Advances in Consumer Research
https://acr-journal.com/
Volume-2 | Issue-4 | Oct 2025

Original Researcher Article

Health Expenditure Driven Growth In India: An Econometric Analysis

Prof. Sudhakar Patra[1*] & Dr. Diptimayee Samal[2]

[1*]RBI Chair Professor, PG Department of Analytical & Applied Economics, Utkal University, Bhubaneswar, Odisha, India,
[2]Assistant Professor, School of Liberal Arts, ASBM University, Bhubaneswar, Odisha, India

Received: 28/08/2025
Revised: 06/09/2025
Accepted: 30/09/2025
Published: 16/10/2025

ABSTRACT
The objective of the paper to analyse the linkages of growth of health expenditure and health outcome in India from 1991-2021. After the structural adjustment programme, healthcare expenditure witnessed a deceleration worldwide with the extreme situation faced by developing countries. So, given the emerging challenges of health problems in the developing world, the financing mechanism of public health services requires more attention in catering healthcare needs of the population more adequately and effectively. This study tried to examine the nexus between health outcomes and health expenditure in India. This study is purely based on secondary sources of data from the Reserve Bank of India, the World Bank Database, and various government reports. The trend of IMR and LEB in India during the period post-reform the LEI has an increasing trend slowly over the period whereas IMR has a declining trend. The Granger-causality Wald test is conducted to establish whether health expenditure affects GDP and vice-versa. Health spending has a positive impact on India's GDP. The correlation between health spending and health outcomes like-LEB, IMR, are significant and Positive for life expectancy at birth and negative for infant mortality rate, the short-run impact on life expectancy with health expenditure is positive and significant, while there is a negative impact of IMR with health expenditure in long-run. This study highlighted that more awareness of the health of the people is necessary if sustainable growth is pursued.

Keywords: Health Expenditure, Health outcome, IMR, LEB, Granger Causality, Time Series

JEL Code- H51, I10, I15

INTRODUCTION

Research on healthcare spending, outcomes, and GDP has provided conflicting results. A study conducted by Balaji (2011)[1] identified no evidence of a long-term causal relationship between healthcare spending and economic growth. In contrast, Elmi and Sadeghi (2012)[2] and Mehrara and Musai (2011)[3] indicate a short-term causal nexus between healthcare spending and GDP. Amiri and Ventelou (2010)[4] also emphasize that there is bidirectional causality between economic growth and healthcare spending. Hooda (2014)[5] investigated how various forms of decentralized governance affected infant and child mortality rates in rural India across states and how they affected the effectiveness of spending on rural health. The findings demonstrated that states with high political and fiscal decentralization have a more significant effect on lowering infant mortality than states with high budgetary but low political decentralization levels, suggesting that fiscal decentralization's effectiveness rises with political decentralization.

Healthcare spending is crucial for both short- and long-term gains. Reeves et al. (2013)[6] and Llori and Babatola (2017)[7]. According to Karaman et al. (2020)[8], one of the key elements of long-term sustainable economic development is good health, a significant component of human capital. According to Karim (2016)[9], Romer (2012)[10], and Sen (2014)[11], According to the neo-classical growth model, a healthier and educated labour force raises per capita income for people and their families, increasing the value of human life. Improvements in medical facilities and opportunities to develop human capital can result from expenditure on health care, which boosts productivity and economic performance. Albulescu et al. (2017)[12], Raghupathi (2015)[13]. An important health effect of increased public spending on emergency aid, curative care, and nutrition and immunization programs is reduced mortality. There have been contradictions in the literature about the relationship between healthcare spending and better health outcomes. Health spending is associated with two health outcomes: more extended life expectancy and reduced child mortality (Karaman et al., Chiristopolos)[14], Kim, and Lane)[15]. For example, one study demonstrated that healthcare spending in OECD countries positively impacted health outcomes, including life expectancy and maternal and neonatal mortality (Karaman). (Kim and Lane)[15] studied 17 OECD countries from 1973to 2000, employing life expectancy at birth and infant mortality as health outcome indicators, and found a positive relationship between health spending and health outcomes. An additional study (Onofrei et al.)[16] showed that increasing health spending increases life expectancy and decreases infant mortality. However, using Spearman's correlation technique, other studies (Lippi et al (2016)[17]. and Mackenbach,1991)[18] demonstrated no connection between mortality rates in European nations and healthcare spending. Some researchers found no correlation between health spending and health status (Deshpande,) [19]. At the same time, another study (van et al.) [20] showed that it is difficult to establish a relationship between healthcare spending and health outcomes (life expectancy). The hypothesis indicates that to improve health outcomes, health investment is essential. According to the literature, a country's health spending level is a crucial indicator of its degree of health investment. This originates from the fact that, through the administration and delivery of health care services, the government may use expenditure on healthcare, particularly public health spending, as a significant policy weapon in any economy. Consequently, empirical researchers have worked to confirm how health spending influences health outcomes.

