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The Causal Effects of Environmental Pollution on Public Health Expenditure and Economic Growth in India: Panel Autoregressive Distributed Lag Estimation

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Abstract

Increasing air pollution and the consequent degradation of environmental quality across the world are posing serious challenges to healthy living, not only through the increasing threat of global warming but also due to increased mortality and morbidity. This paper examines the short- and long-run dynamic relationship between economic growth, air pollution, and public health expenditure in 18 states of India during the period 2007 to 2021, applying panel unit root test, cointegration test, and autoregressive distributed lag (ARDL) estimation method. The ARDL model estimates the long-run dynamic interaction between the variables and distinguishes the short- and long-run effects. The panel ARDL estimates show that GSDP and air pollution have a significant positive long-run effect on public health expenditure in the states of India. The impact of carbon emissions on health expenditure is higher than the effect of GSDP. The much-desired economic growth comes at the cost of environmental degradation that increases the risk of pollution-induced health diseases including mortality, ultimately rising the public healthcare expenditure.

Keywords: Economic Growth, Air Pollution, Public Health Expenditure, Causal Effect, ARDL Estimation

INTRODUCTION

Every living organism depends on the environment, the bio-geo-physical product of the surroundings in which it lives, to satisfy its basic needs. In the peaceful co-existence of the ecosystem, the developed man started exploiting the natural resources, leading to environmental deterioration. Poor environmental quality of air, water, and soil is responsible for many health damages, which increases the risk of illness. Increasing air pollution and the consequent degradation of environmental quality across the world are posing serious challenges to healthy living, not only through the increasing threat of global warming but also due to increased mortality and morbidity. To combat the rising health issues, governments across the globe have to incur huge public expenditure on health which is constantly increasing and are met by an almost immediate increase in the demand for healthcare. The costs of healthcare systems are indisputable and put more pressure on government budgets as well as private individuals. A healthy society is one of the important forms of wealth and is regarded as human capital both for the individual and the nation.

The World Health Organisation defines air pollution as "the presence of materials in the air in such concentration which is harmful to man and his environment". Air pollution is the contamination or presence of unwanted substances (pollutants) in the atmosphere, emitted by both natural and anthropogenic (human activity) sources, making the air harmful and detrimental for human and animal health. Air pollutants are broadly classified as particulate matter and gaseous. The particulate substances include solid and liquid particles. The gaseous include substances that are in the gaseous state at normal temperature and pressure. The particulate matter consists of two types – settleable and suspended.

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The smaller particles remain suspended for long periods in the air. Carbon monoxide (CO_2) combines with the haemoglobin of blood and impairs its oxygen-carrying capacity. Sulphur dioxide (SO_2) combines with water in the air to form sulphurous acid (H_2SO_3), which is the cause of acid rain and causes irritation to the eyes and injury to the respiratory tract. It results in discolouration and deterioration of buildings, sculptures, painted surfaces, fabrics, paper, leather, and so on. Nitrogen dioxide (NO_2) act on unsaturated hydrocarbons giving rise to photochemical smog that causes eye irritation, respiratory troubles, blood congestion, and dilation of arteries. Chlorofluorocarbons from jet plane emissions and refrigerators and carbon tetrachloride react with ozone layers of the stratosphere, depleting the same. Aerosols that are widely used as disinfectants and photochemical oxidants are harmful to humans and plants.

While large-scale industrialisation increases the production of material goods, and urbanisation creates megacities, the ill effects of these activities are the overwhelming concentration of vehicles and transportations that emit gases, which is reflected in the form of various environmental and health issues. The major causes of air pollution are automobile exhaust and industrial emissions; automobiles that inefficiently burn petroleum release 75 per cent of noise and 80 per cent of air pollutants. Carbon monoxide (CO_2) accounts for 50 per cent of the total atmospheric pollutants. Epidemiological studies show that there is a significant association between the concentration of air pollutants and adverse health impacts. The impact of CO_2, SO_2, NO_2, and PM_{10} in the air on respiratory and cardiovascular diseases is quite severe, causing illnesses like eye irritation, asthma, bronchitis, and so on, which invariably reduce efficiency and labour productivity, thus having negative repercussions on national output and affecting the growth of firms and the economy.

