

*Research Article*

# Assessing the Impact of Carbon Emission, Health Expenditure, IMR and GDP On Life Expectancy in India: Using Cointegration Approach

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## Abstract

The present study seeks to find out the impact of carbon emission, economic growth, infant mortality rate, and health expenditure on life expectancy as a measure of health in the Indian context for the period of 2000 to 2020. This paper uses ADF and KPSS tests to check data stationarity and the ARDL model to check cointegration among the aforementioned variables. ARDL test confirms cointegration between the variables and establishes a long-run impact of carbon emissions, infant mortality rate (IMR), health expenditure, and economic growth on life expectancy in India. The study confirms the nexus between life expectancy and carbon emission. It also indicates a positive relationship between life expectancy and economic growth. Further, the negative value of the cointegration coefficient reveals the convergence of the model which means the model is stable. The study shows a way for policymakers to design policies that reduce carbon emissions through the use of green and sustainable energy which can help in the improvement of health indicators. It can act as a torch-bearer for policymakers while formulating policies related to health and the environment.

**Keywords:** Life expectancy; carbon emissions; IMR; ARDL; cointegration, India.

## Introduction

Carbon emission is found as one of the most vital contributing factors to environmental deterioration. To keep up with the economic growth and growing population, developing economies like India, are flooding with higher concentrations of pollutants. Pollutants have negative effects on human health and the environment. By the onset of the 21<sup>st</sup> century climate change has become a burning issue at the global level. India, the world's third-largest emitter of greenhouse gases, is also vulnerable to climate change. It has pledged to reduce carbon intensity by 30 to 35 percent by 2030, compared to 2005 levels. Several researches highlighted that around 3.6 billion population are living under the threat of climate change. Between 2030 to 2050, changes in climatic conditions are expected to cause around 2.5 lakh additional deaths per annum due to undernutrition, malaria, diarrhoea, and heat stress alone. Some research works attributed to approximately 37 percent of heat-related deaths to human-induced climate change. It is found that regions with weak health infrastructure like developing nations will be the least able to cope with the associated climatic risks without assistance to prepare and respond.

The present study is innovative in the sense that it turns out to be interdisciplinary. Health, as a part of human capital and an important parameter of well-being, is being used for investigation in this article. It seeks to portray a relationship between environment and health. Such kinds of studies are limited to nations like India. Moreover, it is discerned that reduced emissions of carbon and other greenhouse gases through better transport, food, and energy-use choices can result in huge gains for health, especially through reduced air pollution. Increasing levels of pollution, particularly CO<sub>2</sub> emissions, not only contribute to global warming, sea level rise, and other climatic changes, but it also causes morbidity and mortality [1]. It further suggested that a reduction in pollution exposure will surely result in improved life expectancy. In 2012, WHO estimated that deaths of around seven million people were attributable to environmental pollution, the single largest health risk worldwide. It also recommended to take action to reduce emissions at both national and local levels. Another report by WHO [2] suggests that to

create a low-carbon development mechanism along with strengthening carbon resilience, investment in the health sector is important.

The increase in atmospheric CO<sub>2</sub> has occurred primarily due to increasing fossil fuel consumption. Reducing CO<sub>2</sub>-driven industrial changes will reduce environmental deterioration, improve public health, reduce inequality, and increase the resilience of individuals, communities, and broader society [3]. UNEP reported that the financial burden of outdoor environmental pollution in developing nations is approximately 5 percent of their GDP. The increase in health expenditure is due to an increase in national income, an aging population, environmental pollution, and an increase in energy intensity. Most of the researchers have considered income as the primary explanatory variable to explain health expenditure. However, it depends upon the income elasticity of health expenditure in different countries using different estimation methods. In general income elasticity of healthcare expenditure is positive and greater than unity for developed countries, while it is less than unity for low to middle-income countries. However, overall elasticity varies over time depending on the data used, estimation methodology, and the stage of the country's economic development and non-economic factors. Aging is also a factor that drives healthcare expenditure. Major studies have highlighted that there exists a positive effect of CO<sub>2</sub> emissions on health expenditure. Particularly in low-income countries healthcare expenditure has increased due to an increase in CO<sub>2</sub> emissions. However, it also depends on technological advances and the income of a particular country. Energy intensity is considered as one of the major drivers of sustainable development and also causes a reduction in poverty and healthcare expenditure. According to an analysis higher overall energy intensity will have a detrimental effect on environmental pollution, while it will increase health care expenditure of any particular country. Health indicators like life expectancy and mortality rates are commonly used as proxy variables to study the impact of carbon emissions on health. The performance of health can also be indicated via health expenditure as a percentage of GDP over the years.