The inquiry concerns whether and to what degree health spending affects health outcomes. The importance of health spending on health outcomes has been studied using the Grossman health capital model, was developed based on Grossman's 1972 seminar, Health Capital and the Demand for Healthcare. Health spending is one of the inputs into the "production" of healthcare under both models, along with other socioeconomic determinants of health that are equally important.

Objectives

(1) To examine the nexus between LEB, IMR and health expenditure in India.

Hypotheses

H1: There is no linkage between health Expenditure and Life Expectancy.
H2: There is no linkage between health expenditure and infant mortality in India.

Data Methodology

This study has compiled secondary sources of data from - macro indicators of RBI bulletin and World Bank database etc. Variables of the study: Healthcare expenditure in (Revenue and Capital), account, Health outcome (Life Expectancy at birth, Infant Mortality Rate.)

Study Period: 1991-2021

Statistical tools and Methods:

Stationarity Test (Unit Root Test)

A stationary time series is essential for avoiding spurious causation in time series analysis. Spurious causality is a high correlation between two non-stationary time series variables with no causal relationship. Traditional regression techniques are incorrect when the series contains a unit root because they become erroneous, and vice versa. A time series is considered stationary (i.e., without a unit root) if its mean, variance, and autocorrelation do not change over time. If not, it is known as a unit root or a non-stationary time series (Gujarati 2009).

A time series of order zero or I (0) will be integrated if the stationarity test indicates that it is stationary at level (without differencing, i.e., Yt). To avoid spurious correlation, a series of order one or I (1) will be integrated if the test indicates that it is stationary at the first difference (i.e., Yt - Yt-1) for each variable. We use a parametric approach that includes the augmented Dickey and Fuller (ADF) test, which was pioneered by Dickey and Fuller (1979), and the Phillips-Perron (PP) unit root tests.

Augmented Dickey-Fuller (ADF) Test

The ADF test is based on the following regression equation:

$$\Delta Yt = \alpha 1 + \alpha 2\, t + \delta Yt - 1 + \sum n\, d\, i = 1\, i \Delta Yt - i + \varepsilon t \quad (3).$$

The equation is $\Delta Yt = Yt - Yt\text{-}1$, with $\alpha 1$ as the constant term, t as the time trend, Δ the first difference operator, n as the optimal number of lags, and εt as the pure white noise term. The null Hypothesis for the ADF test is HO: $\delta = 0$, indicating that the time series is non- stationary (with a unit root).

Phillips-Perron (PP) Test

The Phillips-Perron (PP) test is used to assess the stationarity of each series variable in addition to the Augmented Dickey-Fuller (ADF) test. Unlike the ADF test, the PP test does not require a lagged difference term to determine the level of serial correlation. Therefore, the PP test is based on the following regression equation:

$$\Delta Yt = \alpha 0 + \gamma\, t + \delta\, Yt\text{-}1 + \varepsilon\, t \quad (4).$$

The PP test's null Hypothesis, similar to the ADF test, is HO: $\delta = 0$, indicating that the time series is non-stationary (with a unit root).

Lag Selection Criterion

After analyzing the unit root testing, the next step is to choose the lag length for co- integration because the number of lags captures the dynamics of the series. There are different criteria for the selection of optimal lag length. The requirements help in selecting the appropriate lag order for the model. The lag order chosen is indicated by "*" in the last three columns for each criterion. For example, in the "AIC" column, the lag order with the lowest AIC value is selected as the appropriate lag order based on the AIC criterion. In the "LogL" column, higher values suggest a better model fit. The lag order chosen has the highest LogL value. The "LR" value compares the likelihood of the current model with the previous one. The quality of the current model increases with the LR value. Lower values in the "FPE," "AIC," "SC," and "HQ" columns indicate better model performance based on these criteria.

Bound Test and Long run Relationship

In econometrics, it is a statistical technique used to ascertain whether variables have a long-term relationship, particularly when those variables are integrated in different orders (i.e., I(0) or I(1)) but not I(2). When working with variables with heterogeneous integration orders or small sample sizes, this test is commonly uses the boundaries test to ascertain a co-integration relationship between the variables. The researchers provide the critical values for the bound test, which can be compared to the computed F-statistic based on the number of variables and the significance level.

Heteroscedasticity Test

Regression analysis is a situation in which the variance of the error terms, also known as residuals, varies at different levels of the independent variable. But, the spread or "scatter" of residuals changes when the value of the independent variable changes. This is contrary to homoscedasticity, one of the fundamental tenets of ordinary least squares (OLS) regression, which asserts that the variance of errors is constant.