It is shocking to know that out of the top 30 most polluted cities in the world in 2019, 21 are in India. The Indian cities of Allahabad, Agra, Lucknow, Kanpur, Amritsar, and so on are among the list of top 20 most polluted cities in the world. Delhi has been found to have the highest concentration of ‘respiratory suspended particulate matter’ in the air among the metro cities of India. An interesting point to note is that with the increasing industrial development and pace of output (GDP), carbon emissions, air pollution, and environmental degradation are also increasing, and so does the public health expenditure in India. Studies in various countries have shown that air pollution is one of the most fundamental management challenges and has a significant positive impact on health expenditure in developed and developing countries all around the world (Boachie et al., 2014; Fattahi, 2015; Fattahi et al., 2013; Jie, 2008; Mohammadzadeh et al., 2015; Balan, 2016).

In an attempt to understand the impact of environmental degradation on health expenditure, this paper examines the effects of air pollution and environmental quality, and economic growth on public health expenditure in India. This paper uses the secondary data on Air Quality Index from the Central Board of Pollution and other data from the Reserve Bank of India during the period 2007 to 2021. The outcome variable in this paper is the public health expenditure, and the independent variables are SO_2, NO_2, PM_{10}, and GSDP. Since the outcome variable is influenced by the independent variables with a lag over time, the econometric estimation followed is the panel autoregressive distributed lag (ARDL) model.

REVIEW OF LITERATURE

Fisher and van Marrewijk (1998) developed an extended generations model of human development, where clean air has been a pure public good that could be used as a private input for production model; they showed how pollution can stifle the full potential of economic growth. They point out that firms that profit from pollution crowd out investment in innovation and slow economic growth.

Jerrett et al. (2003) examine the relationship between air pollution and government spending for protecting the environment in Ontario, Canada, using two-stage regression analysis. The estimated results show that air pollution has a direct and statistically significant effect on child hospitalisation due to asthma. After controlling for other variables that influence health expenditure, both total toxic pollution output and per capita municipal environmental expenditure have significant associations with healthcare expenditure.

Yazdi et al. (2014) examine the short- and long-run impacts of environmental quality and income in determining health expenditures in Iran, over the period 1967 to 2010, applying the autoregressive distributed lag model. The cointegration analysis shows that health expenditure, income, sulphur oxide emissions, and carbon monoxide emissions are cointegrated. The estimated short-run and long-run elasticities reveal that income, and sulphur oxide, carbon monoxide, and SPM emissions have statistically significant positive effects on health expenditure in Iran.

Fattahi (2015) examine the urbanisation rate as a factor in the effect of air pollution on public and private health expenditures, using panel data from 1995 to 2011 from developing countries, applying a dynamic generalised method of moments estimation method. The results indicate that air pollution has a positive and significant effect on public and private health expenditures, and the urbanisation rate affects the relationship between air pollution and health expenditures as a reinforcing factor.

Balan (2016) studies the causal relationship between environment and health in EU countries during the period 1995 to 2013, testing causal relationships between life expectancy at birth, carbon dioxide emissions in terms of coal, natural gas, and petroleum consumption, total health expenditures, and educational attainments using the Dumitrescu and Hurlin non-causality test. The analysis shows that there exist causal relationships among health, education, and environmental quality, and environmental quality is a constraint for economic growth and affects education and quality of human life in EU-25 countries.

Yahaya et al. (2016) study the impact of environmental quality on per capita health expenditure in a panel of 125 developing countries for the period 1995 to 2012. The 125 developing countries considered in the paper are having persistent 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 a long-run relationship between per capita health expenditure and carbon monoxide, nitrogen oxide, and sulfur oxide emissions.

Abdullah et al. (2016) analyse the cointegration between environmental quality and national health expenditure in Malaysia from 1970 to 2014, to estimate both short- and long-run impact of environmental quality on public health expenditure using the autoregressive distributed lag (ARDL) model. The ARDL results show that GDP, carbon dioxide, nitrogen dioxide, and sulphur dioxide emissions have a long-run relationship with public health expenditure in Malaysia. Sulphur dioxide emissions, fertility, and infant mortality rate are the significant factors in Malaysia's health expenditure.

Yazdi and Khanalizadeh (2017) explore 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, Syria, and Tunisia) for the period 1995-2014, using autoregressive distributed lag (ARDL) model. The carbon dioxide emissions per capita and PM_{10} emissions are used as measures of environmental quality. A comparison of the ratio of health expenditure to GDP shows that the health expenditure/GDP ratio has been increasing in most countries in the MENA region regardless of differential medical levels. The cross-sectional analysis shows significant differences in the healthcare expenditure of MENA countries with similar levels of economic development. The long-run elasticities show that income and CO_2 and PM_{10} emissions have statistically significant positive effects on health expenditure in the MENA region. It is observed that the income elasticity of health expenditure is just inelastic in the MENA countries.