This paper is structured into five sections. The introduction of study is presented in section 1 and literature review in section 2 followed by hypotheses formulation. Section 3 deals with the methodology, data and variables, and econometric modelling. In section 4, results and interpretations are presented. Finally, section 5 concludes the results with limitations and future directions of the study.

## **Literature review**

In India, there are scant studies that focus on the impact of CO<sub>2</sub> emissions on health. Few studies in India have used child mortality and infant mortality as health indicators. However, they are not sufficient to forecast the overall health effect. As per the EKC hypothesis, with the increase in economic growth environmental deterioration increases only up to a certain threshold physical limit, and after that, it starts declining with a further increase in economic growth. Ghorashi & Rad [4], observed a bi-directional relationship between CO<sub>2</sub> emission and economic growth with the given production technique. More carbon emissions mean more expansion of gross production depending on the output elasticity of CO<sub>2</sub>. This follows that with unchanged technological status, reduction of CO<sub>2</sub> emission will result in cutting down of volume of production or output and income. Khan et al. [5] invalidated the EKC hypotheses for India, which is also supported by the study of Al-Mulali et al. [6] for lower-middle-income countries. Das et al. [7], in a time series analysis, found that over 82 percent of temperature variation was due to CO<sub>2</sub> emission. With the increasing population and income, demand for fossil fuels further increases which ultimately culminates in the magnification of temperature.

The utilization of energy in the process of production, trade, and urbanization creates a detrimental effect on health. The process of production produces a two-way effect: Firstly, the income generated thereby creates a positive impact on the health sector as a whole. Secondly, pollution generated in the process of production has a negative impact on health. Now, the net effect of the two outcomes of production will determine whether it will cause an increase or decrease in human welfare. Rasoulinezhad et al. [8] studied the relationship between economic growth, fossil fuel consumption, mortality, and environmental pollution. This study utilized a generalized method of moments estimation technique and concluded that CO<sub>2</sub> is an important factor in causing mortality from diseases like cardiovascular disease (CVD), cancer, etc., in the Commonwealth of Independent States (CIS) region from the period 1993-2008. Murthy et al. [9] estimated the relationship between CO<sub>2</sub>, economic growth, and life expectancy in D-8 countries for the period 1992-2017. The study revealed a negative

impact of CO<sub>2</sub> on life expectancy. In G-7 countries, CO<sub>2</sub> emissions have a significant impact on health expenditure [10]. In another study, a 1 percent growth in health expenditure leads to a 0.124 percent decrease in carbon emissions over the long term [11].

However, certain studies have observed the reverse of the expected relationship between the variables. A study of Nigeria from 1995-2013 has shown a positive significant relationship between carbon emission and life expectancy [12]. In another study by Rjoub et al. [13], there have been observed positive effects of CO<sub>2</sub> on life expectancy in Turkey. Therefore, the existing literature does not necessarily depict a clear nexus between CO<sub>2</sub> and life expectancy. A study of ECA, MENA and SSA regions suggests a positive association between carbon emissions and life expectancy, which is explained as often industrialization leads to job creation and economic growth, which in turn contribute to better healthcare access, nutrition, and overall resources supporting good health [14]. Moreover, numerous studies have highlighted the severe health-related impacts of increasing CO<sub>2</sub> concentration. Carbon dioxide as a greenhouse gas leads to the surfacing of global temperature. Temperature growth beyond the limit has severe ill consequences on health. Several studies like Sharma et al., and others have shown concern over the negative health effects of rising temperatures in India. Increased death from heat stroke, CVD, viral and infectious diseases, life loss due to floods, etc., are some of the results of ever-increasing temperature and climate change.