Heteroscedasticity can affect the efficiency of the regression estimates, leading to inefficient parameter estimates, biased standard errors, and unreliable hypothesis tests (e.g., t-tests, F-tests). Therefore, detecting and addressing heteroscedasticity is an important part of regression analysis. To understand heteroscedasticity, we look at the model:

$$\mathbf{Yi = \beta 0 + \beta 1xi + \epsilon i}$$

Where:

- y_i = dependent variable
- x_i = independent variable
- ϵi = error term for observation i

Normality Test

A statistical method determines whether a given dataset has a normal distribution (bell curve). The null Hypothesis in a normality test typically states that the data is distributed normally. When the p-value is significant (typically $p < 0.05$), the data does not fit a normal distribution, and the null Hypothesis is rejected. A high p-value, on the other hand, indicates that the data may have a normal distribution and that the null Hypothesis cannot be dismissed.

Serial Correlation (Breusch-Godfrey LM) Test

A standard statistical method for determining if a serial correlation exists in the residuals of a linear regression model is the Breusch-Godfrey LM test. This test is frequently utilized because it may detect higher-order serial correlation in addition to first-order autocorrelation and does not need the error terms to be normally distributed.

The Breusch-Godfrey LM test is based on the Lagrange multiplier (LM) principle, a method for assessing the significance of a group of constraints in a model. In this case, the rule is that the residuals of the regression model should not be serially correlated.

Linear regression model: $yt = \beta 0 + \beta 1xt + \epsilon t$

Where:

- yt = dependent variable
- x_t = independent variable
- ϵt = error term

Autoregressive Distributed Lag (ARDL) Approach

Asymptotic critical values are proposed in two sets by Pesaran et al. (2001). In the first set, all underlying variables are assumed to be integrated at the level, or I (0). On the other hand, in the second set, I(1), all underlying variables are expected to be integrated into order one, indicating a long-term relationship between the variables. This study tests for co-integration between the variables using the Autoregressive Distributed Lag (ARDL) method. This approach is superior to other conventional methods, including those put forth by Engle and Granger (1987), Johansen (1991), and Gregory and Hansen (1996). The result cannot be inferred if the F-statistics in between the lower and upper critical bounds. The null Hypothesis cannot be refuted. if the F-statistic is less than the lower critical bound. The model's long- and short-term coefficients can be estimated if the variables have a long-term relationship.

The first step is to determine whether the variables have a long-term relationship. The second step is to estimate the long-run coefficients of the model. The ARDL Long Run Form and Bound test determines whether the variables have a long-term relationship. The null Hypothesis that there is no long-term relationship among the coefficients of lagged variables, πi, is examined by the well-known F-statistic.

H0: $\pi 1 = \pi 2 = \pi 3 = \pi 4 = \pi 5 = 0$ (no cointegration i.e., no long-run relationship) Against the alternative Hypothesis,

H1: $\pi 1 \neq 0, \pi 2 \neq 0, \pi 3 \neq 0, \pi 4 \neq 0\ \pi 5 \neq 0$ (Cointegration)

An ARDL (Autoregressive-distributed lag) is a parsimonious infinite lag-distributed model. The term “autoregressive” shows that along with getting explained by the xt, yt also gets explained by its lag. The equation of ARDL (m, n) is as follows:

$$Yt = \beta 0 + \beta 1 Y_{t-1} + \beta 2LHEt + B 3 LHE_{t-1} + \varepsilon t$$

Y = Health Outcome Variable (LEB, IMR)

LHEXP= Log of total health expenditure

εt is the disturbance term, and

βi’s are coefficients for short-run and

αi’s are coefficients for long-run relationships.

RESULT AND DISCUSSION

Result of Stationarity Test (Unit Root Test)

In time series analysis, a stable time series is necessary to avoid spurious causation. Spurious causality occurs when two non-stationary time series variables have a high correlation but no causal relationship. We use a parametric method to conduct the Phillips- Perron (PP) unit root tests (Phillips & Perron, 1988) and the augmented Dickey and Fuller's (ADF) test, which originated with Dickey and Fuller (1979).

