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Carbon Emissions and Public Health in India: VECM Estimation of the Causal Relationship between Air Pollution and Public Health Expenditure

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Abstract: Globally rising environmental degradation is a result of increasing carbon emissions due to high population pressure on space and resources and the ever-enlarging industrialisation. The consequent pollutions have cascading effects on health and cause rising public healthcare expenditure. The growing air pollution has direct adverse effects on fertility and mortality, reducing human fertility and rising mortality. This paper analyses the causal relationship between carbon emission, air pollution, health, fertility, mortality, gross domestic product and public healthcare expenditure in India for the years 2000-2001 to 2022-2023. The vector error correction model estimates show that public health expenditure increases significantly with the increase in CO2 emission. A one percentage increase in carbon emission increases public health expenditure by 0.36%. For a one percentage increase in GDP and total fertility rate, the public health expenditure increases respectively by 0.02 and 0.98%. The VECM estimates suggest that approximately 36.4% of the long-run disequilibrium in the relationship between air pollution and public health expenditure is adjusted over the years.

Keywords: carbon emission, air pollution, environment quality, public health, public health expenditure, vector error correction mechanism

Introduction

The world is growing at an unprecedented rate as a response to new inventions and fast innovations in technology, especially in the industrial and service sectors. The growing manufacturing activities increase energy consumption causing high levels of harmful air pollutants such as carbon monoxide, sulfur, nitrous and carbon dioxide. The main air pollutant, carbon dioxide (CO2) causes lethal oxygen-deficient environments, especially in urban and congested places. The high concentration of carbon emissions in the atmosphere, as high as 350 parts per million (PPM) causes changes in global climatic patterns and global warming. The high environmental pollution and consequent degradation in the quality of the environment eventually harm human health lead leading to higher healthcare expenditure both by the governments and individuals.

Among the various environmental pollutions, air pollution causes both chronic and acute diseases in humans like various respiratory ailments resulting in increased morbidity and hospitalisation. Across the globe, nearly 7 million deaths in 2016 were due to household and ambient air pollution, of which about 94% occurred in low and middle-income countries (WHO, 2018). With increasing air pollution-related ill-health, the cost of healthcare is also increasing. A healthy society is viewed as one of the important forms of wealth that are regarded as human capital both for the individual and the nation. Good health is also important for increasing worker productivity. The increasing damage to the environment by carbon emissions, coupled with the increasing health and illness burden, is the immediate cause for the increasing share of government spending on healthcare in almost every country (Boachie *et al*. 2014; Fattahi, 2015; Fattahi *et al*. 2013; 2015; Jie, 2008; Mohammadzadeh *et al*. 2015). Improving air quality will decrease the burden of air-borne diseases which will reduce both individual and public health expenditures.

Apart from general health issues associated with air pollution and environmental degradation, carbon emissions-induced air pollution has multiple adverse effects on fertility and mortality in populations. Though the mortality effects are well-researched and clearly understood, the fertility effects of air pollution are less known. Air pollution is highly related to increased risk of cancer, and cardiovascular and respiratory disorders that are the primary causes of death in modern times. Studies have shown that air pollutants disrupt human endocrines and exert genotoxic effects, thereby causing human infertility. The adverse effects of air pollutants on human infertility are decreased conception and live births and increased miscarriage and stillbirths (Frutos *et al*. 2015). Specifically, air pollutant particulate matter of 2.5 mm and between 2.5 and 10 mm reduces fecundability and sulfur dioxide, carbon monoxide and nitrogen dioxide increase miscarriage and stillbirths in females (Conforti *et al*. 2018).

In India also, public expenditure on health is sizable. The gross domestic product, carbon dioxide emission and public health expenditure all show increasing trends while the infant mortality rate and total fertility rate are showing an increasing trend. An interesting point to note is that with the increasing pace of output (GDP), the emission is also increasing and so is the public health expenditure in India. In an attempt to understand the effect of carbon dioxide emissions on public health expenditure in India, this paper analyses the short and long-run causal relationship among gross domestic product, carbon dioxide emission, infant mortality rate, total fertility rate and public health expenditure. In the empirical analysis, this paper uses time series data collected from the

World Bank, Reserve Bank of India and NITI Aayog over the period from 2000-2001 to 2022-2023.

Literature Review

There exists a vast literature and ample evidence that carbon dioxide emission causes greater damage to the environment and health and increases healthcare expenditure in almost all countries. Almost all studies used similar variables and approaches and demonstrated that there is a long-run relationship between carbon dioxide emission and public health expenditure. All studies have shown the existence of a disequilibrium relationship between carbon emissions and public health expenditure, but there is no consensus on the quantum of correction made each period in the long-run relationship. Only a few econometric studies that used a closely relevant methodology to this paper are reviewed here just to show the appropriateness of the empirical estimation method.

Jerrett *et al*. (2003) explore the relationship between healthcare expenditure and quality of the environment, represented by air pollutants and government spending for protecting the environment in Ontario, Canada. The unit root test is used to test the stationarity and the cointegration test is used to find the long-run relationship between the variables. The two-stage regression results show that air pollution impacts significantly child hospitalisation due to asthma. Controlling other influencing factors of health expenditure, the study finds significant associations between healthcare expenditure and toxic pollution output as well as per capita municipal environmental expenditure.

Yahaya *et al*. (2016) examine the impact of environmental quality on per capita health expenditure in a panel of 125 developing countries for a period of 1995 to 2012. The 125 developing countries considered in the paper are having assiduous health complications as well as a steady increase in health expenditures. The pollutants of the environment considered are carbon dioxide, carbon monoxide and nitrous oxide. The unit root test shows carbon monooxide, nitrogen oxide and sulfur oxide emissions cause an increasing per capita health expenditure in these countries.

Abdullah *et al*. (2016) analyse the cointegration between environmental quality and socioeconomic factors for national health expenditure in Malaysia from 1970 to 2014 using the autoregressive distributed lag (ARDL) model. The ADF unit root test rejects the null hypothesis of non-stationarity showing that most of the variables considered are stationary at first difference. The ARDL results show that GDP, carbon dioxide, nitrogen dioxide and sulphur dioxide emissions have a long-run relationship with health expenditure in Malaysia.

Yazdi and Khanalizadeh (2017) examine the role of environmental quality and economic growth in the determination of health expenditure in the Middle East and North Africa region (MENA - Algeria, Djibouti Egypt, Iran, Iraq, Jordan, Lebanon Libya, Morocco, Syrian and Tunisia) for the period 1995-2014. The CO2 emissions per capita and PM10 emissions (micrograms per cubic meter) are used as measures of environmental quality. Empirically, the study uses a unit root test for stationarity, a multivariate cointegration test and an error-correction mechanism. To analyse the existence of the long-run relationship, the autoregressive distributed lag (ARDL) model is applied. A comparison of the ratio of health expenditure to GDP in the MENA shows that the health expenditure/GDP ratio increases in most countries. Though the cross-sectional analysis shows some differences in the healthcare expenditure of MENA countries with similar levels of economic development, in the long run, regardless of medical levels, expenditure on healthcare in the MENA countries is increasing.