Raeissi et al. (2018) analyse the short- and long-run impacts of air pollution on private and public health expenditure in Iran for the period 1972-2014 applying time series methods. To explore the impact of environmental quality on health expenditure, the paper uses carbon dioxide 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; third-rank and first-rank lags have been identified as optimal for models. The estimated results show that the coefficient of CO_2 on health expenditure is significantly positive.

Fazli and Abbasi (2018) study the relevance of the Kuznets curve of energy intensity in D-8 countries – Iran, Turkey, Malaysia, Pakistan, Egypt, Bangladesh, Indonesia, and Nigeria – during 1990-2014 using panel autoregressive distributed lag model. The static and dynamic, and the panel ARDL estimates show the applicability of the Kuznets curve for energy intensity in D-8 economies and the study estimates USD3931.25 as the per capita income threshold. In the long run, urbanisation rate and the degree of industrialisation have a positive and significant effect on the GDP of consuming energy of D-8 countries.

Zaidi and Saidi (2018) analyse the long- and short-run nexus between health expenditure, carbon dioxide and nitrous oxide emissions, and economic growth in the Sub-Saharan African countries, using annual data during the period 1990-2015, applying the autoregressive distributed lag model and the VECM Granger causality test for checking the direction of causality. The ARDL results show that while economic growth has a positive effect, carbon dioxide and nitrous oxide have a negative effect on health expenditure in the long run in the Sub-Saharan African countries. The estimates reveal that a 1 per cent increase in per capita GDP leads to a 0.33 per cent increase in health expenditure, whereas a 1 per cent increase in CO_2 and NO emissions decreases health expenditure by 0.06 per cent and 0.58 per cent, respectively. The VECM Granger causality results show that there is a one-way relationship going from health expenditure to GDP per capita and a two-way causality between CO_2 emissions and GDP per capita and between health expenditure and CO_2 emissions.

Badulescu et al. (2019) investigate the long-term and the short-term relationship between economic growth, environmental pollution and non-communicable diseases, and health expenditures in 28 European Union countries during 2000-2014, applying the panel autoregressive distributed lag model. The ARDL results show that both in the long and short run economic growth is one of the most important factors influencing health expenditures in all the EU countries. While in the short run the effect of CO_2 emissions is negative, in the long run, the effect is positive on health expenditure in EU countries. When the interaction between NCDs and environmental expenditure is introduced in the estimating model, the variation in environmental expenditure is a change in the effect of the NCDs on health expenditure.

Blazquez-Fernandez et al. (2019) analyse the differential relationship between air pollution and health expenditure in 29 high- and low-income OECD countries during the period 1995-2014. The study also examines the impact of per capita income and environmental air quality as determinants of health expenditure. The estimated results show that per capita income has a positive but insignificant effect on health expenditure, and that about 80-90 per cent of previous expenditure explain current expenditure showing anchorage effect, implying the significance of lag-time in health expenditure.

Haseeb et al. (2019) examine the short-term, as well as the long-term impact of economic growth, environmental pollution, and energy consumption on health and R&D expenditures in ASEAN countries using data from 2009 to 2018, applying the autoregressive distributed lag model. The findings reveal that environmental pollution, energy consumption, and economic growth have a significant long-run positive impact on health expenditure, as well as on the R&D expenditure of ASEAN countries. Further, environmental pollution and economic growth have a significant impact on R&D expenditure in the short run; however, energy consumption is not a significant factor in the R&D expenditure.

Wang et al. (2019) examine the dynamic linkages among CO_2 emissions, health expenditure, and economic growth in the presence of gross fixed capital formation and per capita trade in Pakistan during 1995-2017, applying the autoregressive distributive lag model. The empirical results show that there exists a significant long-run, as well as short-term causal relationship between health expenditure, CO_2 emissions, and economic growth in Pakistan. The Granger causality results reveal a bidirectional relationship between health expenditures and CO_2 emissions and between health expenditures and economic growth. Short-run unidirectional causality is running from carbon emissions to health-related expenditure.

In the Indian context, Ghosh (2010) studies the cointegration and causality between carbon dioxide emissions and economic growth for the time span 1971-2006 using a multivariate framework applying the autoregressive distributed lag (ARDL) bounds-testing approach, complemented by the Johansen-Juselius maximum likelihood procedure. The study fails to establish a long-run equilibrium relationship and long-term causality between carbon emissions and economic growth. However, there exists bidirectional short-run causality between emission and growth. Hence, in the short run, any effort to reduce carbon emissions could lead to a fall in the national income. The paper also finds a unidirectional short-run causality running from economic growth to energy supply and energy supply to carbon emissions. The absence of causality running from energy supply to economic growth implies that in India, energy conservation and energy efficiency measures can be implemented to minimise the wastage of energy across the value chain. The absence of long-run causality between carbon emissions and economic growth implies that in the long run, focus should be on harnessing energy from clean sources to curb carbon emissions, which would not impair economic growth.