Table-1 Results of stationarity test

Augmented Dickey Fuller (ADF) (at Level)					
With Cons	t-Statisti	LGDP	LHE	LIMR	LLEB
		-0.55	4.58	-1.77	-1.4
	Prob.	0.87	1	0.39	0.57
Significant		n0	n0	n0	n0
With Con & Trend	t-Statisti	-1.79	2.59	-1.35	1.24
	Prob.	0.03	0.01	0.85	0.03
Significant		**	***	No	**
Augmented Dickey Fuller (at First Difference)					
With Cons	t-Statistics	d(LGDP)	d(LHE)	d(LIMR)	d(LLEB)
		-6.29	-2.4	-2.13	12.25
	Prob.	0	0.15	0.24	1
Significant		***	n0	n0	n0
With Con & Trend	t-Statisti	-6.26	-4.22	-3.95	11.06
	Prob.	0	0.01	0.03	0.01
Significant		***	***	**	***

Source-Calculated by the author using E-views
Note: (*) Significant at the 10%; (**) Significant at the 5%; (***) Significant at the 1%. And (no) Not Significant

The result of an Augmented Dickey-Fuller (ADF) test in table-1 which identifies if a time series is non-stationary (has a unit root) or stationary (does not). In both cases (with constant and with constant & trend), one of the variables is stationary at the level. The p-values are higher than (0.1), so the null hypothesis (non-stationarity) cannot be rejected. At the First Difference, most variables (e.g., d(LGDP), d(LHE), d(LLFR), d(LDR)) become stationary. LGDP Stationary at the 1% level (p = 0.00). LHE and LMMR Stationary at the 5% level (with constant & trend; p = 0.03,0.05 respectively). LDR Stationary at the 1% level (p = 0.00).

Result of Stationarity Test Phillips-Perron (PP) Test

Apart from the Augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test also evaluates each time series variable's stationarity characteristics. Unlike ADF, the PP test does not require the introduction of a lagged difference term, which is essential to choose the level of serial correlation.

Table-2 Results of Philips Perron Test of Stationarity

Philips Perron (at Level)					
		LGDP	LHE	LIMR	LLEB
	t-Statistic	-0.58	6.76	11.5	-1.81
With Const	*Prob.*	0.86	1.00	1.00	0.37
Significant		n0	n0	n0	n0
With Con & Trend	t-Statistic	-1.83	1.24	-1.29	5.13
	Prob.	0.05	0.03	0.87	1.00
Significant		**	**	n0	n0
Philips Perron (at First Difference)					
		d(LGDP	d(LHE)	d(LIMR)	d(LLEB)
	t-Statistic	-6.27	-1.8	-1.27	12.25
With Const	*Prob.*	0.01	0.37	0.63	1
Significant		***	n0	n0	n0
With Con & Trend	t-Statistic	-6.24	-1.03	-2.73	12.2
	Prob.	0.00	0.02	0.02	0.04
Significant		***	**	**	**

Source-Calculated by the author using E-views
(Note: (*) Significant at the 10%; (**) Significant at the 5%; (***) Significant at the 1%. And (no) Not Significant)

The Result of the Stationarity Test using the Phillips-Perron (PP) test to ascertain the stationarity test result are given in table-2. (LGDP, LHE and LFR) is stationary at level (both 5%,10%) At level First, the difference in GDP is significant at a 1% level (p = 0.00) in both cases. GDP becomes stationary after the first differencing. Health Expenditure Significant at 5% level (p = 0.02) with constant & trend. Health expenditure becomes stationary after the first differencing. In both cases, LMMR (p = 0.03) and LEB were Significant at a 1% level (p = 0.00). It becomes stationary after first differencing. Labor Force Participation Rate Significant at 1% level (p = 0.00). It becomes stationary after first differencing. Death Rate is Significant at 1% level (p = 0.00) in both cases. It becomes stationary after first differencing.

Linkage between Life Expectancy at Birth and Health Expenditure

Numerous indicators have been devised to assess the resources of health systems, including the number of physicians, hospital beds, computed tomography scanners, and health expenditures (total health expenditures per capita, health expenditures as a percentage of GDP, and health expenditures as a percentage of all expenditure in total health expenditure) (Or, 2000; Ramesh & Mirmirani, 2007; Baltagi & Moscone, 2010). The indicator utilized in this study to evaluate the health input is the total amount of health expenditures per capita. The health system results are expressed using mortality indicators (mortality rate, infant mortality rate, potential years of life lost) and longevity indicators (life expectancy at birth, life expectancy at 65, healthy life expectancy) for the overall population. When assessing a population's health, these indicators are considered reliable stand-ins (Show et al., 2002; Cutler et al., 2006; Or, 2000; Poças & Soukiazis, 2010). According to Jen et al. (2010), a nation's population is healthier if its life expectancy is higher. The study takes life expectancy into account while evaluating the state of health.

