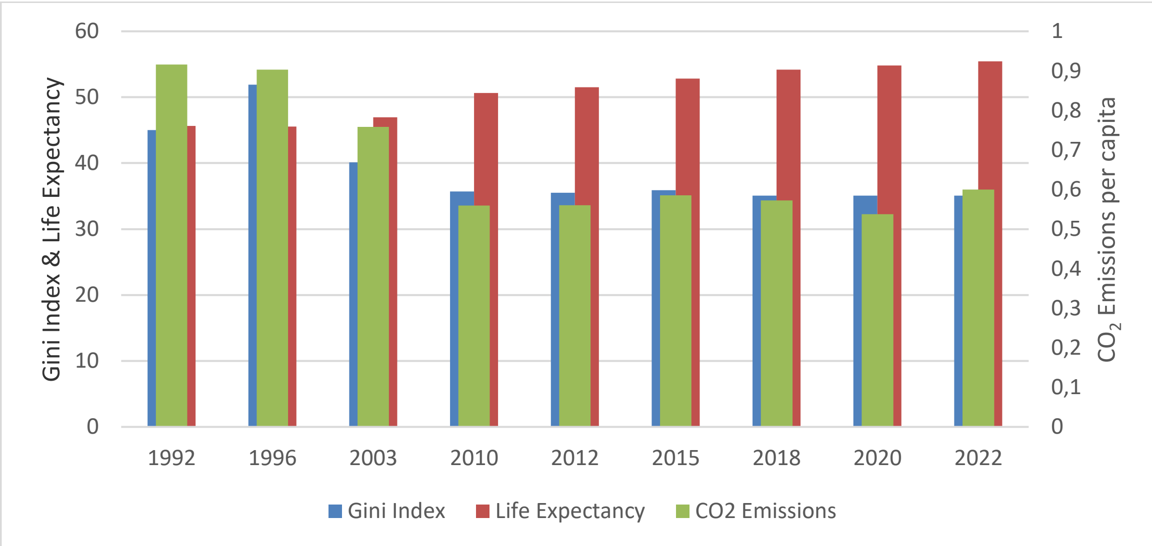
Figure 1 shows that the average life expectancy of Nigerians is increasing. The rate fell in 1991 and then began to increase at a low rate till 2000. It however increased greatly from 2001 and has been increasing at an increasing rate thereafter. The life expectancy rate in Nigeria was 45.9 years in 1990, fell to 45.8 years in 1991, increased to 46.5 years in 2001, and then increased further to 51.3 in 2011 and 54.3 years in 2018. According to WHO (2023), life expectancy in Nigeria was 52.89 years in 2020, 55.12 years in 2021, and 55.44 years in 2022. According to the World Life Expectancy Ranking, Nigeria is ranked 192th position out of 194th in the world with Chad and the Central Africa Republic preceding it, as well as followed by Lesotho, meaning that the country has one of the lowest life expectancies in the world (Life Expectancy in Nigeria, 2023). One of the factors that can contribute to low health outcomes measured using life expectancy is environmental degradation. As per the statistics of the United States Environmental Protection Agency, CO2 emission is 76% of the total global greenhouse gas emission. China contributes higher with 30% CO2 emissions than USA 15%, European Union 9%, India 7%, Russia 5%, Japan 4% and the rest of 30% is emitted by all the remaining countries (Shah et al., 2020).

Africa is the region that will be most affected by climate change in all prognoses with temperatures exceeding 1.5°C, despite having the lowest emissions and the least amount of GHG emissions (WEF, 2022). Nigeria, one of Africa country's carbon emissions has been fluctuating over the years. From Figure 2, CO2 emission in metric tons per capita was as high as 0.71 in 1990 and increased to 0.86 in 1992, the highest so far in the country over the last three decades. It fell to 0.76 in 1994 and afterward fluctuated. The lowest CO2 emission in metric tons per capita for the past three decades in Nigeria was in 2009 with 0.48. In 2018, CO2 emission in metric tons per capita was 0.66.