Mohapatra and Giri (2016), in an attempt to test the Environmental Kuznets Curve hypothesis at the state level in India, analyse the relationship between economic development and different air quality measures like SO_2, NO_2, and SPM emissions, in industrial and residential locations in 15 major states of India during 1991-2003. The study notes that several developmental factors like scale effect, composition effect, and pollution abatement effect contribute to the changing emissions of these air quality parameters. These factors generally include the scale effect, composition effect and the pollution abatement effect. The fixed effects pooled data estimates reveal a statistically insignificant directional inverted U-shaped EKC relationship for both industrial and residential locations. Further, the study finds that developmental factors like population density, urbanization, and policy variables are significant in explaining the relationship between economic development and environmental quality in most states of India. The calculated turning point of SDP per capita ranges between USD163.46 and USD408.66 for different air quality parameters to decline in the states of India.

DATA AND METHODOLOGY

This paper analyses the short- and long-run dynamic relationship between economic growth, air pollution (NO_2, SO_2, and PM_{10}), and health expenditure in 18 states in India during the period 2007 to 2021. The panel data on the air quality index is collected from the Central Board of Pollution, Government of India, and the data on gross state domestic product is sourced from the Reserve Bank of India. As the outcome variable, health expenditure is influenced by the independent variables, SO_2, NO_2, PM_{10}, and GSDP, with a lag; the panel autoregressive distributed lag model is therefore the appropriate estimation method. The panel data combines cross-section and time-series data and controls for individual heterogeneity; it is better suited for studying the dynamics of change.

Panel Unit Root Test: Before proceeding to the estimation, the data is to be checked for stationarity or the presence of unit root. Generally, the time series data contains unit root and is non-stationary. The time series data is required to be stationary to avoid any inconsistencies in coefficient estimation. Therefore, it is critical to check the stationarity properties and to identify the integration order of the series. It is standard that a variable is said to be stationary if it has a time-invariant mean, time-invariant variance, and the value of the covariance between the two time periods depends only on the distance or gap or lag between the two time periods and not the actual time at which the covariance is computed.

The first-generation panel-based unit root tests assume that the data is independent and identically distributed (i.i.d.) across individuals (Quah, 1994; Breitung and Mayer, 1994). The general panel unit root test is based on the following univariate regression:

$$\Delta y_{it} = \rho_i y_{it-1} + \gamma x_{it} + u_{it}$$
$$i = 1,2,\dots,n \quad t = 1.2,\dots,T \tag{1}$$

Where, x_{it} are the exogenous variables in the model, including any fixed effects or individual trends, ρ_i are the autoregressive coefficients, and the errors u_{it} are assumed to be a mutually independent idiosyncratic disturbance. If $|\rho_i| < 1$, y_i is said to be weakly (trend) stationary and if $|\rho_i| = 1$, it implies that y_i contains a unit root.

Levin, Lin, and Chu Test: Levin, Lin, and Chu (2002) generalise Quah's model to allow for heterogeneity of individual deterministic effects and heterogeneous serial correlation structure of the error term, assuming homogeneous first-order autoregressive parameters. Imposing a cross-equation restriction on the first-order partial autocorrelation coefficients under the null, this procedure leads to a test of a much higher power than performing a separate unit root test for each individual. The structure of the LLC analysis can be specified as follows:

$$\Delta y_{it} = \rho_i y_{it-1} + \alpha_{oi} + \alpha_{1i} t + u_{it} \tag{2}$$

Where, α_{oi} refers to the individual effects and α_{it} the time trend. The LLC tests the null hypothesis (H_0: $\rho_i = \rho < 0$) against the alternative (H_1: $\rho_i = \rho < 0$) for all i. If u is assumed to be independently distributed across individuals and a stationary invertible ARMA process for each individual is followed:

$$u_{it} = \sum_{j=1}^{\infty} \theta_{ij} u_{it-j} + \varepsilon_{it} \tag{3}$$

The finite-moment conditions are assumed to assure the weak convergence in Phillips-Perron unit root test (Phillips & Perron, 1988).