Result of Lag Selection

The selected lag order is specified by an asterisk ("*") in the last three columns for each criterion. For example, In the **AIC** column, the lag order with the lowest AIC value is considered optimal. In the **LogL** column, the highest value indicates a better model fit. The **LR** value compares the likelihood of the current model with the previous one, where higher values suggest the current model is better. Similarly, lower **FPE.**

Table-3 Lag Selection Criterion

Lag	Log L	LR	FPE	AIC	SC	HQ
0	95.63	NA	5.38E-06	-6.45	-6.36	-6.42
1	200.4	187.91	5.15E-09	-13.4	-13.12	-13.32
2	237.6	61.45*	5.27e-10*	-15.69*	-15.22*	-15.54*

Source: Computed by Author Using E-views* Indicates lag order selected by the criterion

The Table-3 systematically evaluates various lag orders based on different model selection criteria. At lag 2, the lowest **FPE**, **AIC**, **SC**, and **HQ** values are observed, indicating superior model performance. The **LR** value is also highest at this Lag, suggesting significant improvement compared to the previous Lag. Therefore, lag 2 is selected as the optimal lag length for the model across most criteria.

Result of Bound Test and Long Run Relationship

The bound test determines whether life expectancy at birth and health spending have a long-term cointegration connection.

Table-4 Results of Bound Test

Test Statistic	Value		K			
F-statistic	9.87					
Significance	10%		5%		1%	
Sample Size	I (0)	I (1)	I (0)	I (1)	I (0)	I (1)
30	3.3	3.8	4.09	4.7	6	6.8
Asymptotic	3	3.5	3.62	4.2	4.9	5.6

Source: Computed by Author using EViews

The bound test and long-term relationship results are examined in Table 5.6 above. The Bound Test evaluates a long-term cointegration connection between the variables. The calculated F-statistic (9.87) is larger than the upper bound values concerning all significance levels. Thus, the null hypothesis is disproved. There is substantial evidence that the variables have a long-term cointegration relationship.

Table-5 Result of Short-Run Cointegration

Dependent Variable: D(LLEB)				
Max. dependent lags: 2 (Fixed)				
Fixed-lag linear regressors: LHE				
Selected model: ARDL (2,2)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
COINTEQ*	-0.37	0.09	-4.11	0.00
D (LLEB (-1))	2.20	0.70	21.38	0.00
D(LHE)	0.22	0.08	2.57	0.00

D (LHE (-1))	0.011	0.009	1.22	0.00
R-squared	0.95	Mean dependent var		0.00
Adj R-squared	0.95	SD dependent var		0.00
S.E. of regression	0.075	Akaike info criterion		-11.08
SSR	1.97E-05	Schwarz criterion		-10.89
Log likelihood	164.77	Hannan-Quinn criteria.		-11.02
F-statistic	198.04	Durbin-Watson stat		2.1
Prob(F-statistic)	0.00			

Source-Authors own Calculation

Short-Run ARDL Equation: **D(LLEB) = -0.37 COINTEQ + 2.20 D (LLEB (-1)) - 0.22 D(LHE) + 0.011 D (LHE (-1))**

The Error Correction Technique represents the speed at which a shock is adjusted to restore equilibrium. A coefficient of (-0.37) indicates a gradual adjustment process, with each period reflecting a correction of 37% of the long-run equilibrium deviation. The lagged change in life expectancy is favourable (Coefficient (2.20), t-Statistic (21.38)) and has a highly significant impact, indicating persistence in the changes over time. First Difference of Health Expenditure (Coefficient (0.22), t-Statistic (2.57) indicates Highly significant (p = 0.00)). Changes in health spending and life expectancy have a short-term negative correlation. The short-run expansion in life expectancy is reduced by (0.22) units for every unit increase in health expenditure, presumably due to delayed effects. The Coefficient (0.01) t-statistic (3.57) is significant; (p = 0.00), according to the first Difference of Health Expenditure. In the short run, health spending and life expectancy have a statistically significant relationship. 95% of the variation can be described by the model, according to the R-squared (0.95), which indicates a very excellent fit. Adjusted R- squared (0.95). The overall model is statistically significant. Durbin-Watson Statistic (2.10), Overall the Previous changes in life expectancy strongly influence its current changes. Immediate changes in health expenditure negatively affect life expectancy in the short run, but lagged effects are insignificant. This may indicate that the benefits of health investments require more time to manifest in improved life expectancy.

Table-6 Result of Long Run Estimation

Variable *	Coefficient	Std. Error	t-Statistic	Prob.
LHE (-1)	0.11	0.013	8.65	0.00
C	1.1	0.08	13.47	0.00
Note: * Coefficients derived from the CEC regression.				