Technological innovation and development may help in environmental pollution mitigation efforts and may also decrease healthcare expenditure through low carbon footprint healthcare supply chains [15]. Gunduz [16] utilized the hidden cointegration approach to analyse the impact of the US carbon footprint on health expenditure between 1970 to 2016. During the analysis, it was found that there exists a cointegration relationship between the long-term carbon footprint and health expenditure. Further, an increase in carbon footprint will increase the health expenditure budget. Taghizadeh-Hesari [17] used the panel Vector Error Correction Model (VECM) and panel generalized moment method (GMM) to analyse data of ten Southeast Asian countries from 2000 to 2016 and studied the relationship between energy use and health expenditure. They found that an increase in carbon emissions brought about by the use of fossil fuels will increase per capita health expenditure, while the use of renewable energy will reduce per capita health expenditure. Yazdi et al. [18] found a positive relationship between carbon monoxide, sulphur dioxide, and health expenditure. Another study used the recently linked ARDL bootstrap app with structural separators to study the relationship between clean energy consumption, economic growth, and carbon emissions. They found a short-term and long-term relationship between economic growth and carbon emissions for G7 countries.

Aye [19] suggested that without resorting to environment-friendly approaches and techniques, the quality of the environment will only worsen as a result of increased emission of CO<sub>2</sub> in the process of industrialization. Rahman et al. [20] found that in the world's most polluted countries, higher CO<sub>2</sub> emissions result in lower life expectancy. Adebayo and Akinsole [21] analysed time series data from 1971 to 2018. They used the wavelet coherence method to examine the relationship between energy consumption, CO<sub>2</sub> emissions, and economic growth in Thailand. The results suggest that changes in economic growth led to changes in the frequency of CO<sub>2</sub> emissions. Also, both short-term and long-term CO<sub>2</sub> emissions are positively correlated with GDP growth.

Therefore, from the above review of literature, it is clear that there is extensive literature available related to health, carbon emission, environmental deterioration and economic growth across the globe. However, in India fewer studies have been conducted to study such a relationship. The present work will attempt to find a relationship between life expectancy and other explanatory variables viz., carbon emission, infant mortality rate, GDP per capita and domestic health expenditure. Following are the hypotheses formulated to answer the research questions of the present study.

Hypothesis:

H<sub>0</sub>: There is no relationship between carbon emissions and life expectancy.

H<sub>0</sub>: Economic growth does not impact life expectancy.

H<sub>0</sub>: Infant Mortality Rate has no impact on life expectancy.

H<sub>0</sub>: There is no significant relationship between health expenditure and life expectancy.

Therefore, the paper attempts to test the aforementioned hypotheses against its alternatives. The following section will delve into methodology and econometric modelling.

**Methodology**

**Data and variables**

This research paper analyses the relationship between life expectancy and its explanatory variables like carbon emissions, gross domestic product (GDP), infant mortality rate (IMR), and health expenditure. The data is taken from the world development indicator [25] for the period 2000-2020 for the time series analysis. The carbon emission is taken in kt (kilo tonnes), GDP per capita at constant price 2015 US\$, domestic health expenditure as a percentage of GDP, infant mortality (per thousand live births), and life expectancy at birth in total years.

**Econometric Modelling**

The study uses the ARDL long-term forms and bounds test to test the long-run impact of carbon emission and other variables on life expectancy. Before putting it into equation form, we converted the data into log form, which is symbolized as: life expectancy as LLE, carbon emission as LCE, health expenditure as HE, infant mortality rate as LIMR, and gross domestic product as LGDP. The variables can be depicted mathematically in the log form equation as follows:

$$LLE_t = \gamma + \sum_{i=1}^P \gamma_1 \Delta LLE_{t-1} + \sum_{i=1}^P \gamma_2 \Delta LCE_{t-1} + \sum_{i=1}^P \gamma_3 \Delta LGDP_{t-1} + \sum_{i=1}^P \gamma_4 \Delta LIMR_{t-1} + \sum_{i=1}^P \gamma_5 \Delta HE_{t-1} + \mu_1 LLE_{t-1} + \mu_2 LCE_{t-1} + \mu_3 LGDP_{t-1} + \mu_4 LIMR_{t-1} + \mu_5 HE_{t-1} + \epsilon_t$$