Source: Author's Computation from World Bank Database (2023)

Figure 2: Co2 Emission (Metric Tons Per Capita) in Nigeria



Source: Author's Computation from World Bank Database (2023)

Figure 3: The Joint Movement of Income Inequality (Gini Index), Environmental Degradation (Co_2 Emission), and Health outcomes (Life Expectancy) in Nigeria

Figure 3 gives an insight into the changes in environmental degradation, income inequality, and life expectancy over time in Nigeria. It shows that although the changes in income inequality and environmental degradation decreased and increased at different times of the year in the past decades, life expectancy continued to show increasing changes in Nigeria during the same period. Income inequality and CO_2 emissions interact to influence health outcomes in Nigeria through multiple pathways, including environmental degradation, limited access to healthcare, and socio-economic disparities. High-income inequality often results in unequal access to clean air, water, and quality healthcare services, thereby exacerbating health challenges among low-income populations (Akinyemi et al., 2022). Studies have shown that increased CO_2 emissions contribute to air pollution, which is linked to respiratory diseases, cardiovascular complications, and premature mortality, particularly among vulnerable groups (Ezeanya & Okonkwo, 2021).

The importance of this study centres on its effort to address a significant gap in the understanding of how environmental quality, income inequality, and economic indicators

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interact over the long run in Nigeria. Previous research has often treated these variables in isolation. For example, Al-Mulali et al, (2015) focused on environmental degradation in relation to economic growth, yet social dimensions such as income inequality were not considered. In a similar manner, Pata et al, (2022) examined income inequality trends without exploring their environmental consequences. This segmented approach leaves a gap in policy-relevant knowledge, particularly within the context of sustainable development. Nigeria, as a rapidly growing economy, continues to experience increased income disparity and environmental challenges alongside economic expansion. The long-term effects of these patterns remain unclear in existing studies. Employing an econometric framework approach allows for an integrated analysis of both short-run adjustments and long-run equilibrium among these variables.

RESEARCH METHOD

This study adopted an ex-post facto research design to investigate the long-run relationship among environmental quality, income inequality, and economic indicators in Nigeria. The design is appropriate as it utilizes historical data without manipulating any variables. The study employed secondary data obtained from reputable sources, including the World Development Indicators (WDI), the World Governance Indicators (WGI), and the Central Bank of Nigeria (CBN). The data span the period from 1990 to 2023 and cover key variables relevant to the study's three objectives. These variables include life expectancy (LER), Gini coefficient (GINI), carbon dioxide emissions (CO2), per capita gross domestic product (PGDP), energy consumption (EC), and infant mortality rate (IFMR), all sourced from WDI (2023). Additionally, government capital expenditure (GCE) was drawn from the CBN (2023), while political stability and absence of violence/terrorism (PST) were sourced from the WGI (2023). The variable on deforestation (DFT) was also extracted from WDI (2023). The data were analyzed using the Autoregressive Distributed Lag (ARDL) bounds testing approach to cointegration to determine the presence of long-run relationships among the variables. This method is suitable due to its flexibility in handling variables integrated at levels I(0) or I(1), but not I(2). Diagnostic tests, including unit root tests (ADF and PP), multicollinearity tests, and residual diagnostics, were conducted to ensure the reliability and robustness of the model. All estimations were carried out using EViews 12 statistical software. The model results guided the interpretation of both short-run and long-run dynamics.

The unit root test was conducted to check if there is stationarity in the variables. Establishing stationarity is of paramount importance because, without it, data processing may yield biased results. This, in turn, leads to unreliable interpretations and conclusions. Stationarity, in this context, refers to the constancy of statistical characteristics within a time series, including parameters like mean, variance, and autocorrelation, which remain unchanged over time. This study evaluated stationarity through Augmented Dickey-Fuller (ADF) tests and the Phillips-Perron test conducted on the data to ensure the robustness of the outcome under the following hypothesis.

Ho: Variable contains unit root hence non-stationary.

H1: Variable does not contain unit root hence stationary.

These tests are performed on the original data series, as well as the first-order differenced series. The decision criterion involves rejecting the null hypothesis if the ADF and Phillips-Perron test statistic values exceed the critical value at a chosen significance level (in absolute terms).

RESULT AND DISCUSSION

The results of the ADF and Phillips-Perron unit root test can be found in the Appendix section, and a summary is presented in Table 1 below.