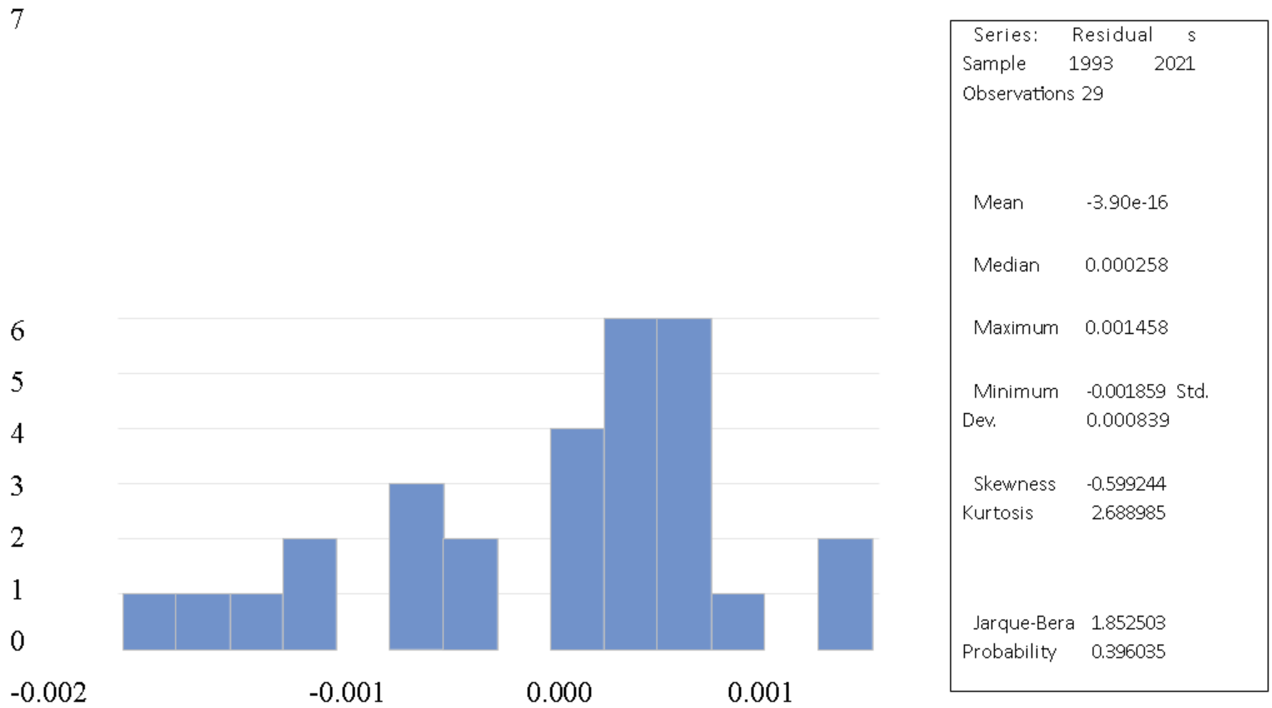
Source-Authors own Calculation

ARDL Equation can be written as: $\mathbf{Y_t = 1.10 + 0.11\ LHE_{t-1} + €_t}$

Table-6 represents ARDL (Autoregressive Distributed Lag) model results for long-term estimation. In the long term, the dependent variable is positively and statistically significantly impacted ($p < 0.05$) by the lagged value of the dependent variable (LHE (-1). In the long term, the dependent variable rises by (0.11) units for every unit increase in LHE (-1). Because the constant term is statistically significant, the dependent variable will have a baseline value of (1.10) when all other variables are zero. Both variables are statistically significant at the 1% level, as indicated by their (p-values of 0.00).

According to this model, the dependent and lagged dependent variables exhibit a positive long-term relationship. The relationship is statistically robust, as shown by the low p-values and high t-statistics.

Normality Test Result (Model-1)



In the above figure-indicates the probability value is more than 5%, indicating that the null hypothesis of normality is not rejected. Hence, the model is usually distributed.

Table-7 Result of Serial Correlation (Breusch – Godfrey LM) Test

Null hypothesis: No serial correlation at up to 2 lags			
F-statistic	0.11	Prob. F (2,21)	0.9
Obs*R-squared	0.28	Prob. Chi-Square (2)	0.86

Source- Computed by Author

The F-statistic has a probability of 0.90 (p-value), and it is 0.11. p-value is 0.86, and Obs*R-squared (0.28). The null hypothesis cannot be rejected because of the high p-values (0.90 and 0.86). This indicates that, up to two lags, the model's residuals show no indication of serial correlation. Serial correlation is absent, indicating that the model's lag structure specification is accurate.

Table-8 Result of Heteroscedasticity

Heteroskedasticity Test: ARCH			
F-statistic	0.36	Prob. F (1,26)	0.54
Obs*R-squared	0.39	Prob. Chi-Square (1)	0.53

Source-Authors own Calculation

The Heteroskedasticity Test (ARCH Test) determines whether the variance of the residuals is homoscedastic (constant) or heteroscedastic (varies). We cannot rule out the null hypothesis since the p-value (0.54) is substantially more significant than the F- statistic (0.36). This implies that there is no discernible heteroscedasticity in the residuals. The conclusion of homoscedasticity is confirmed by a p-value of 0.53 and an Obs*R- squared of 0.39. The F-statistic and chi-square test results indicate that the model is not heteroscedastic.