Raeissi *et al.* (2018) analyse the short-run and long-run impact of air pollution on private and public health expenditure in Iran applying time series methods for the period 1972-2014. To explore the impact of environmental quality on health expenditure, the paper uses CO2 emissions as an indicator of environmental quality. The Dickey-Fuller test has been used to determine the stationarity of the variables and the Wald test has been used to explore the long-term relationships among the variables. With cointegration among the variables, the SBC has been used to determine the optimal lag and third-rank and first-rank lags have been identified as optimal for models. The estimated results show that the coefficient estimate of carbon emissions on health expenditure is significantly positive.

Blazquez-Fernandez *et al.* (2019) analyse the causal relationship between air pollution and health expenditure in 29 OECD countries for the period 1995-2014 applying panel data econometric methods. The estimated results show that per capita income and health expenditure are positively related. However, much of the impact of current health expenditure is explained by the previous health expenditure. Further noting income heterogeneity, the study finds that the effect of previous health expenditure is more dominant in higher-income than in lower-income countries within the OECD countries. The paper argues that health management policies in developed countries should focus on cleaner fuels to control air pollution and the consequent health expenditure.

In the Indian context, Ghosh, (2010) probes cointegration and causality between carbon dioxide emissions and economic growth. The study applies the autoregressive distributed lag (ARDL) bounds testing approach, complemented by the Johansen-Juselius maximum likelihood procedure in a multivariate framework incorporating energy supply, investment and employment for the period 1971-2006. The study finds a short-run bidirectional causality but no evidence of a long-run equilibrium relationship between carbon emissions and economic growth. In the short-run, there is a unidirectional causality running from economic growth to energy supply but no causality running from energy supply to economic growth, and a unidirectional causality running from energy supply to carbon emissions. Hence, an attempt to reduce carbon emissions in the short run may dampen national income, while in the long run shift to clean energy sources that reduce carbon emissions would not impair economic growth. Overall, there exists ample evidence that carbon dioxide emissions cause greater damage to the environment and health of humans and healthcare expenditure is huge and increasing in almost all countries.

Data and Methodology

As the objective of this paper is to analyse the causal effect of air pollution on public health expenditure in India, this paper uses variables like public health expenditure, carbon dioxide emission, infant mortality rate, total fertility rate and gross domestic product for empirical analysis. In this paper, carbon dioxide emission is taken as a measure of air pollution. The data are derived from the Reserve Bank of India, World Bank and NITI Aayog for the time period 2000-2001 to 2022-2023. Since the data are time series, the usual tests for time series analysis like graphical method, Augmented Dickey-Fuller test, correlogram, determination of optimal lag length, cointegration, and VECM analysis are performed. The graphical method and Augmented Dickey-Fuller (ADF) test are used to test stationarity and a correlogram is applied to check the autocorrelation of the variables. The cointegration test is performed to check if there exists a long-run relationship between the variables, followed by the error correction mechanism (ECM) to check the adjustment or correction taking place in the disequilibrium.

Augmented Dicky-Fuller Stationarity test: A time series data stationary if and only if it has a constant mean and variance. Therefore, it is advisable to test for a unit root in the data before estimation. The Augmented Dicky-Fuller test checks for the stationarity or otherwise of a series. The ADF test checks the autocorrelation in the time series for statistical significance. The ADF equation is specified as:

$$y_t = \rho y_{t-1} + u_t \tag{1}$$

where u_t is a white noise error term. When the unit root is present in the series, $\rho = 1$, and the model is a random walk without drift as there is no intercept in the equation, implying that yt is dependent on its own lag term only, which is a non-stationary stochastic process.

The presence of unit root is checked in three alternative ways:

$$y_t \text{ is a random walk: } \Delta y_t = \delta y_{t-1} + u_t \tag{2}$$

$$y_t \text{ is a random walk with drift: } \Delta y_t = \beta_0 + \delta y_{t-1} + u_t \tag{3}$$

y_t is a random walk with drift around a deterministic trend:

$$\Delta y_t = \beta_0 + \beta_1 t + \delta y_{t-1} + u_t \tag{4}$$

In each case, the hypothesis is:

H_0: $\delta = 0$ i.e. there is a unit root or the time series is non-stationary.

H_1: $\delta < 0$ i.e. the time series is stationary.

Adding the lagged values of the dependent variable ?yt, the ADF test specified is:

$$\Delta y_t = \beta_0 + \beta_1 t + \delta y_{t-1} + \Sigma_{i=1}^{m} \alpha_i y_{t-i} + \varepsilon_t \tag{5}$$

The null hypothesis is rejected if (tau) statistic is higher than the critical value, meaning the data is stationary. Each series in the data set is checked for stationarity at levels, and if it is not, then the data is made stationary by finding the first difference and so on, or the variables are transformed, till all the variables are made stationary before empirical analysis.

Correlogram and Auto-Correlation Function (ACF): The randomness of the data set is usually checked with a correlogram by computing lagged autocorrelations. A correlogram depicts the autocorrelation function (ACF), the correlation between values in a series and past values. When data are random, the time-lagged autocorrelations are to be near zero. The ACF for k lags denoted by ρ_k, $-1 < \rho_k < +1$, is defined as:

$$\rho_k = r_k / r_0 = \text{Covariance/Variance} \tag{6}$$

The plot of ρ_k against k is the correlogram. If the ACF shows a declining trend from the first lag, it implies that the variable is not stationary.

Optimal Lag Length: The determination of optimal lag for the variables is very essential for further tests like cointegration tests and econometric analysis like vector autoregression (VAR) and vector error correction mechanism (VECM). The optimal lag is evaluated by criteria like the Akaike (AIC), Bayesian (BIC), Schwarz (SIC) and Hannan-Quinn (HQIC) information criteria and final prediction error (FPE) criterion. The commonly used AIC ranks the plausible statistical models for a better fit and chooses the 'best' one that neither under-fits nor over-fits.

The AIC is computed as:

$$AIC = -2(log\text{-}likelihood) + 2k \tag{7}$$

where k is the number of model parameters and n is the number of observations. The SIC criterion for model selection is based on the likelihood function:

$$SIC = k \ln(n) - 2\ln(\hat{L}) \tag{8}$$

where $\hat{L} = p(x \mid \hat{\theta}, m), m$ is the model, x is the data and $\hat{\theta}$ are the to-be-inferred parameters of the model. The HQIC is a criterion given as:

$$HQIC = -2L_{max} + 2kln[ln(n)] \tag{9}$$

where L_{max} is the log-likelihood. The final prediction error criterion (FPE) chooses an optimal model that minimises the error in the model fitting:

$$FPE = v_n\left(1 + \frac{2p}{n-p}\right) \tag{10}$$

where v_n is an index of the prediction error, n is the number of data points and p is the number of parameters in the model.

Cointegration Test: The cointegration analysis is applied when all the series are non-stationary at the base level and are integrated of order one i.e. I(1). If there exists a long-term or equilibrium relationship between the variables, they are cointegrated. Sometimes the variables may be individually I(1) at the first difference but the linear combination of these variables may be I(0). This means that even though individually they attain stationarity at the first difference, together they are non-stationary at the base level i.e. they are cointegrated. In the presence of cointegrated I(1) variables, there should be an equilibrium long-run relationship, though there may be short-run divergence. Therefore, instead of individually checking for the unit root for each variable in time series data, the cointegration test checks the long-run relationship between the variables.