Table 1: Summary of ADF Unit Root Test Results

Variables	Test Stat in level	Test Stat. in First Diff.	5% Critical Value	Test Stat in level	Test Stat. in First Diff.	5% Critical Value	Order of Integration
	ADF Unit Root Test			**Phillips-Perron Unit Root Test**			
CO_2	--3.79493	-	-3.55297	-3.644902	-	-3.552973	1(0)
EC	-2.962227	-5.487076	-3.55776	-2.397873	-9.606970	-3.557759	1(1)
GCE	2.296667	-	-1.95441	8.676437	-	-2.954021	1(0)
GINI	-2.698222	-5.818858	-3.55776	-2.743509	-5.988187	-3.557759	1(1)
LER	5.172709	-	-1.95133	3.803449	-	-1.951332	1(0)
PGDP	-2.648317	-2.661561	-1.95169	-1.684679	-2.633600	-1.951687	1(1)
PST	-1.607298	-8.444792	-1.95169	-2.566108	-8.168383	-3.557759	1(1)
DFT	-1.974131	-5.631527	-3.557759	-2.025044	-5.632525	-3.557759	1(1)
IFMR	-3.977397	-	-3.574244	-5.501241	-	-1.951332	1(0)

Source: Author's Computation from E-Views 10

Following the decision rule which is to reject the null hypothesis if the ADF statistic value exceeds the critical value at a chosen level of significance (in absolute terms), and accept stationarity when ADF statistics is greater than the criteria value, it can be observed from Table 1 that there is a mix of the order of integration. At first order 1(1), we have energy consumption, Gini coefficient, per capita GDP, deforestation, and Political Stability and Absence of Violence/Terrorism. The remaining variables are of order 1(0). Having obtained a mixed order of level and first difference, the ARDL Bound test can now be conducted to check for the presence of a long-run relationship in the three models as this meets the conditions under which the test could be applied.

Correlation Analysis

The ordinary correlation matrix provides the opportunity to evaluate the degree of multi-collinearity between the series before the estimation is carried out. This only shows the non-

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existence of multi-collinearity within the series. The table 2 shows the correlation matrix for the various models estimated in this research.

Table 2: Correlation Matrix of the Variables

Panel 1a: Correlation Matrix for Objectives One and Two (LER)

VARIABLES	LER	CO_2	GINI	PGDP	EC	GCE	PST	DFT
LER	1.000000							
CO_2	-0.705641	1.000000						
GINI	-0.174187	0.128976	1.000000					
PGDP	0.654833	-0.664451	-0.066254	1.000000				
EC	0.160333	0.127556	0.063742	0.119152	1.000000			
GCE	0.693233	-0.598481	-0.603851	0.592698	0.322569	1.000000		
PST	-0.757651	0.728253	-0.097421	-0.721797	-0.098738	-0.362074	1.000000	
DFT	-0.739826	0.765782	0.335071	-0.707786	-0.166204	-0.757484	0.664363	1.000000

Panel 1b: Correlation Matrix for Objectives One and Two ***(IFMR)***

VARIABLES	IFMR	CO_2	GINI	PGDP	EC	GCE	PST	DFT
IFMR	1.000000							
CO_2	0.706350	1.000000						
GINI	0.249746	0.128976	1.000000					
PGDP	-0.634340	-0.764451	-0.066254	1.000000				
EC	-0.131233	0.127556	0.063742	0.119152	1.000000			
GCE	-0.718331	-0.598481	-0.603851	0.592698	0.322569	1.000000		
PST	0.730699	0.728253	-0.097421	-0.621797	-0.098738	-0.362074	1.000000	
DFT	0.688148	0.565782	0.335071	-0.707786	-0.166204	-0.757484	0.664363	1.000000

Panel 2: Correlation Matrix for Objective Three

VARIABLES	LER	CO_2	GINI	PGDP	EC	GCE	PST	CO_2*GINI

LER	1.000000							
CO_2	-0.614136	1.000000						
GINI	-0.525180	0.496089	1.000000					
PGDP	0.552317	-0.661073	-0.493092	1.000000				
EC	0.627994	-0.468604	-0.581111	0.595101	1.000000			
GCE	0.678541	-0.535290	-0.511042	0.626870	0.706792	1.000000		
PST	-0.452189	0.678559	0.558797	-0.621797	-0.524186	-0.377499	1.000000	
CO_2*GINI	-0.662982	0.510733	0.604952	-0.626154	-0.596464	-0.658573	0.693910	1.000000