The Phillips-Perron procedure is to first run the Augmented Dickey-Fuller (ADF) unit root test for each cross-section of the equation:

$$\Delta y_{it} = \rho_i y_{it-1} + \sum_{k=1}^{p_i} \gamma_{ik} \Delta y_{it-k} + \delta_i x_{it} + u_{it} \quad (4)$$

However, the individual unit root tests have limited power, as there may be too many unit roots in panel data. Therefore, the LLC runs two auxiliary regressions:

Δy_{it} on Δy_{it-k} and x_{it} to obtain the residuals $\hat{e}_{it}$ (5)

$y_{i,t-1}$ on Δy_{it-k} and x_{it} to obtain the residuals $\hat{v}_{it-1}$ (6)

The next step is to standardise the errors as:

$$\tilde{e}_{it} = \hat{e}_{it}/\hat{\sigma}_{ui} \quad (7)$$

$$\tilde{v}_{it-1} = \hat{v}_{it}/\hat{\sigma}_{ui} \quad (8)$$

Where, σ_{ui} denotes the standard error from each ADF. The final step is to run the pooled OLS regression:

$$\tilde{e}_{it} = \rho \tilde{v}_{it-1} + \hat{u}_{it} \quad (9)$$

The Levin-Lin-Chu null hypothesis for panel unit root test is: H_0: $\rho_i = \rho < 0$.

Panel Cointegration Test: When the variables are static in their first differences, the Pedroni cointegration test is applied to test for the existence of a long-run cointegration among the other variables in the panel data (Pedroni, 1999; 2004). The Pedroni cointegration test employs seven statistics, viz. four within-dimension panel v-statistic, panel ρ-statistic, panel PP-statistic, panel ADF-statistic, and three between-dimension group ρ-statistic, group PP-statistic, and group ADF-statistic, to test the null hypothesis of no cointegration against the alternative hypothesis of cointegration. These seven test statistics allow heterogeneity in the panel, both in the short-run dynamics as well as in the long-run slope and intercept coefficients.

The Pedroni panel cointegration test is based on the following panel regression model:

$$y_{it} = \alpha_i + \delta_i t + \gamma_t + \beta_{mi} x_{mit} + e_{it} i = 1, \ldots, N; \quad t = 1, \ldots, T; \; m = 1, \ldots, M \quad (10)$$

Where, i represents the cross-section units, t the time, and m the number of regressors. In this setup, α is the individual-specific intercept or fixed effects parameter and deterministic trends which varies across individual cross-sectional units, δ_i is individual-specific time effects, and the parameter γ_t allows for the possibility of common effects that are shared across individual members of the panel in any given period. The residual-based panel cointegration test of Pedroni (1999; 2004) uses the first difference of panel regression:

$$\Delta y_{it} = \beta_{mi} \Delta x_{mit} + \eta_{it} \quad (11)$$

The long-run variance of the estimated residuals from the first differenced panel regression is computed as:

$$\hat{\psi}_{it}^2 = \frac{1}{T} \sum_{t=1}^{T} \hat{\eta}_{it}^2 + \frac{2}{T} \sum_{k=1}^{p_i} \left(1 - \frac{k}{p_i+1}\right) \sum_{t=k+1}^{T} \hat{\eta}_{it} \hat{\eta}_{it-k} \quad (12)$$

The panel-ρ and group-ρ statistics are obtained from the panel regression residuals from the panel regression:

$$\hat{e}_{it} = \hat{\rho}_i \hat{e}_{it-1} + \hat{\mu}_{it} \quad (13)$$

The long-run variance ($\hat{\sigma}_i^2$) and the contemporaneous variance ($\hat{s}_i^2$) of $\hat{\mu}_{it}$ are then computed as:

$$\hat{\sigma}_i^2 = \frac{1}{T} \sum_{t=1}^{T} \hat{\mu}_{it} \quad (14)$$

$$\hat{s}_i^2 = \frac{1}{T} \sum_{t=1}^{T} \hat{\mu}_{it} + \frac{2}{T} \sum_{k=1}^{p_i} \left(1 - \frac{k}{p_i+1}\right) \sum_{t=k+1}^{T} \hat{\mu}_{it} \hat{\mu}_{it-k} \quad (15)$$

Then, compute λ_i as:

$$\lambda_i = \frac{1}{2} (\hat{\sigma}_i^2 - \hat{s}_i^2) \quad (16)$$

The panel-t and group-t statistics are again computed from the panel regression residuals as:

$$\hat{e}_{it} = \hat{\rho}_i \hat{e}_{it-1} + \sum_{k=1}^{p_i} \hat{\rho}_{ik} \Delta \hat{e}_{it-k} + \hat{\mu}_{it}^* \quad (17)$$

The variance of $\hat{\mu}_{it}^*$ is computed as:

$$\hat{s}_i^{*2} = \frac{1}{T} \sum_{t=1}^{T} \hat{\mu}_{it}^{*2} \text{ and } \tilde{s}_{NT}^{*2} \equiv \frac{1}{N} \sum_{i=1}^{N} \hat{s}_i^{*2} \quad (18)$$