where,  $\Delta$ ,  $\gamma$ , and  $\epsilon$  are the difference operator, the drift component (intercept) and the conventional white noise error term, respectively. The null hypothesis of no cointegrating relationship between the variables is  $H_0: \mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5 = 0$ , against the alternative hypothesis of cointegration  $H_1: \mu_1 = \mu_2 \neq \mu_3 \neq \mu_4 \neq \mu_5 \neq 0$ . Pesaran et al. [22] and Narayan [23] have provided two sets of F critical values (lower bound and upper bound) for large samples and small samples, respectively. If the calculated value of the F statistic exceeds the upper bound critical value, then cointegration exists among the variables. On the other hand, if the calculated value of the F statistic is less than the lower bound critical value, then no cointegration exists among the variables. However, the inference remains inconclusive if the calculated F statistic lies between the two critical bounds.

Table 1. Unit Root Test Results

Variables	ADF Test		KPSS Test	
	At Level	At Difference	At Level	At Difference
LCE	1.096068	-2.209802	0.163284*	0.197388*
LGDP	-1.748490	-0.488009	0.072434***	0.153610*
HE	-2.540485	-4.269598	0.106646***	0.096353***
LLE	3.713616	-8.525633	0.162372*	0.154892*
LIMR	-6.963189	-0.837323	0.173160*	0.152344*

Source: Calculated by the authors

Note:

\*, \*\* and \*\*\* indicates significance level at 1%, 5% and 10%, respectively

**Results and Discussions**

Before we test for cointegration, it is necessary to run unit root tests to check the stationarity of data. For this purpose, the Augmented Dickey-Fuller (ADF) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test are used. In the ADF test, the Null hypothesis is data has a unit root and it is accepted both at level and first difference for all variables. Therefore, to further check the stationarity of data KPSS test is used. In this, the Null hypothesis is such that the variable is stationary. After the KPSS test null hypothesis is accepted as all variables are found stationary for both level and first difference at different significance levels. As mentioned in Table 1, the test reveals that most variables are non-stationary in the ADF test, however, they are stationary at both levels and first

difference in the KPSS test. Now, since the stationarity of data is proved we can move further to check the cointegration among variables.

Table 2 reports the results of the ARDL bounds test of cointegration. As aforesaid, if the value of the F statistic lies above the upper bound, then we can infer that there exists a long-run relationship among variables. The result reveals that the calculated value of the F statistic lies above the upper bound at the conventional significance level. Therefore, there it confirms the long-run impact of carbon emission, GDP, health expenditure and infant mortality on life expectancy at the conventional 5% significance level.

Table 2. ARDL Bounds Test Result

F Statistic	<b>44.32</b>	
Critical Value (T =19)		
	Lower Bound, I(0)	Upper Bound, I(1)
10%	2.2	3.09
<b>5%</b>	<b>2.56</b>	<b>3.49</b>
2.50%	2.88	3.87
1%	3.29	4.37

Source: Calculated by the authors

Table 3. Long-run coefficients based on ARDL

Panel 1: Long run coefficients			Panel 2: Diagnostic Tests	
Variable	Coefficient	t-Statistic		
HE	-0.043887	-4.039408	R-squared	0.999778
LGDP	0.101110	2.061318	Adjusted R-squared	0.999601
LCO <sub>2</sub>	-0.079064	-2.050968	Schwarz criterion	-17.59422
LIMR	-0.153279	-3.688064	Durbin-Watson stat	2.316069
C	5.171095	9.863007	Jarque Bera	0.993117

Source: Calculated by the authors

Table 3 reports the long-run coefficients based on ARDL test. It consists of two panels. Panel 1 shows the long-run coefficients of the variables. The negative coefficient of carbon emission and infant mortality rate establishes a dynamic nexus of life expectancy with CO<sub>2</sub> and IMR. As carbon emission and IMR increases, the life expectancy decreases. 0.079% decrease in life expectancy is explained 1% increase in carbon emissions. IMR has a significant inverse relationship with life expectancy.