Source: Author's Computation, E-view 10

Panel 3a: Correlation Matrix for Objective Four ***(CO_2)***

VARIABLES	CO_2	EC	PGDP	GCE	PST	GINI
CO_2	1.000000					
EC	0.127556	1.000000				
PGDP	-0.664451	0.119152	1.000000			
GCE	-0.598481	0.322569	0.592698	1.000000		
PST	0.728253	-0.098738	-0.721797	-0.362074	1.000000	
GINI	0.128976	0.063742	-0.066254	-0.603851	-0.097421	1.000000

Panel 3b: Correlation Matrix for Objective Four ***(DFT)***

VARIABLES	DFT	EC	PGDP	GCE	PST	GINI
DFT	1.000000					
EC	-0.166204	1.000000				
PGDP	-0.707786	0.119152	1.000000			
GCE	-0.757484	0.322569	0.592698	1.000000		
PST	0.664363	-0.098738	-0.621797	-0.362074	1.000000	
GINI	0.335071	0.063742	-0.066254	-0.603851	-0.097421	1.000000

Source: Author's Computation, E-view 10

The correlation matrix examines the degree of multi-collinearity between the series before the estimation. The result of the correlation matrix of all the variables of interest is shown in table 2. The result from panels 1 and 3 shows no signs of correlation, as some variables

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possess weak or no correlations in the matrix. This shows that the variables are free of multi-collinearity issues.

Co-integration Test

A cointegration test is carried out to identify if some set of non-stationary time series variables possess a long-run equilibrium relationship or not. This study used the ARDL F-Bound test since the unit root test shows that the variables are stationary at both level and first order. The results of the bound testing approach for the three models are presented in Table 3 and can also be seen in the Appendix sections.

Given the null hypothesis:
$H_0=\beta_0=\beta_1 =$ -----------$\beta_n = 0$ (no cointegration among the variables)
Decision rule:
Case 1: Reject H_0 if the F-value is greater than the upper bound
Case 2: Accept H_0 if the F-value is less than the lower bound
Case 3: Inconclusive if the F-value falls between the lower and upper bounds.

Table 3: Bounds Test Result Objective One and Two

Panel 1a: Bounds Test Result for *LER Estimation*: Objective One and Two (Model 1)

Test Statistic	Value	K
F-Statistic	10.04213	7

Critical Value Bounds		Asymptotic: n=1000
Significance	**1(0) Bound**	**1(1) Bound**
10%	1.92	2.89
5%	2.17	3.21
2.5%	2.43	3.51
1%	2.73	3.9

Panel 1b: Bounds Test Result *for IFMR Estimation*: Objective One and Two (Model 1)

Test Statistic	Value	K
F-Statistic	16.04935	7

Critical Value Bounds		Asymptotic: n=1000
Significance	**1(0) Bound**	**1(1) Bound**
10%	1.92	2.89
5%	2.17	3.21
2.5%	2.43	3.51
1%	2.73	3.9

Panel 2: Bounds Test Result Objective Three (Model 2)

Test Statistic	Value	K
F-Statistic	11.84256	6

Critical Value Bounds		Asymptotic: n=1000
Significance	**1(0) Bound**	**1(1) Bound**
10%	1.92	2.89
5%	2.17	3.21
2.5%	2.43	3.51
1%	2.73	3.9

Source: Author's computation E-views 10

From Table 3, the value of the F-statistic in the first model shows the joint significance of the lagged level variables is 10.04213 and 16.04935 which are greater than the upper bound I (1) at a 5% level of significance. Therefore, we reject the null hypothesis and conclude that a long-run relationship exists between the dependent variable (health outcomes) and the independent variables (carbon emission, Gini coefficient, gross domestic product per capita, energy consumption, deforestation, and government capital expenditure)

The second model has its F-statistics at 11.84 which is greater than the joint significance of the lagged level variables at the upper bound I (1) at a 5% level of significance. Hence, this study concludes that a long-run relationship exists between health outcomes and the independent variables (carbon emission, Gini coefficient, carbon emission, Gini coefficient, gross domestic product per capita, Political Stability, and Absence of Violence/Terrorism (PST), and energy consumption).