The cointegration equation is specified as a regression equation:

$$y_t = \alpha + \beta x_t + u_t \text{ and } u_t = (y_t - \beta_0 - \beta_1 x_t) \tag{11}$$

where β is known as the cointegrating parameter. Although y_t and x_t are I(1) individually and have stochastic trends, the linear combination of them is I(0), and hence the individual stochastic trends are cancelled out by the linear combination of the two series. The usual cointegration tests are the Engel-Granger and Johansen cointegration tests. For multiple cointegrating relationships, the

Johansen test is used. Johansen proposes two different likelihood ratio tests - trace and maximum eigenvalue statistics - for testing the number of cointegrating relations, *r*.

Trace Test: In a diagonal matrix, the trace is the sum of diagonal elements. The trace test tests the null hypothesis of r cointegrating relations against the alternative of *k* linear combinations or cointegrating relations, where *k* is the number of endogenous variables, for $r = 0,1,\ldots, k$-1. The trace test is specified as:

$$LR_{tr}(r \mid k) = -T\Sigma_{i-r+1}^{k} \ln(1-\lambda_i) \tag{12}$$

where T is the sample size and λ_i is the i-th largest eigenvalue of the coefficient matrix.

Maximum Eigen Value Test: The maximum eigenvalue test slightly differs from the trace test in the alternate hypothesis. It tests the null hypothesis of r cointegrating relations against the alternative of r+1 cointegrating relations. The maximum eigenvalue test statistic is specified as:

$$LR_{max}(r|r + 1)= -T \log?(1 - \lambda_{r+1}) = LR_{tr}(r|k)- LR_{tr}(r + 1|k) \tag{13}$$

Rejection of the null hypothesis implies that a stationary process exists for only one possible combination of the non-stationary variables.

Vector Error Correction Mechanism: The vector error correction mechanism (VECM), suggested by Sargan (1975) and Engle and Granger (1987), adjusts the disequilibrium in the long run. When two variables y and x are cointegrated, the VECM model establishes the long and short-run equilibrium relationships between the variables. The VECM adds a lagged error correction term to the fit of the first differences of non-stationary variables. The error-correction term (ECT), which exhibits the prior disequilibrium from the long-run relationship, is the lagged residual from the cointegrating equation of one of the variables on the other at levels. With multiple variables, the ECT is a vector, the length equal to the number of cointegrating vectors i.e. cointegrating relationships among the variables. The VECM for cointegrated series is specified as:

$$\Delta y_t = \beta_0 + \Sigma_{i=1}^{n}\beta_1 \Delta y_{t-i} + \Sigma_{i=1}^{n}\delta_i \Delta x_{t-i} + \gamma z_{t-1} + u_t \tag{14}$$

$$z_{t-1} = y_{t-1} = \hat{\beta}_0 - \hat{\beta}_1 x_{t-1} \tag{15}$$

where z is the error correction term which shows the influence of lagged deviation from long-run equilibrium on the short-run dynamics. The speed of adjustment in y returning to equilibrium for a change in *x* is given by the coefficient of the ECT.

Empirical Analysis

In the empirical analysis, the variables are used in natural logarithmic and first difference form to obtain more robust results. Table 1 presents the definition and descriptive statistics of variables used in the empirical analysis.

Table 1: Descriptive Statistics of Variables

Variable	*Definition*	*Mean*	*Std. dev.*
lnPHE	Public health expenditure on health and health-related expenditures (percent of GDP)	-0.019	0.248
lnGDP	Gross domestic product (Rs. At constant prices)	13.95	1.341
$lnCO_2$	Carbon dioxide emissions (metric tons per capita)	1.189	0.513
lnIMR	Number of child death per 1000 live births of children under one year of age	4.248	0.302
lnTFR	Number of children born per woman in the reproductive age	1.195	0.212

Augmented Dicky Fuller Stationarity Test: The ADF test results for stationarity at levels and first difference are presented in Table 2 and Figure 1. All variables, except infant mortality rate and GDP, are non-stationary at levels. The null hypothesis that the series contains unit root could not be rejected as the computed t-values are lower than the critical t-value. On the other hand, at the first difference, the variables become stationary. All of the first differenced variables are statistically significant at 5% level.

Table 2: Augmented Dicky Fuller Test for Stationarity

Variable	*Method*	*At level*		*At first difference*	
		ADF statistic	*p-value*	*ADF statistic*	*p-value*
lnPHE	With drift	-6.081	0.000	-3.949	0.046
	With drift and trend	-5.251	0.0008	-3.754	0.0323
	Without drift	-5.696	0.000	-3.679	0.006
lnGDP	With drift	-0.256	0.921	-3.335	0.021
	With drift and trend	-2.107	0.5227	-3.273	0.002
	Without drift	2.721	0.997	-1.036	0.020
$lnCO_2$	With drift	-3.800	0.006	-4.989	0.0003
	With drift and trend	-2.183	0.483	-6.338	0.000
	Without drift	0.552	0.830	-4.608	0.000
lnIMR	With drift	1.122	0.996	-4.740	0.000
	With drift and trend	-0.913	0.942	-4.914	0.002
	Without drift	-7.289	0.000	-0.688	0.041
lnTFR	With drift	0.620	0.988	-8.264	0.000
	With drift and trend	-3.967	0.019	-8.270	0.000
	Without drift	-4.513	0.000	-2.312	0.022

Note: At first difference, all variables are significant at 5% level.