Linkage between Infant Mortality Rate and Health Expenditure

There is no significant correlation between public health spending and lowering the infant and child mortality rate, according to the relationship between public health spending and IMR (Filmer & Pritchett, 1994; Musgrove, 1996). However, some believe the results may differ if the correct sample is used (Bhalotra, 2007). These authors who advocate an increase in public health spending feel that, in many instances, child and infant mortality can be brought down by spending on simple things like prenatal care, proper childbirth attendance, immunization and effective management of malnutrition and other diseases (Kumar et al., 2013) (Bhalotra, 2007). Thus, it is important to determine which school of thought is closer to the answer and whether a government initiative to increase public health spending benefits the poorer sections of society in dire need of medical facilities.

Table-9 Result of Lag Selection

Lag	Log L	LR	FPE

0	75.97	NA	2.09E-05
1	224.57	266.46	9.75E-10
2	237.77	21.83*	5.20E-10*

Source-Authors own Calculation

The most suitable lag length for the ARDL (Auto-Regressive Distributed Lag) model based on several factors. FPE (final prediction error), SC (Schwarz Criterion), LR (likelihood ratio), AIC (Akaike Information Criterion), HQ (Hannan-Quinn Criterion), and log L (log-likelihood). The symbol "*" signifies statistical significance for LR. Lag 2 is, therefore, chosen as the ideal lag length. Lag 2 is the ideal lag length since it exhibits a significant LR value and reduces AIC, SC, and HQ.

Table-10 Result of Bound Test and Long run relationship

Test Statistic	Value		K			
F-statistic	7.09					
Significance	10%		5%		1%	
Sample Size	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
30	3.30	3.79	4.09	4.66	6.02	6.76
Asymptotic	3.02	3.51	3.62	4.16	4.94	5.58

Source-Authors own Calculation

The results of the Bound Test and the Long-Term Relationship between IMR and Health Expenditure indicates that the calculated F-statistic (7.09) is greater than the upper bound values at all significance levels. The null hypothesis is no longer valid. The findings strongly suggest that the variables in the model have a long-term cointegration connection. The shared long-term trend demonstrates a stable long-term equilibrium relationship between the variables.

Table-11 Result of Long–Run Cointegration

Variable *	Coefficient	Std. Error	t-Statistic
LHE(-1)	-0.38	0.16	-2.3
C	4.62	0.95	4.86

Source-Authors own Calculation

ARDL Equation can be written as:

$\mathbf{Y_t = 4.62 - 0.38\ LHE_{t-1} + €_t}$

The long-term estimation outcomes from an Autoregressive Distributed Lag (ARDL) model. Indicates that a one-unit increase in lagged LHE leads to a (0.38)-unit long-term drop in LIMR, according to the Coefficient of LHE (-1) (-0.38). The p-value (0.02) and t-statistic (-2.30) show that this Coefficient is statistically significant at the 5% level. This is the long-term relationship's intercept. According to the relationship, lagged LHE significantly lowers LIMR over time. This model suggests a negative correlation between the dependent and lagged dependent variables. The statistical robustness of the association is shown by the low p- values and high t-statistics, as well as negative causality among the lagged dependent variable and the dependent variable in the long run. The high t-statistics and low p-values indicate that the relationship is statistically robust.

Table-12 Result of Short-Run Cointegration

Dependent Variable: D(LIMR)				
x. dependent lags: 2 (Fixed)				
ed-lag linear regressors: LHE				
Selected model: ARDL (2,2)				
Able	efficient	Error	Statistic	b.
INTEQ*	2	8	5	
IMR (-1))				
HE)	5	8	7	
HE(-1))	20	06	3	
Quared		an dependent var		1
usted R-squared		. dependent var		
. of regression	31	ike info criterion		78
squared resid	E-05	warz criterion		59
Likelihood	.35	nan-Quinn criter.		72
Atistic	.32	bin-Watson stat		2
b(F-statistic)				