The result shows that LE decreases by 0.153% for every 1% increase in IMR. It further shows a positive relationship between GDP and life expectancy. For every 1% increase in GDP, life expectancy rises by 0.101%. However, the results reveal a theoretically opposite relationship between health expenditure and life expectancy. Since health expenditure has a negative coefficient, so life expectancy decreases by 0.043% for 1% increase in health expenditure. This may be due the insufficient data or because health expenditure as a percentage of GDP is quite low, which is why it is giving an inappropriate result.

Panel 2 of table 3 reveals the diagnostic tests of the model. The values of R-squared and adjusted R-squared show the goodness of fit of the model. It reveals that there exists a strong relationship between the dependent and independent variables. The diagnostic tests reveal the parametric stability of the model. However, there exists almost no autocorrelation in the model which is shown by Durbin – Watson stat (2.316069). Further, Jarque-Bera

statistic is used to check the normality of sample data. The results (0.993117) reveal the non-normality of the data set.

Therefore, based on the above results we have rejected the first three null hypotheses and have accepted their alternatives. Then, we accepted the fourth hypothesis showing the insignificant relationship between health expenditure and life expectancy, and rejected its alternative.

The results of CUSUM and cumulative sum of squares of recursive residuals (CUSUMSQ) tests are shown in the plot of parametric stability graph (Figure 1 & 2 resp.). The results reveal that long-run coefficients are statistically stable at the conventional significance level.