Lag Length selection Criteria

The lag length for the autoregressive distributed lag model was done using Akaike Information. Since the study used E-views 10 which gives a chance for automatic selection of lag lengths, the study selected maximum lag lengths of 1 and 2 are shown in the appendix sections of the main regression output.

The ARDL Lag length selection criteria as presented under the appendix section for models 1 and 2 showed that after the evaluations, the system automatically selected ARDL(1, 0, 1, 1, 0, 0, 2) and ARDL(1, 1, 2, 1, 1, 2, 1, 2) for model one and two, respectively.

Test for Autocorrelation (Breusch Godfrey)

The Autocorrelation test is used to check if the error terms of different observations are correlated with each other which is against the assumptions of OLS. Autocorrelation is manifested by OLS estimators which are not BLUE (Best linear unbiased estimates). In our study, the Breusch-Godfrey Serial Correlation LM Test is used to detect the presence of autocorrelation for the three models. The result is presented in Table 4.9 and also shown in the Appendix section.

The hypothesis for this autocorrelation test is

H0 = There is no serial correlation.

Therefore, the decision rule is if the P value is less than the chosen level of significance (0.05 or 5%), then we reject the null hypothesis that there is no serial correlation and accept the alternate hypothesis that there is a serial correlation.

Table 4: Summary of Breusch-Godfrey Serial Correlation LM Test.

Panel 1a: Model 1 (Objective One and Two) *LER*

	Test Statistic	**P-Value**
F- Statistic	0.533812	0.4771
Observed R^2	1.175327	0.2783
Durbin Watson test statistic	2.144571	

Panel 1b: Model 1 (Objective One and Two) *IFMR*

	Test Statistic	**P-Value**
F- Statistic	1.023040	0.3278
Observed R^2	2.043137	0.1529
Durbin Watson test statistic	2.354966	

Panel 2: Model 2 (Objective Three)

	Test Statistic	**P-Value**

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F- Statistic	1.641909	0.2377
Observed R^2	7.356728	0.0253
Durbin Watson test statistic	2.223318	

Source: Author's computation, E-view 10

Panel 3a: Model 3 (Objective Four) *CO_2*

	Test Statistic	P-Value
F- Statistic	0.021899	0.8856
Observed R^2	0.075246	0.7838
Durbin Watson test statistic	2.079150	

Source: Author's computation, E-view 10

Panel 3b: Model 3 (Objective Four) *DFT*

	Test Statistic	P-Value
F- Statistic	0.199589	0.6656
Observed R^2	0.672559	0.4122
Durbin Watson test statistic	1.788339	

Source: Author's computation, E-view 10

Based on this, the probability value of the F-statistics for the three models as seen in Table 4.9 is greater than 0.05. Hence, the null hypothesis of no serial correlation is accepted for the three models. This is confirmed by the Durbin-Watson test statistic from the primary estimations of the ARDL Models.

Test for Heteroscedasticity (ARCH)

The Heteroscedasticity test is conducted to ascertain if the variance of the error term is constant for all observations. This forms one of the assumptions of the ordinary least square (OLS) which if the assumption does not hold; we face the problem of heteroscedasticity. Therefore, to confirm that the variance of the error term is constant, the ARCH heteroscedasticity test was adopted. This result is presented in Table 4.10 and Appendix section.

Hypothesis

$H_0 = \beta_1 = \beta_2 = \beta_3 = 0$ (absence of heteroskedasticity)

$H_1 = \beta_1 \neq \beta_2 \neq \beta_3 \neq 0$ (presence of heteroskedasticity)

Decision Rule: Accept the null hypothesis (H_0) that there is no heteroscedasticity in the residuals if the P-value is greater than 0.05.