Pedroni (1999; 2004) computes the panel cointegration statistics from panel-ρ, panel-t, group-ρ, and group-t statistics, and shows that the test statistics are standard normally distributed. Then, the null hypothesis of no cointegration for the panel cointegration test is the same for each statistic:

Null hypothesis: H_0: H0: $\rho_i = 1 \; \forall i$ (19)

However, there is a difference in the alternative hypothesis for the between-dimension-based and within-dimension-based panel cointegration tests. The between-dimension-based statistics does not require the common value of ρ:

Alternative hypothesis: H_1: $H_1: \rho_i < 1 \ \forall i$ (20)

The within-dimension-based statistics requires a common value for $\rho_i = \rho$:

Alternative hypothesis: H_1: $H_1: \rho_i = \bar{\rho} < 1 \ \forall i$ (21)

Under the alternative hypothesis, all the panel cointegration test statistics diverge to negative infinity. Thus, the left tail of the standard normal distribution is used to reject the null hypothesis.

Panel Autoregressive Distributed Lag Model: After the unit root and cointegration tests, the ARDL model is to be estimated to analyse the long-run dynamic interaction between the variables. The ARDL model distinguishes between short- and long-run coefficients. The estimating panel ARDL equation is specified as:

$$lnHE_{it} = \alpha_i + \sum_{j=1}^{p} \alpha_{1ij} lnHE_{it-j} + \sum_{j=0}^{q_1} \alpha_{2ij} lnGSDP_{it-j} + \sum_{j=0}^{q_2} \alpha_{3ij} lnSO_{2\,it-j} + \sum_{j=0}^{q_3} \alpha_{4ij} lnNO_{2\,it-j} + \sum_{j=0}^{q_4} \alpha_{5ij} lnPM_{10\,it-j} + \varepsilon_{it} \quad (22)$$

Where, the error term is ε_{it} white noise and varies across cross-section and time, *p* represents the lags of the dependent variable, the health expenditure of the states, and *q* represents the lags of the independent variables, gross state domestic product and air pollutants SO_2, NO_2, and PM_{10} levels in each state of India.

Pooled Mean Group (PMG) Estimation: To estimate the panel ARDL regression, the Pesaran, Shin and Smith (1999; 2001) likelihood-based pooled mean group (PMG) technique is used. The PMG estimator has a number of advantages, Firstly, the PMG estimation combines both averaging and pooling of coefficients, allowing the intercepts, short-run coefficients, and error variances to differ freely across groups. Secondly, in instances where the number of the cross-sections is rather small, as in this paper, the PMG estimator is less sensitive to outliers and can simultaneously correct the problem of serial autocorrelation. Thirdly, the PMG estimator also constrains the long-run coefficients to be identical across groups. This homogeneity restriction leads to consistent estimates of the parameters. Fourthly, this likelihood-based estimation corrects the endogenous regressors problem by choosing an appropriate lag structure for both dependent and independent variables.

Table 1 presents the definition and descriptive statistics of variables in the empirical analysis. Table 2 presents the results of the panel unit root test to determine whether the variables are stationary. If the variables contain a unit root, the next step is to check if there is a cointegration relationship between variables. The panel unit root test shows that all the variables are stationary at levels at the 5 per cent significance level. The Pedroni-Johansen cointegration Fisher test results are presented in Table 3. The seven Pedroni test statistics are grouped into two categories: group-mean statistics that average the results of individual country test statistics and panel statistics that pool the statistics along the within-dimension. The Pedroni test results fail to reject the null hypothesis of no cointegration between the variables. Thus, there is no long-run relationship between health expenditures, GDP, SO_2, NO_2, and PM_{10} emissions.

Table 1: Descriptive Statistics of Variables

Variable	*Description*	*Mean*	*Std. Dev.*
Health expenditure	Public health expenditure of states (₹crores)	547.18	408.61
GSDP	State income or GSDP at factor cost (₹ lakhs)	35314655	24385683
SO_2	Sulphur dioxide in the air (per cubic metre)	10.57	3.23
NO_2	Nitrogen oxide in the air (per cubic metre)	31.68	12.63
PM_{10}	Solid particles and liquid droplets in the air (per cubic metre)	138.24	58.40
Observations		214	

Table 2: Panel Unit Root Test

Variable	*T-Statistic*	*P-Value*
GSDP	−2.05**	0.02
SO_2	−1.87**	0.03
NO_2	−3.78**	0.00
PM_{10}	−2.51**	0.00
GSDP	−3.38**	0.00

Note: **Significant at 5 per cent level.