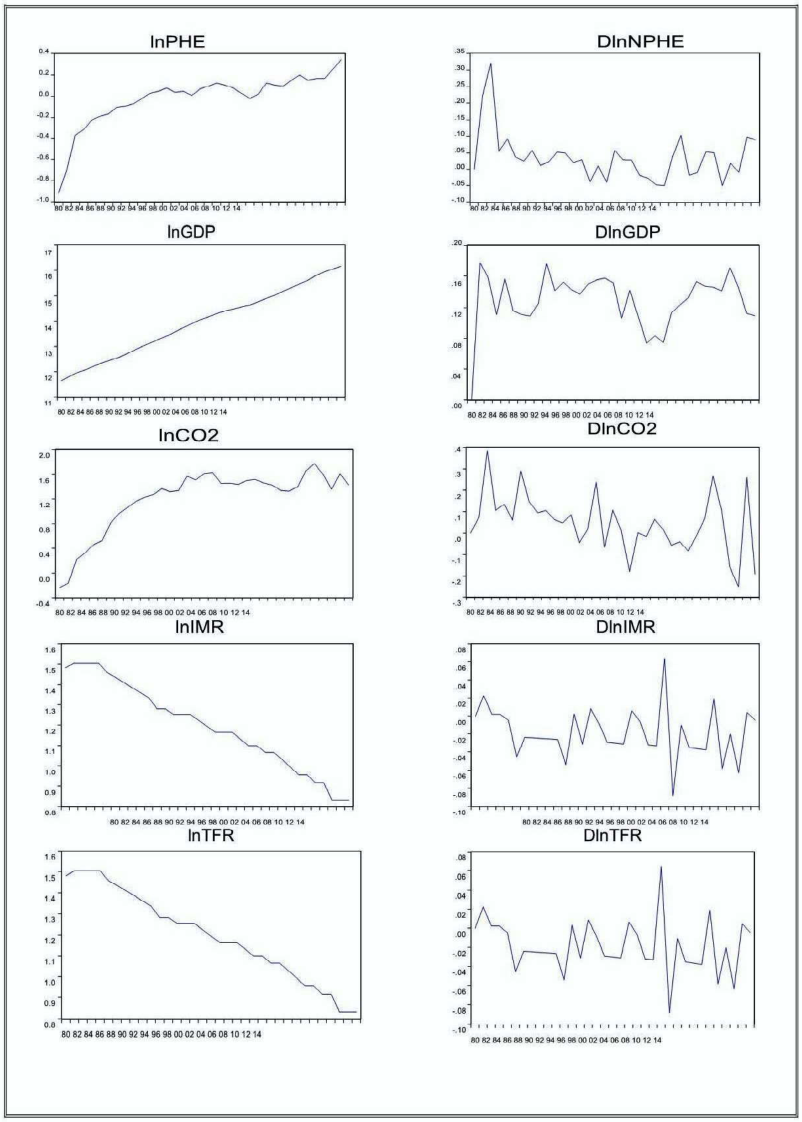

Figure 1: Stationarity of Variables at Level and First Difference

Correlogram and Auto-Correlation function: Tables 2a to 2e depict the correlogram of the variables lnPHE, lnGDP, lnCO2, lnIMR, and lnTFR respectively at levels. For all variables, the autocorrelation function at lag 1 has a very high value and decays gradually as the number of lags increases. The variables are autoregressive as there is a sudden cutoff in the partial autocorrelation (PAC).

Table 2a: Correlogram of Public Health Expenditure in India (level)

<table>
<tr><th>AC</th><th>PAC</th><th>Lags</th><th>AC</th><th>PAC</th><th>Q-statistic</th><th>Prob.</th></tr>
<tr><td>. |***** |</td><td>. |***** |</td><td>1</td><td>0.722</td><td>0.722</td><td>19.881</td><td>0.000</td></tr>
<tr><td>. |**** |</td><td>. | .|</td><td>2</td><td>0.500</td><td>-0.045</td><td>29.710</td><td>0.000</td></tr>
<tr><td>. |*** |</td><td>. |*.|</td><td>3</td><td>0.409</td><td>0.134</td><td>36.494</td><td>0.000</td></tr>
<tr><td>. |**|</td><td>. | .|</td><td>4</td><td>0.326</td><td>-0.020</td><td>40.931</td><td>0.000</td></tr>
<tr><td>. |** |</td><td>. | .|</td><td>5</td><td>0.272</td><td>0.051</td><td>44.119</td><td>0.000</td></tr>
<tr><td>. |*.|</td><td>. | .|</td><td>6</td><td>0.211</td><td>-0.038</td><td>46.099</td><td>0.000</td></tr>
<tr><td>. |*.|</td><td>. | .|</td><td>7</td><td>0.154</td><td>-0.008</td><td>47.191</td><td>0.000</td></tr>
<tr><td>. |*.|</td><td>. | .|</td><td>8</td><td>0.119</td><td>0.001</td><td>47.869</td><td>0.000</td></tr>
<tr><td>. | .|</td><td>. | .|</td><td>9</td><td>0.068</td><td>-0.054</td><td>48.098</td><td>0.000</td></tr>
<tr><td>. | .|</td><td>. | .|</td><td>10</td><td>0.004</td><td>-0.063</td><td>48.099</td><td>0.000</td></tr>
<tr><td>. | .|</td><td>. | .|</td><td>11</td><td>-0.027</td><td>-0.003</td><td>48.138</td><td>0.000</td></tr>
<tr><td>. | .|</td><td>. | .|</td><td>12</td><td>-0.030</td><td>0.016</td><td>48.189</td><td>0.000</td></tr>
<tr><td>. | .|</td><td>. | .|</td><td>13</td><td>-0.027</td><td>0.01</td><td>48.233</td><td>0.000</td></tr>
<tr><td>. | .|</td><td>. | .|</td><td>14</td><td>-0.016</td><td>0.027</td><td>48.249</td><td>0.000</td></tr>
<tr><td>. | .|</td><td>. | .|</td><td>15</td><td>-0.027</td><td>-0.03</td><td>48.297</td><td>0.000</td></tr>
<tr><td>. | .|</td><td>. | .|</td><td>16</td><td>-0.045</td><td>-0.021</td><td>48.435</td><td>0.000</td></tr>
</table>

Table 2b: Correlogram of Gross Domestic Product in India (level)

<table>
<tr><th>AC</th><th>PAC</th><th>Lags</th><th>AC</th><th>PAC</th><th>Q-statistic</th><th>Prob.</th></tr>
<tr><td>.|*******|</td><td>. |*******|</td><td>1</td><td>0.912</td><td>0.912</td><td>31.647</td><td>0.000</td></tr>
<tr><td>. |******|</td><td>. | . |</td><td>2</td><td>0.824</td><td>-0.040</td><td>58.297</td><td>0.000</td></tr>
<tr><td>. |***** |</td><td>. | . |</td><td>3</td><td>0.737</td><td>-0.044</td><td>80.297</td><td>0.000</td></tr>
<tr><td>. |*****|</td><td>. | . |</td><td>4</td><td>0.651</td><td>-0.047</td><td>98.005</td><td>0.000</td></tr>
<tr><td>. |**** |</td><td>. | . |</td><td>5</td><td>0.568</td><td>-0.030</td><td>111.960</td><td>0.000</td></tr>
<tr><td>. |****|</td><td>. | . |</td><td>6</td><td>0.487</td><td>-0.045</td><td>122.560</td><td>0.000</td></tr>
<tr><td>. |*** |</td><td>. | . |</td><td>7</td><td>0.408</td><td>-0.044</td><td>130.240</td><td>0.000</td></tr>
<tr><td>. |** |</td><td>. | . |</td><td>8</td><td>0.330</td><td>-0.045</td><td>135.470</td><td>0.000</td></tr>
<tr><td>. |** |</td><td>. | . |</td><td>9</td><td>0.255</td><td>-0.040</td><td>138.710</td><td>0.000</td></tr>
<tr><td>. |*. |</td><td>. | . |</td><td>10</td><td>0.185</td><td>-0.032</td><td>140.490</td><td>0.000</td></tr>
<tr><td>. |*. |</td><td>. | . |</td><td>11</td><td>0.118</td><td>-0.040</td><td>141.240</td><td>0.000</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>12</td><td>0.055</td><td>-0.040</td><td>141.410</td><td>0.000</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>13</td><td>-0.007</td><td>-0.050</td><td>141.410</td><td>0.000</td></tr>
<tr><td>.*| . |</td><td>. | . |</td><td>14</td><td>-0.066</td><td>-0.050</td><td>141.680</td><td>0.000</td></tr>
<tr><td>.*| . |</td><td>. | . |</td><td>15</td><td>-0.123</td><td>-0.051</td><td>142.660</td><td>0.000</td></tr>
<tr><td>.*| . |</td><td>. | . |</td><td>16</td><td>-0.176</td><td>-0.043</td><td>144.770</td><td>0.000</td></tr>
</table>

Table 2c: Correlogram of Carbon Dioxide Emissions in India (level)