Table 5: Summary of Heteroskedasticity Test

Panel 1a: Model 1 (Objective One and Two) *LER*

	Test Statistic	P-Value
F- Statistic	0.128822	0.7223
Observed R^2	0.137097	0.7112

Panel 1b: Model 1 (Objective One and Two) ***IFMR***

	Test Statistic	P-Value
F- Statistic	0.271786	0.6061
Observed R^2	0.287832	0.5916

Panel 2: Model 2 (Objective three)

	Test Statistic	P-Value
F- Statistic	0.233530	0.6325
Observed R^2	0.247641	0.6187

Panel 3a: Model 3 (Objective Four) CO_2

	Test Statistic	P-Value
F- Statistic	0.149138	0.7023
Observed R^2	0.158945	0.6901

Panel 3b: Model 3 (Objective Four) ***DFT***

	Test Statistic	P-Value
F- Statistic	3.271766	0.0812
Observed R^2	3.138709	0.0765

Source: Author's Computation from E-Views 10

Therefore, this study accepts the null hypothesis of the absence of heteroscedasticity given that the P-values of the three models are all greater than 0.05.

Model specification test

The diagnostic test conducted for the models is the CUSUM test to certify the stability of the model. The null hypothesis being tested here is that the $CUSUM_t$ statistic is drawn from a $CUSUM_{(t-k)}$ distribution, thus the $CUSUM_{(t-k)}$ is a symmetric distribution centered at 0 with its dispersion increasing as t-k does.

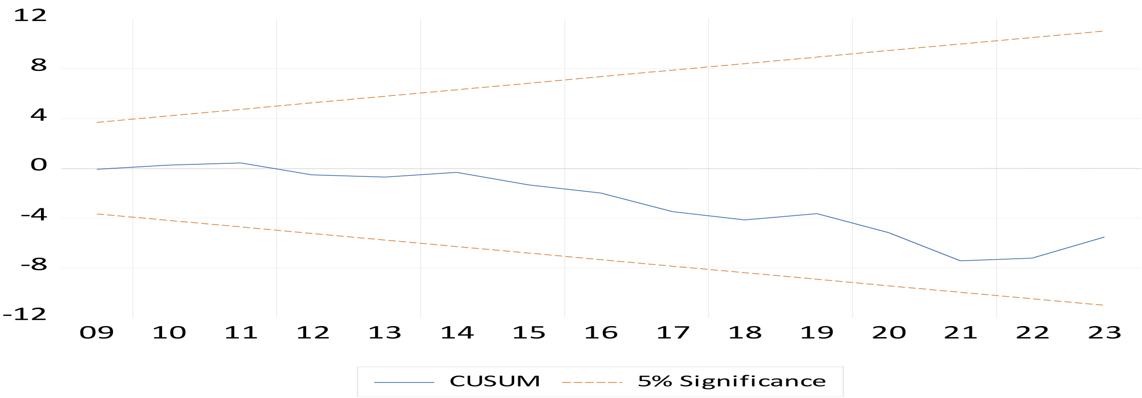

Figure 4: Model 1 (Objective One and Three)

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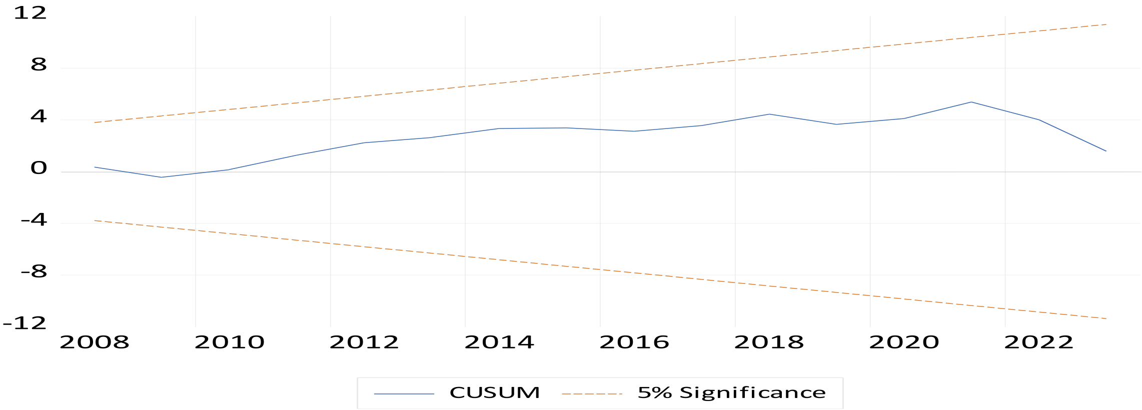