### Parameter Stability

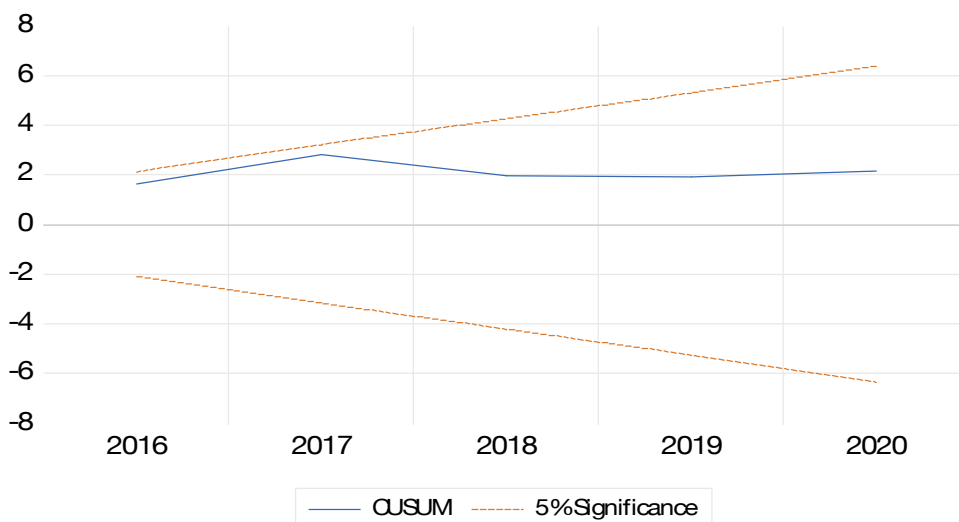


Figure 1. Plot of Cumulative Sum of Recursive Residuals

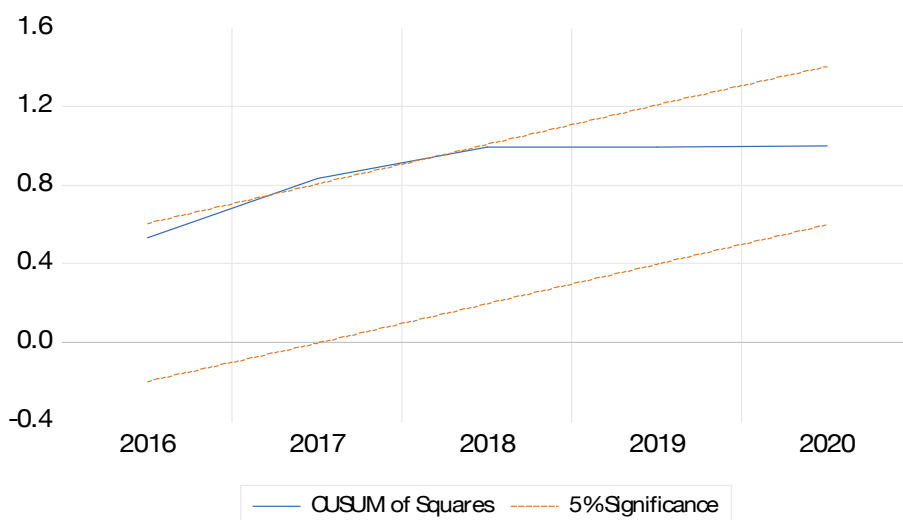


Figure 2. Plot of Cumulative Sum of Squares of Recursive Residuals

### Conclusion and policy implication

The natural and man-made factors causing climate change have a profound impact on health parameters. The interdisciplinary nature of the study seeks to bring about a thorough relationship between environment and health. The idea is innovative as it picturizes the interconnection of two different subjects of research. The study attempted to establish an empirical research model to assess the impact of carbon emission, health expenditure, infant mortality, and economic growth on life expectancy in India for the period 2000 to 2020. The paper used the ARDL approach to analyse the long-run forms and bounds test, and cointegration among variables [22, 23]. The model confirms a long-run relationship between the variables. Based on the results of the model, we have rejected the first three null hypotheses and established the relationship between the variables by accepting the alternate hypotheses. However, we have accepted the fourth hypothesis of the insignificant relationship between HE and LE by rejecting its alternative. The value of the cointegration coefficient (-0.041892) proves the stability of the model revealing convergence.

It is evident from the model there is a dynamic nexus between life expectancy and carbon emission (a 0.079% decrease in life expectancy is explained by a 1% increase in carbon emissions) which is in line with the works of Murthy et al. [9] and Rahman et al. [21]. However, Rjoub et al. [13] and Osei-Kusi et al. [14] in their study depicted a positive association between carbon emissions and life expectancy. Therefore, more studies in this area are required to be done with larger samples to support the results. The study also reveals a negative relationship between IMR and life expectancy and a positive relationship between GDP and life expectancy, defining the significant relationship between the variables. LE decreases by 0.153% for every 1% increase in IMR and for every 1% increase in GDP, life expectancy rises by 0.101%. However, the results reveal a theoretically opposite and statistically insignificant relationship between health expenditure and life expectancy. It shows that as health expenditure increases, life expectancy decreases, which is why we have accepted the fourth null hypothesis. This may be due the insufficient data or because health expenditure as a percentage of GDP is quite low, which is why it is giving an inappropriate result. It is supported by the study of Zaman et al. [24] which shows an inverse relationship between life expectancy and health expenditure specifying reasons.

The diagnostic results on the ARDL model are crucial to check the correctness of the results. The values of R-squared and adjusted R-squared show a strong relationship between the dependent and independent variables. The Durbin-Watson test shows near to no autocorrelation in the model. The results of CUSUM and CUSUM squares reveal that long-run coefficients are statistically stable at the conventional 5% significance level.

The outcomes of the study suggest that a reduction in the level of CO<sub>2</sub> emission causes an increase in life expectancy in India. It implies that a reduction in fossil fuel consumption and an inclination towards more green and sustainable energy use can help in increasing life expectancy. The study, therefore, confirms the established relation between carbon emission and life expectancy along with the relationship of other health proxy variables and life expectancy as discussed in the literature review for different countries. It is also an addition to literature in India in the 21<sup>st</sup> century. The study sought to reduce all possible econometric biases. It fills the research gap in the existing literature on health and carbon emissions. It can act as a torch-bearer for policymakers while formulating policies related to health and the environment.

### **Limitations and Future Directions**

Concerning the limitation of our work, it must be mentioned that it has taken time series data of twenty years only due to non-availability of data. Future studies should increase the sample size. Further, the health expenditure reveals an inappropriate result which might be due to data insufficiency, abnormal COVID year or because health expenditure as a percentage of GDP is quite low to give a significant result. Finally, the study opens up the scope for researchers to extend it further using different variables and novel econometric techniques.

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