<table>
<tr><th>AC</th><th>PAC</th><th>Lags</th><th>AC</th><th>PAC</th><th>Q-statistic</th><th>Prob.</th></tr>
<tr><td>. |******|</td><td>. |******|</td><td>1</td><td>0.843</td><td>0.843</td><td>27.073</td><td>0.000</td></tr>
<tr><td>. |***** |</td><td>.*| . |</td><td>2</td><td>0.679</td><td>-0.11</td><td>45.161</td><td>0.000</td></tr>
<tr><td>. |**** |</td><td>. |*. |</td><td>3</td><td>0.571</td><td>0.100</td><td>58.357</td><td>0.000</td></tr>
<tr><td>. |*** |</td><td>.*| . |</td><td>4</td><td>0.460</td><td>-0.094</td><td>67.197</td><td>0.000</td></tr>
<tr><td>. |** |</td><td>. | . |</td><td>5</td><td>0.350</td><td>-0.040</td><td>72.497</td><td>0.000</td></tr>
<tr><td>. |** |</td><td>.*| . |</td><td>6</td><td>0.238</td><td>-0.099</td><td>75.033</td><td>0.000</td></tr>
<tr><td>. |*. |</td><td>. | . |</td><td>7</td><td>0.164</td><td>0.052</td><td>76.273</td><td>0.000</td></tr>
<tr><td>. |*. |</td><td>. | . |</td><td>8</td><td>0.103</td><td>-0.041</td><td>76.779</td><td>0.000</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>9</td><td>0.044</td><td>-0.017</td><td>76.877</td><td>0.000</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>10</td><td>-0.003</td><td>-0.024</td><td>76.878</td><td>0.000</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>11</td><td>-0.038</td><td>-0.012</td><td>76.957</td><td>0.000</td></tr>
<tr><td>.*| . |</td><td>. | . |</td><td>12</td><td>-0.071</td><td>-0.043</td><td>77.243</td><td>0.000</td></tr>
<tr><td>.*| . |</td><td>. | . |</td><td>13</td><td>-0.094</td><td>0.003</td><td>77.767</td><td>0.000</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>14</td><td>-0.135</td><td>-0.110</td><td>78.89</td><td>0.000</td></tr>
<tr><td>.*| . |</td><td>. | . |</td><td>15</td><td>-0.171</td><td>-0.018</td><td>80.774</td><td>0.000</td></tr>
<tr><td>.*| . |</td><td>. | . |</td><td>16</td><td>-0.175</td><td>0.034</td><td>82.85</td><td>0.000</td></tr>
</table>

Table 2d: Correlogram of Infant Mortality Rate in India (level)

<table>
<tr><th>AC</th><th>PAC</th><th>Lags</th><th>AC</th><th>PAC</th><th>Q-statistic</th><th>Prob.</th></tr>
<tr><td>. |******|</td><td>. |******|</td><td>1</td><td>0.897</td><td>0.897</td><td>30.665</td><td>0.000</td></tr>
<tr><td>. |******|</td><td>. | . |</td><td>2</td><td>0.799</td><td>-0.032</td><td>55.711</td><td>0.000</td></tr>
<tr><td>. |***** |</td><td>. | . |</td><td>3</td><td>0.704</td><td>-0.036</td><td>75.771</td><td>0.000</td></tr>
<tr><td>. |**** |</td><td>.*| . |</td><td>4</td><td>0.606</td><td>-0.070</td><td>91.124</td><td>0.000</td></tr>
<tr><td>. |**** |</td><td>. | . |</td><td>5</td><td>0.514</td><td>-0.034</td><td>102.52</td><td>0.000</td></tr>
<tr><td>. |*** |</td><td>. | . |</td><td>6</td><td>0.436</td><td>0.014</td><td>110.99</td><td>0.000</td></tr>
<tr><td>. |*** |</td><td>. | . |</td><td>7</td><td>0.364</td><td>-0.021</td><td>117.11</td><td>0.000</td></tr>
<tr><td>. |** |</td><td>. | . |</td><td>8</td><td>0.293</td><td>-0.046</td><td>121.22</td><td>0.000</td></tr>
<tr><td>. |** |</td><td>. | . |</td><td>9</td><td>0.222</td><td>-0.057</td><td>123.67</td><td>0.000</td></tr>
<tr><td>. |*. |</td><td>. | . |</td><td>10</td><td>0.152</td><td>-0.052</td><td>124.87</td><td>0.000</td></tr>
<tr><td>. |*. |</td><td>. | . |</td><td>11</td><td>0.096</td><td>0.015</td><td>125.37</td><td>0.000</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>12</td><td>0.039</td><td>-0.054</td><td>125.45</td><td>0.000</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>13</td><td>-0.013</td><td>-0.029</td><td>125.46</td><td>0.000</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>14</td><td>-0.050</td><td>0.015</td><td>125.62</td><td>0.000</td></tr>
<tr><td>.*| . |</td><td>. | . |</td><td>15</td><td>-0.087</td><td>-0.044</td><td>126.11</td><td>0.000</td></tr>
<tr><td>.*| . |</td><td>. | . |</td><td>16</td><td>-0.123</td><td>-0.036</td><td>127.14</td><td>0.000</td></tr>
</table>

Table 2e: Correlogram of Total Fertility Rate in India (level)

<table>
<tr><th>AC</th><th>PAC</th><th>Lags</th><th>AC</th><th>PAC</th><th>Q-statistic</th><th>Prob.</th></tr>
<tr><td>. |*******</td><td>. |*******</td><td>1</td><td>0.922</td><td>0.922</td><td>32.355</td><td>0.000</td></tr>
<tr><td>. |******|</td><td>*| . |</td><td>2</td><td>0.832</td><td>-0.113</td><td>59.545</td><td>0.000</td></tr>
<tr><td>. |***** |</td><td>*| . |</td><td>3</td><td>0.733</td><td>-0.110</td><td>81.307</td><td>0.000</td></tr>
<tr><td>. |***** |</td><td>. | . |</td><td>4</td><td>0.647</td><td>0.040</td><td>98.817</td><td>0.000</td></tr>
<tr><td>. |**** |</td><td>.*| . |</td><td>5</td><td>0.553</td><td>-0.116</td><td>112.04</td><td>0.000</td></tr>
<tr><td>. |*** |</td><td>. | . |</td><td>6</td><td>0.469</td><td>0.003</td><td>121.86</td><td>0.000</td></tr>
<tr><td>. |*** |</td><td>.*| . |</td><td>7</td><td>0.38</td><td>-0.082</td><td>128.55</td><td>0.000</td></tr>
<tr><td>. |** |</td><td>. | . |</td><td>8</td><td>0.301</td><td>-0.010</td><td>132.9</td><td>0.000</td></tr>
<tr><td>. |** |</td><td>. | . |</td><td>9</td><td>0.229</td><td>-0.006</td><td>135.52</td><td>0.000</td></tr>
<tr><td>. |*. |</td><td>. | . |</td><td>10</td><td>0.166</td><td>-0.023</td><td>136.94</td><td>0.000</td></tr>
<tr><td>. |*. |</td><td>. | . |</td><td>11</td><td>0.102</td><td>-0.059</td><td>137.5</td><td>0.000</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>12</td><td>0.048</td><td>0.007</td><td>137.63</td><td>0.000</td></tr>
<tr><td>. | . |</td><td>*| . |</td><td>13</td><td>-0.008</td><td>-0.081</td><td>137.63</td><td>0.000</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>14</td><td>-0.057</td><td>-0.011</td><td>137.83</td><td>0.000</td></tr>
<tr><td>.*| . |</td><td>. | . |</td><td>15</td><td>-0.102</td><td>-0.028</td><td>138.51</td><td>0.000</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>16</td><td>-0.152</td><td>-0.114</td><td>140.09</td><td>0.000</td></tr>
</table>

As the variables at levels are non-stationary, the first difference is taken and the correlogram of the first differenced series is presented in Tables 3a to 3e respectively.