Table 3: Panel Cointegration Test

Statistic	Within-Dimension				Between-Dimension		
	T-Statistic	P-Value	Weighted Statistic	P-Value	Statistic	T-Statistic	P-Value
Panel v-statistic	−3.506	0.99	−2.55	0.99	Group ρ-statistic	6.073	1.00
Panel ρ-statistic	4.78	1.00	4.43	1.00	Group PP-statistic	1.687	0.95
Panel PP-statistic	4.345	1.00	2.58	0.99	Group ADF-statistic	3.362	0.99

Table 4: Panel ARDL Estimates of Health Expenditure

Variable	Short-Run		Variable	Long-Run	
	Coefficient	T-Statistic		Coefficient	T-Statistic
D(lnGSDP)	−3.353(7.477)	0.448[0.655]	lnGSDP	1.889*(1.018)	5.320[0.000]
D($\ln SO_2$)	−5.102(9.629)	0.374[0.709]	$\ln SO_2$	4.195*(2.649)	5.138[0.000]
D($\ln NO_2$)	−2.456(2.215)	1.109[0.270]	$\ln NO_2$	4.487*(3.708)	3.009[0.003]
D($\ln PM_{10}$)	−1.496	0.134[0.894]	$\ln PM_{10}$	3.459*(1.758)	4.832[0.000]
Constant	8.232(8.128)	1.215[0.227]			
Cointegrating equation	0.0123(0.025)	0.502[0.617]			

Note: D denotes first differences. Absolute t-values. Standard errors in parentheses. P-values in brackets.

The estimated panel ARDL results are presented in Table 4. In the short run, the coefficients of the first differenced variables are negative; however, none of them are statistically significant. Hence, there seems to be no immediate response of health expenditure, either to economic growth or to pollution, in the states of India. The effects of air pollution on healthcare are really felt only in the long run. In the long run, all the estimated coefficients are positive and statistically significant. The GDP has a positive long-run effect on health expenditure in the states of India, implying that an increase in real GDP increases the health expenditure of states by nearly 2 per cent. The estimated coefficients of SO_2, NO_2, and PM_{10} show that pollution has the potential to spur the long-run public health spending in the states of India. An increase in the air pollution levels increases state health expenditure by 3-4 per cent in the long run.

CONCLUSION

This paper focuses on examining the relationship between air pollution, health expenditure, and economic growth in the states of India for the period 2007-2021. The air pollutants considered are SO_2, NO_2, and PM_{10} emissions. In the estimation, the panel autoregressive distributed lag model is used, as the effects of air pollution on public health expenditure persist over time. The results of the panel ARDL model show that GSDP and air pollution have a significant positive long-run effect on public health expenditure in the states of India. The impact of carbon emissions on health expenditure is higher than the response to that of GSDP. With economic growth in the Indian states, the consumption of crude oil, gasoline, kerosene, diesel, and fuel oil increases pollution, thus degrading the environmental quality, causing health issues, and increasing state health expenditure. The much-desired economic growth comes at the cost of environmental degradation that increases the risk of pollution-induced health diseases including mortality, ultimately rising the healthcare expenditure.

REFERENCES

Abdullah, H., Azam, M., & Zakariya, S. K. (2016). The impact of environmental quality on public health expenditure in Malaysia. *Asia Pacific Journal of Advanced Business and Social Studies*, *2*(2), 365-379.

Badulescu, D., Simut, R., Badulescu, A., & Badulescu, A. V. (2019). The relative effects of economic growth, environmental pollution and non-communicable diseases on health expenditures in European Union countries. *International Journal of Environmental Research and Public Health*, *16*(24), 5115.

Balan, F. (2016). Environmental quality and its human health effects: A causal analysis for the EU-25. *International Journal of Applied Economics*, *13*(1), 57-71.

Blazquez-Fernandez, C., Cantarero-Prieto, D., & Pascual-Saez, M. (2019). On the Nexus of air pollution and health expenditures: New empirical evidence. *Gaceta Sanitaria*, *33*(4), 389-394.

Boachie, M. K., Mensah, I. O., Sobiesuo, P., Immurana, M., Iddrisu, A.-A., & Kyei-Brobbey, I. (2014). Determinants of public health expenditure in Ghana: A cointegration analysis. *Journal of Behavioural Finance Entrepreneurship Account Transport*, *2*(2), 35-40.

Breitung, J., & Meyer, W. (1994). Testing for unit roots in panel data: Are wages on different bargaining levels cointegrated? *Applied Economics*, *26*(4), 353-361.