Figure 5: Model 1 (Objective One and Three)

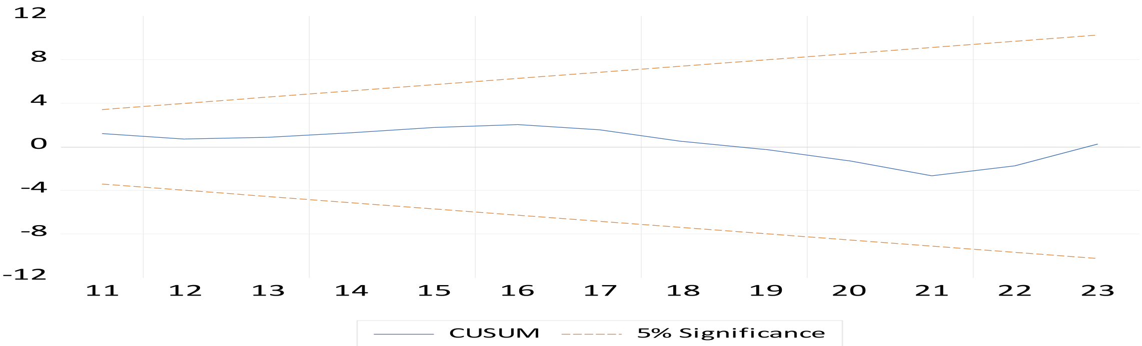

Figure 6: Model 2 (Objective Three)

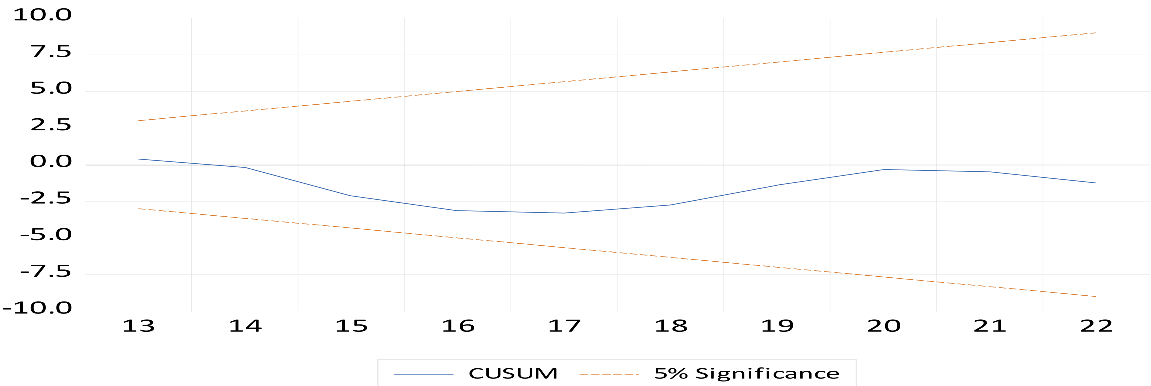

Figure 7: Model 3 (Objective Four)