Table 3a: Correlogram of Public Health Expenditure in India (first difference)

<table>
<tr><th>AC</th><th>PAC</th><th>Lags</th><th>AC</th><th>PAC</th><th>Q-statistic</th><th>Prob.</th></tr>
<tr><td>. |*** |</td><td>. |*** |</td><td>1</td><td>0.44</td><td>0.44</td><td>7.182</td><td>0.007</td></tr>
<tr><td>. |*. |</td><td>. *| . |</td><td>2</td><td>0.133</td><td>-0.075</td><td>7.859</td><td>0.02</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>3</td><td>0.071</td><td>0.052</td><td>8.060</td><td>0.045</td></tr>
<tr><td>.s | . |</td><td>. | . |</td><td>4</td><td>0.041</td><td>-0.003</td><td>8.130</td><td>0.087</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>5</td><td>0.047</td><td>0.035</td><td>8.221</td><td>0.144</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>6</td><td>0.06</td><td>0.031</td><td>8.378</td><td>0.212</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>7</td><td>0.039</td><td>-0.003</td><td>8.448</td><td>0.295</td></tr>
<tr><td>. |*. |</td><td>. |*. |8</td><td>0.126</td><td>0.134</td><td>9.197</td><td>0.326</td><td></td></tr>
<tr><td>. |*. |</td><td>. | . |</td><td>9</td><td>0.106</td><td>-0.009</td><td>9.743</td><td>0.372</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>10</td><td>0.007</td><td>-0.056</td><td>9.746</td><td>0.463</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>11</td><td>-0.071</td><td>-0.073</td><td>10.016</td><td>0.529</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>12</td><td>-0.158</td><td>-0.128</td><td>11.408</td><td>0.494</td></tr>
<tr><td>.*| . |</td><td>. | . |</td><td>13</td><td>-0.152</td><td>-0.042</td><td>12.758</td><td>0.467</td></tr>
<tr><td>.*| . |</td><td>. | . |</td><td>14</td><td>-0.111</td><td>-0.041</td><td>13.508</td><td>0.487</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>15</td><td>-0.03</td><td>0.053</td><td>13.567</td><td>0.559</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>16</td><td>0.027</td><td>0.031</td><td>13.618</td><td>0.627</td></tr>
</table>

Table 3b: Correlogram of Gross Domestic Product in India (first difference)

AC	*PAC*	*Lags*	*AC*	*PAC*	*Q-statistic*	*Prob.*
. |*. |	. |*. |	1	0.144	0.144	0.793	0.373
. |*. |	. | . |	2	0.079	0.059	1.038	0.595
. |*. |	. |*. |	3	0.152	0.136	1.977	0.577
.*| . |	.*| . |	4	-0.146	-0.197	2.867	0.58
. | . |	. | . |	5	-0.039	-0.009	2.931	0.711
.*| . |	.*| . |	6	-0.161	-0.17	4.092	0.664
.*| . |	. | . |	7	-0.095	0.011	4.507	0.720
.*| . |	.*| . |	8	-0.116	-0.122	5.149	0.741
***| .|	**| . |	9	-0.349	-0.297	11.213	0.261
.*| . |	.*| . |	10	-0.122	-0.089	11.987	0.286
.*| . |	.*| . |	11	-0.121	-0.087	12.777	0.308
. | . |	. | . |	12	-0.047	0.018	12.901	0.376
. | . |	.*| . |	13	0.019	-0.094	12.922	0.454
. | . |	.*| . |	14	-0.022	-0.092	12.952	0.530
. |*. |	. | . |	15	0.097	-0.042	13.563	0.559
. | . |	. | . |	16	0.032	-0.052	13.631	0.626

Table 3c: Correlogram of Carbon Dioxide Emissions in India (first difference)

AC	*PAC*	*Lags*	*AC*	*PAC*	*Q-statistic*	*Prob.*
. | . |	. | . |	1	0.055	0.055	0.114	0.735
. | . |	. | . |	2	0.044	0.041	0.189	0.91
. |*. |	. | . |	3	0.076	0.072	0.424	0.935
. |*. |	. |*. |	4	0.099	0.091	0.836	0.934
. |*. |	. |*. |	5	0.100	0.087	1.271	0.938
. |*. |	. |*. |	6	0.130	0.113	2.028	0.917
. |*. |	. | . |	7	0.098	0.074	2.471	0.929
. |*. |	. |*. |	8	0.114	0.086	3.095	0.928
. | . |	. | . |	9	-0.014	-0.056	3.105	0.96
.*| . |	.*| . |	10	-0.086	-0.134	3.488	0.967
. | . |	. | . |	11	-0.011	-0.059	3.495	0.982
. | . |	. | . |	12	0.000	-0.043	3.495	0.991
. |*. |	. |*. |	13	0.118	0.107	4.313	0.987
.*| . |	.*| . |	14	-0.092	-0.101	4.833	0.988
. | . |	. | . |	15	0.025	0.05	4.873	0.993
. | . |	. | . |	16	-0.061	-0.043	5.124	0.995

Table 3d: Correlogram of Infant Mortality Rate in India (first difference)

<table>
<tr><th>AC</th><th>PAC</th><th>Lags</th><th>AC</th><th>PAC</th><th>Q-statistic</th><th>Prob.</th></tr>
<tr><td>. |*. |</td><td>. |*. |</td><td>1</td><td>0.135</td><td>0.135</td><td>0.697</td><td>0.404</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>2</td><td>-0.142</td><td>-0.163</td><td>1.486</td><td>0.476</td></tr>
<tr><td>. |** |</td><td>. |** |</td><td>3</td><td>0.24</td><td>0.297</td><td>3.814</td><td>0.282</td></tr>
<tr><td>. | . |</td><td>**| . |</td><td>4</td><td>-0.061</td><td>-0.208</td><td>3.972</td><td>0.410</td></tr>
<tr><td>.*| . |</td><td>. | . |</td><td>5</td><td>-0.189</td><td>-0.043</td><td>5.521</td><td>0.356</td></tr>
<tr><td>. | . |</td><td>.*| . |</td><td>6</td><td>-0.062</td><td>-0.155</td><td>5.692</td><td>0.458</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>7</td><td>-0.04</td><td>0.030</td><td>5.766</td><td>0.567</td></tr>
<tr><td>. |*. |</td><td>. |*. |</td><td>8</td><td>0.08</td><td>0.128</td><td>6.076</td><td>0.639</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>9</td><td>0.028</td><td>-0.010</td><td>6.115</td><td>0.728</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>10</td><td>-0.096</td><td>-0.096</td><td>6.597</td><td>0.763</td></tr>
<tr><td>. |*. |</td><td>. | . |</td><td>11</td><td>0.09</td><td>0.053</td><td>7.031</td><td>0.797</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>12</td><td>0.025</td><td>-0.049</td><td>7.068</td><td>0.853</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>13</td><td>-0.184</td><td>-0.082</td><td>9.066</td><td>0.768</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>14</td><td>-0.045</td><td>-0.041</td><td>9.192</td><td>0.819</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>15</td><td>-0.102</td><td>-0.168</td><td>9.860</td><td>0.828</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>16</td><td>-0.185</td><td>-0.086</td><td>12.200</td><td>0.73</td></tr>
</table>