Fattahi, M. (2015). The role of urbanization rate in the relationship between air pollution and health expenditures: A dynamic panel data approach. *International Letter of Society Humanist Science*, *53,* 68-72.

Fattahi, M., Assari, A., Sadeghi, H., & Agharpour, H. (2013). Air pollution and public health expenditure: Compare developed and developing countries. *Journal of Economic Development Research*, *11*(3), 111-132.

Fazli, P., & Abbasi, E. (2018). Analysis of the validity of Kuznets Curve of energy intensity among d-8 countries: Panel-ARDL approach. *International Letters of Social and Humanistic Sciences*, *81*(1), 1-12.

Fisher, E. O. N., & Van Marrewijk, C. (1998). Pollution and economic growth. *Journal of International Trade and Economic Development*, *7*(1), 55-69.

Ghosh, S. (2010). Examining carbon emission economic growth Nexus for India: A multivariate cointegration approach. *Energy Policy*, *38*(6), 3008-3014.

Haseeb, M., Kot, S., Hussain, H. I., & Jermsittiparsert, K. (2019). Impact of economic growth, environmental pollution, and energy consumption on health expenditure and R&D expenditure of ASEAN countries. *Energies, MDPI Open Access Journal*, *12*(19), 1-21.

Jerrett, M., Eyles, J., Dufournaud, C., & Birch, S. (2003). Environmental influences on healthcare expenditures: An exploratory analysis from Ontario, Canada. *Journal of Epidemiology and Community Health*, *57*(5), 334-338.

Jie, H. (2008). Industrialization, environment and health: The impacts of industrial SO_2 emission on public health in China. *Chinese Journal of Population Resources and Environment*, *6*(1), 14-24.

Levin, A., Lin, C. F., & Chu, C. S. J. (2002). Unit root tests in panel data: Asymptotic and finite-sample properties. *Journal of Econometrics, 108*(1), 1-24.

Mohammadzadeh, Y., Ghahramani, H., & Nazariyan, E. (2015). Environmental, health and health care costs. *Health Information Management Journal*, *12*(4), 495-505.

Mohapatra, G., & Giri, A. K. (2009). Economic development and environmental quality: An econometric study in India. *Management of Environmental Quality*, *20*(2), 175-191.

Pedroni, P. (1999). Critical values for cointegration tests in heterogeneous panels with multiple regressors. *Oxford Bulletin of Economics and Statistics, 61,* 653-670.

Pedroni, P. (2004). Panel cointegration: Asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis. *Econometric Theory*, *20*(3), 597-625.

Pesaran, M. H., Shin, Y., & Smith, R. J. (1999). Pooled mean group estimation of dynamic heterogeneous panels. *Journal of the American Statistical Association, 94*(446), 621-634.

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds Testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, *16*(3), 289-326.

Phillips, P., & Perron, P. (1988). Testing for a unit root in time series regressions. *Biometrika*, *75*(2), 335-346.

Quah, D. (1994). Exploiting cross-section variation for unit root inference in dynamic data. *Economics Letters, 44*(1), 9-19.

Raeissi, P., Harati-Khalilabad, T., Rezapour, A., Hashemi, S. Y., Mousavi, A., & Khodabakhshzadeh, S. (2018). Effects of air pollution on public and private health expenditure in Iran: A time series study (1972-2014). *Journal of Preventive Medicine and Public Health*, *51*(3), 140-147.

Wang, Z., Asghar, M. M., Saidi, S. A. H., & Wang, B. (2019). Dynamic linkages among CO_2 emissions, health expenditures, and economic growth: Empirical evidence from Pakistan. *Environment Science and Pollution Research*, *26*(36), 136248-36263.

Yahaya, A., Nor, N. M., Habibullah, M. S., Ghani, J. A., & Noor, Z. M. (2016). How relevant is environmental quality to per capita health expenditures? Empirical evidence from panel of developing countries. *Springer Plus*, *5*(925), 1-15.

Yazdi, S. K., & Khanalizadeh, B. (2017). Air pollution, economic growth and health care expenditure. *Economic Research*, *30*(1), 1181-1190.

Yazdi, S. K., Tahmasebi, Z., & Mastorakis, N. E. (2014). Public healthcare expenditure and environmental quality in Iran. In N. E. Mastorakis, P. M. Pardolas & M. N. Katehakis (Eds.), *Recent Advances in Applied Economics* (pp. 126-134). Lisbon, Portugal: WSEAS Press.

Zaidi, S., & Saidi, K. (2018). Environmental pollution, health expenditure and economic growth in the sub-Saharan African Countries: Panel ARDL approach. *Sustainable Cities and Society*, *41,* 833-840.