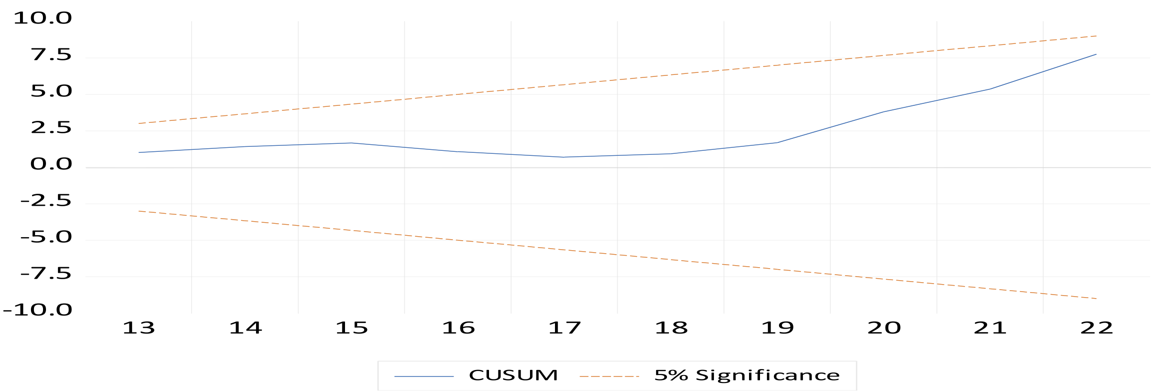

Figure 8: Model 3 (Objective Four)
Source: Author's Computation from E-Views 10

The plot 4-8 illustrates the Cumulative Sum (CUSUM) of recursive residuals used to assess the stability of model parameters over time. The blue line represents the CUSUM statistic, while the dashed orange lines mark the 5% significance bounds. Since the CUSUM line remains within the upper and lower bounds throughout the sample period (from observation 13 to 22), the model parameters are considered stable at the 5% significance level. No structural break or instability is indicated within the observed time frame, confirming the reliability of the model estimates over the examined period.

Discussion

This study employed ADF and Phillips-Perron unit root tests, correlation analysis, and ARDL Bound testing to assess the long-run relationship among environmental quality (CO_2), income inequality (GINI), and various economic indicators in Nigeria. The unit root test revealed a mixture of I(0) and I(1) variables, validating the use of the ARDL model. The Bound test results indicated a statistically significant long-run relationship, particularly for models estimating life expectancy rate (LER) and infant mortality rate (IFMR), with F-statistics exceeding upper critical bounds.

This finding agreed with Galadima et al, (2022), who found a stable long-run equilibrium between economic growth and CO_2 emissions in Nigeria using similar ARDL methodology. In contrast, Usman et al, (2022) argued that income inequality had no significant long-run association with environmental quality when corruption was included as a moderating variable. In a related study, Chen et al, (2022) discovered that fiscal policy variables such as government capital expenditure (GCE) positively influenced environmental outcomes, consistent with the positive correlation between GCE and LER in this study.

The correlation matrix revealed no strong multicollinearity among variables, affirming the robustness of the estimation model. For instance, GCE and PGDP were positively associated with LER, while CO_2 and political instability (PST) were negatively related, supporting Escaleras and Kottaridi (2014) who reported that macroeconomic stability and public investment significantly shape health and environmental outcomes. In contrast, Pata et al, (2022) found PST to have an indirect effect on environmental degradation via income disparities. Moreover, the study's result that CO_2 and income inequality (CO_2*GINI) negatively influenced LER aligns with Smith et al, (2022), who found that higher income disparities exacerbated environmental decline. Similarly, Berthe and Elie (2015) confirmed that inequality amplifies the adverse health effects of environmental degradation.

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CONCLUSION

This study empirically examined the long-run relationship among environmental quality, income inequality, and key economic indicators in Nigeria using robust econometric techniques. The findings revealed that environmental quality is significantly influenced by income distribution patterns, economic growth, energy consumption, and industrial activity. In particular, the results indicated a long-run equilibrium relationship, suggesting that these variables are interconnected over time. While economic growth and industrial expansion contributed positively to national output, they also exerted adverse effects on environmental quality, thus highlighting the existence of an environmental trade-off in Nigeria's development trajectory.

Moreover, the analysis showed that income inequality exacerbates environmental degradation, reinforcing the need for inclusive economic policies. Policies that prioritize equitable income distribution and green growth strategies are therefore critical for sustainable development. The study underscores the importance of integrating environmental sustainability into Nigeria's macroeconomic planning while addressing structural inequalities and promoting energy efficiency. In light of these findings, targeted policy interventions are recommended to reduce emissions through cleaner production processes, equitable wealth redistribution, and investments in renewable energy. This research contributes to the understanding of the complex interactions between inequality, growth, and the environment in a developing economy and provides empirical evidence to guide policy for achieving the dual goals of environmental preservation and socio-economic equity in Nigeria.

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