Table 3e: Correlogram of Total Fertility Rate in India (first difference)

<table>
<tr><th>AC</th><th>PAC</th><th>Lags</th><th>AC</th><th>PAC</th><th>Q-statistic</th><th>Prob.</th></tr>
<tr><td>**| . |</td><td>**| . |</td><td>1</td><td>-0.307</td><td>-0.307</td><td>3.593</td><td>0.058</td></tr>
<tr><td>. |*. |. |</td><td>. |</td><td>2</td><td>0.149</td><td>0.060</td><td>4.461</td><td>0.107</td></tr>
<tr><td>.*| . |</td><td>. | . |</td><td>3</td><td>-0.074</td><td>-0.014</td><td>4.680</td><td>0.197</td></tr>
<tr><td>. |*. |. |</td><td>. |</td><td>4</td><td>0.076</td><td>0.047</td><td>4.920</td><td>0.296</td></tr>
<tr><td>.*| . |</td><td>. *| . |</td><td>5</td><td>-0.201</td><td>-0.179</td><td>6.668</td><td>0.246</td></tr>
<tr><td>. |** |</td><td>. |*. |</td><td>6</td><td>0.247</td><td>0.153</td><td>9.397</td><td>0.152</td></tr>
<tr><td>**| . |</td><td>.*| . |</td><td>7</td><td>-0.250</td><td>-0.131</td><td>12.294</td><td>0.091</td></tr>
<tr><td>. |*. |</td><td>. | . |</td><td>8</td><td>0.095</td><td>-0.045</td><td>12.725</td><td>0.122</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>9</td><td>-0.186</td><td>-0.155</td><td>14.449</td><td>0.107</td></tr>
<tr><td>. | . |</td><td>**| . |</td><td>10</td><td>-0.053</td><td>-0.207</td><td>14.593</td><td>0.148</td></tr>
<tr><td>. |*. |</td><td>. |** |</td><td>11</td><td>0.169</td><td>0.240</td><td>16.129</td><td>0.136</td></tr>
<tr><td>.*| . |</td><td>**| . |</td><td>12</td><td>-0.192</td><td>-0.241</td><td>18.213</td><td>0.109</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>13</td><td>0.062</td><td>0.039</td><td>18.438</td><td>0.142</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>14</td><td>0.031</td><td>-0.015</td><td>18.498</td><td>0.185</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>15</td><td>0.037</td><td>0.066</td><td>18.587</td><td>0.233</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>16</td><td>-0.040</td><td>0.050</td><td>18.695</td><td>0.285</td></tr>
</table>

Optimal Lag Length: Table 4 shows the optimal lag length for all variables under various criteria. Almost all criteria identify lag length 1 as the optimal lag length.

Table 4: Optimal Lag Length of Variables for Cointegration Analysis

Variable	*Optimal lag*	*LL*	*LR*	*FPE*	*AIC*	*HQIC*	*SIC*
lnPHE	1	57.209	73.005*	0.0018*	-3.450*	-3.359*	-3.420*
lnGDP	2	79.181	9.369*	0.0005*	-4.617*	-4.480*	-4.571*
$lnCO_2$	1	25.961	77.517*	0.0137*	-1.452*	-1.361*	-1.421*
lnIMR	1	71.659	144.321*	0.0008*	-4.221*	-4.131*	-4.191*
lnTFR	1	81.844	142.663*	0.0004*	-4.839*	-4.748*	-4.808*

Note: * lag order identified by the criterion. * significant at 5% level.

Cointegration Test: The long-run relationship between the variables is identified by the Johansen cointegration test. The trace and max eigenvalue statistics presented in Table 5 reject the null hypothesis that the variables are not cointegrated as the computed values are greater than the critical value and statistically significant at least at 5% level. The variables are cointegrated and have one cointegrating equation.

Table 5: Johansen Trace and Maximum Eigen Value Tests of Cointegration

Hypothesised	*At level*				*At first difference*			
no. of CE(s)	*Eigen value*	*Trace statistic*	*Critical value*	*Prob.*	*Eigen value*	*Trace statistic*	*Critical value*	*Prob.@*
None *	0.753	91.983	69.818	0.003	0.753	46.215	33.876	0.001
At most 1	0.522	45.767	47.856	0.077	0.522	24.374	27.584	0.122
At most 2	0.356	21.393	29.797	0.333	0.356	14.566	21.131	0.320
At most 3	0.185	6.826	15.494	0.597	0.185	6.753	14.264	0.518
At most 4	0.002	0.073	3.841	0.787	0.002	0.0730	3.841	0.787

Note: There exists one cointegrating equation * 0.05 significance level. @ MacKinnon-Haug-Michelis (1999) p-values.

The presence of cointegration in the series implies a long-run relationship in the variables. The cointegration equation is:

$$ECT_{t-1} = 1.000lnPHE_{t-1} + 0.490lnGDP_{t-1} + 0.002lnCO2_{t-1} - 0.559lnIMR_{t-1} + 4.341lnTFR_{t-1} - 9.67 \quad (16)$$

Hence, the vector error correction mechanism (VECM) is to be used. The error correction term (ECT) shows the speed with which the short-run fluctuations return to the long-run equilibrium values following an exogenous shock. A negative sign in the ECM indicates a back move towards equilibrium while a positive sign indicates divergence from equilibrium. The range of coefficients is between 0 and 1, a coefficient value of 1 indicates full adjustment and a 0 value implies no adjustment over the lagged periods. Table 6 presents the VECM estimates. The estimated coefficient of the error correction coefficient is significantly negative and shows that about 36.4% of the deviations from long-run equilibrium are adjusted every year.

Table 6: VECM Estimates of Causal Relationship between Emissions and Public Health Expenditure

LNPHE(-1)	1
LNGDP(-1)	0.490 (-0.124) [3.938]
LNCO2(-1)	-0.002 (-0.062) [-0.040]
LNIMR(-1)	-0.559 (-0.464) [-1.203]
LNTFR(-1)	4.341 (-0.868) [5.000]
C	-9.674

Variable	D(lnPHE)	D(lnGDP)	DlLnCO2)	D(lnIMR)	D(lnTFR)
Coint. eq1	-0.364(5.80)	-0.048(1.39)	-0.5572.78)	0.032(0.86)	-0.082(2.23)
D(lnPHE(-1))	-0.020(0.13)	-0.162(1.95)	-0.370(0.77)	0.160(1.77)	0.009(0.10)
D(lnGDP(-1))	0.068(0.223)	0.571(3.44)	0.277(0.29)	-0.244(1.35)	-0.233(1.32)
D(lnCO2(-1))	-0.059(0.90)	0.028(0.77)	0.049(0.23)	-0.049(1.25)	0.003(0.07)
D(lnIMR(-1))	-0.072(0.68)	0.031(0.46)	-0.151(0.21)	0.071(0.82)	0.198(1.24)
D(lnTFR(-1))	0.550(1.92)	0.068(0.43)	0.604(0.66)	-0.139(0.81)	-0.321(1.91)
Constant	0.044(1.05)	0.063(2.77)	0.027(0.20)	0.000(0.006)	0.011(0.45)
Adj. R-squared	0.619	0.229	0.126	-0.023	0.223
F- statistic	9.677	2.584	1.766	0.880	2.527
Log-likelihood	61.895	81.553	23.602	78.757	79.584
AIC	-3.327	-4.518	-1.006	-4.349	-4.399
SIC	-3.010	-4.201	-0.689	-4.031	-4.082

Note: Absolute t-values in parentheses.

In order to find the long-term causality, the system of equations for each variable are estimated with lags. The estimated VECM with PHE as the target variable is:

$$LnPHE_t = -0.364ECT_{t-1} - 0.020lnPHE_{t-1} + 0.067lnGDP_{t-1} - 0.058lnCO2_{t-1} \\ -0.058lnCO2_{t-1} + 0.207lnIMR_{t-1} + 0.549lnTFR_{t-1} + 0.043 \quad (17)$$

To find the statistical significance of the coefficient of the cointegrating equation the following estimated equation is used and the results are presented in Table 7:

D(lnPHE) = C(1)*[lnPHE(-1)+0.490*lnGDP(-1)-0.002*lnCO2(-1)-0.559*lnIMR(-1)
+4.341*lnTFR(-1)-9.674]+C(2)*D(lnPHE(-1))+C(3)*D(lnGDP (-1))
+C(4)*D(lnCO2(-1))+C(5)*D(lnIMR(-1))+C(6)*D(lnTFR(-1))+C(7) (18)

Table 7: Statistical Significance of Coefficients of Cointegrating Equations

Variable	*Coefficient*	*Std. error*	*p-value*
C(1)	-0.364	0.062	0.000
C(2)	-0.020	0.150	0.894
C(3)	0.067	0.301	0.823
C(4)	-0.058	0.065	0.376
C(5)	0.207	0.306	0.504
C(6)	0.549	0.286	0.066
C(7)	0.043	0.041	0.302

In Table 7, C(1) denotes the coefficient of the cointegrating equation. The significantly negative error correction term [C(1)] shows the existence of a long-run relationship in variables. While C(7) is the constant term. C(2) is the coefficient of the lagged dependent variable. The other terms, C(3), C(4), C(5) and C(6) are short-run coefficients which exhibit the presence of short-run relationships in the variables.

The short-run relationships are tested with the Wald test and the results are presented in Table 8. The greater than 0.05 chi-square probability rejects the null hypothesis of no short-run causality in the variables and confirms the causal effect of independent variables on the dependent variable.

Table 8: Wald Test for Short-Run Causality

Test statistic	*Test value*	*Prob.*
F-Statistic	1.253	0.313
Chi-square	5.01	0.285
Null hypothesis	C(3)=C(4)=C(5)=C(6)=0	
Normalised restriction (= 0)	Value	Std. error
C(3)	0.067	0.301
C(4)	-0.058	0.065
C(5)	0.207	0.306
C(6)	0.549	0.286

The presence of serial correlation is tested with the Breusch-Godfrey serial correlation LM test. As the test results presented in Table 9 show the Breusch-Godfrey LM test rejects the null hypothesis of no serial correlation in the variables at 0.05 chi-square probability.

Table 9: Breusch-Godfrey LM Test for Serial Correlation

F-statistic	*0.271*	*Prob.*	*0.606*	
Obs*R-squared	0.354	Prob. chi-square	0.551	
Variable	Coefficient	Std. error	t-statistic	Prob.
C(1)	-0.028	0.083	-0.339	0.737
C(2)	-0.104	0.252	-0.414	0.681
C(3)	0.022	0.308	0.073	0.942
C(4)	0.008	0.068	0.118	0.906
C(5)	-0.049	0.325	-0.150	0.881
C(6)	0.155	0.416	0.372	0.712
C(7)	0.002	0.042	0.050	0.960
RESID(-1)	0.199	0.382	0.521	0.606
R-squared	0.010	Mean dependent variable		1.08E-16
Adjusted R-square	-0.266	Std. dev. dependent variable		0.037
S.E. of regression	0.042	AIC		-3.277
Sum squared residual	0.044	SIC		-2.914
Log-likelihood	62.073	HQIC		-3.155
F-statistic	0.038	Durbin-Watson statistics		1.816
Prob.(F-statistic)	0.999			

The dynamic stability of the model is presented in Figure 2. As the stability line of the model is within the range, the model is dynamically stable.

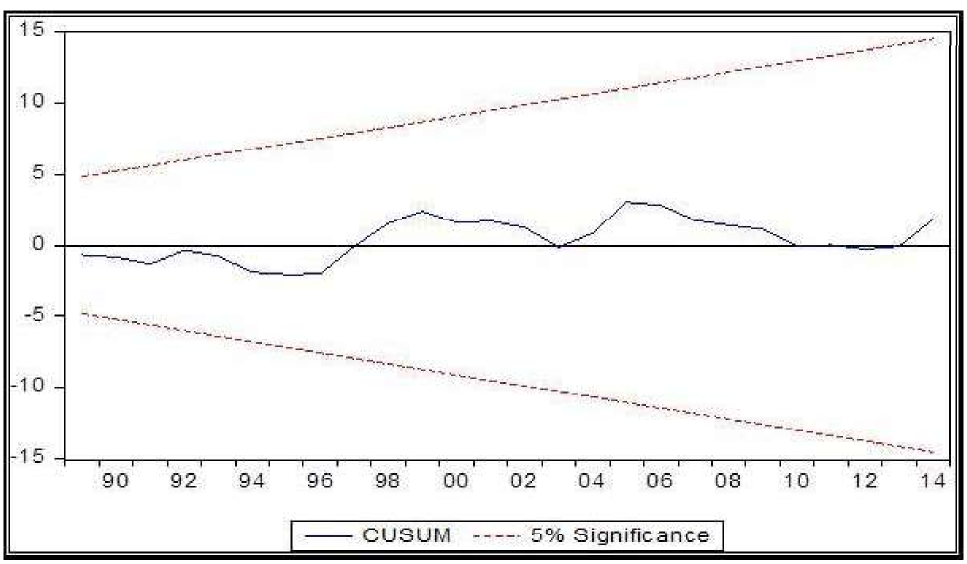

Figure 2: Dynamic Stability of the Model

Conclusion

Health is central to the well-being of people. Increasing air pollution and consequent carbon emissions degrade the environmental quality and have cascading effects on health and as a result healthcare expenditure. This paper analyses the effect of carbon dioxide emissions on public health expenditure in India over the period 2000-2001 to 2022-23. Empirically, the short and long-run causal relationship between gross domestic product, carbon dioxide emissions, infant mortality rate, total fertility rate and public health expenditure is estimated by time series analysis. The stationarity of the series is tested with the Augmented Dickey-Fuller test. The ADF test finds that at levels some variables are stationary but at first difference all variables are stationary. The optimal lag length is identified with AIC, SIC, HQC and FPE criteria and the identified lag length is 1. The cointegration test is used to find the presence of the long-run relationship in the variables. One cointegrating equation is obtained by the trace and maximum eigenvalue statistics. The disequilibrium is corrected by the Vector Error Correction Mechanism (VECM) by including the error correction term. The VECM results show that every lagged year approximately 36.4 % of the departure from long-run equilibrium is corrected. The dynamic stability check shows that the model is stable. This study finds that with a 1% increase in carbon emission, public health expenditure is increasing by about 0.36%. With a 1% increase in GDP and TFR, public health expenditure is increasing by around 0.02% and 0.98% respectively. Thus, rising carbon emissions and the consequent air pollution and environmental degradation are significantly associated with rising health issues and the related increase in public health expenditure in India.

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