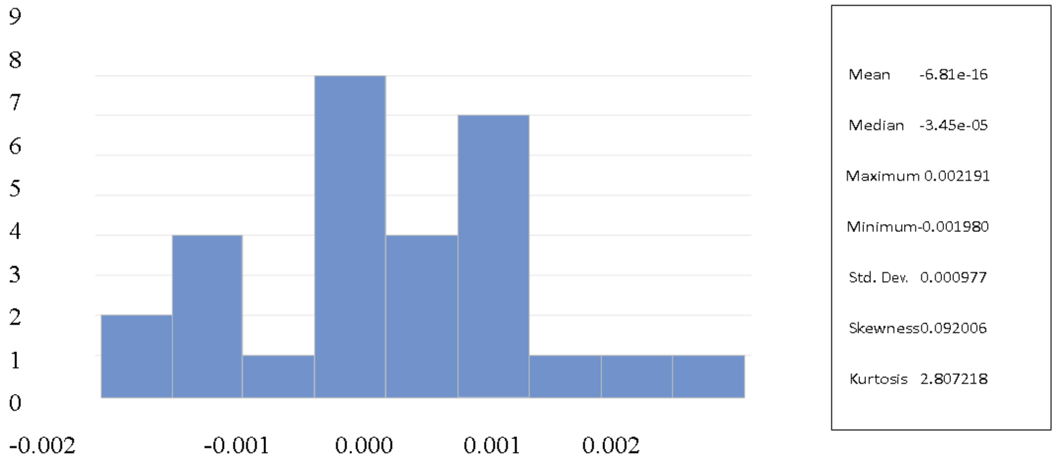
Source-Authors own Calculation

D(LIMR) = -0.42 COINTEQ + 0.70 D (LIMR (-1)) - 0.35 D(LHE) - 0.020 D (LHE (-1))

The coefficient (-0.42) is negative as expected in an error-correction model. This implies that about 2% of the disequilibrium from the previous period's shock is corrected each period. The p-value (0.03) indicates marginal significance, is significant at 5%. Δ (LIMR (-1)) (0.70). indicates that 1-unit increase in the lagged first difference of

LIMR leads to a (0.70) unit increase in LIMR in the short run. Highly significant (p-value = 0.00). The change in LHE and its lagged difference seem to have no significant effect on LIMR in the short run). R- squared (0.94) indicates that 94% of the variation in the dependent variable (ΔLIMR) is explained by the model. Adjusted R-squared (0.94). Similarly, high, showing the model is well-fitted. Durbin-Watson statistics (2.572) Indicates no autocorrelation issues. F-statistic (149.32). The overall model is highly significant (p-value = 0.00). The short-run dynamics indicate that the lagged dependent variable has a significant effect, but LHE and its lagged values have no immediate impact.

Figure-2 Normality Test Result



Source-Computed by author

Here the probability value is more than 5% which indicate that the null hypothesis of normality is not rejected. Hence, the model is normally distributed.

Table-12 Result of SERIAL CORRELATION (BREUSCH - GODFREY LM) TEST

Breusch-Godfrey Serial Correlation LM Test:			
Null hypothesis: No serial correlation at up to 2 lags			
F-statistic	10.65	Prob. F (2,21)	0.91
Obs*R-squared	14.6	Prob. Chi-Square (2)	0.77

Source-Authors own Calculation

The results of the Breusch-Godfrey LM Test, often known as the Serial Correlation Test. The null hypothesis cannot be rejected since the p-value (0.91) is significantly higher than the f-statistic (10.65). This suggests no apparent serial connection in the residuals up to two lags. So, the test statistic has no serial correlation, as indicated by the Probability (0.77) and Obs*R-squared (14.60) values. The F-statistic and p-value indicate no serial correlation in the residuals.

Table-13 Result of Heteroscedasticity

Heteroskedasticity Test: ARCH			
F-statistic	0	Prob. F (1,26)	0.92
Obs*R-squared	0.01	Prob. Chi-Square (1)	0.91

Source- Computed by Author

The Heteroskedasticity Test (ARCH Test) determines if the residuals' variance is heteroscedastic (varies) or homoscedastic (constant). We are impotent to reject the null hypothesis because the p-value (0.92) and the F-statistic = (0.00) is significantly greater than (0.05). This suggests that the residuals do not exhibit any discernible heteroscedasticity. Homoscedasticity is supported by the chi-square test p-value of 0.91 and Obs*R-squared = 0.01. The model does not exhibit heteroscedasticity, according to the findings of the chi-square test and the F-statistic. Throughout time, the residuals' variance remains constant.

Findings and Conclusion

1. The stationary tests like Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) Test are used to check whether a time series is stationary (does not have a unit root) or non- stationary (has a unit root). Here, one of the variables is stationary at the level for both cases (with constant and with constant and trend). The p-values are higher than (0.1). At First Difference, most variables become stationary at the first difference. LGDP Stationary at the 1% level (p = 0.00). LHEXP and MMR Stationary at the 5% level. LDR Stationary at the 1% level (p = 0.00), here all the variables are stationary (both level & their first difference which indicates a positive sign for moving any model formulation.

2. The Bound Test determines whether a long-run cointegration relationship exists among the variables. The calculated F-statistic (17.87) exceeds the upper bound values across all significance levels. This indicates that the null hypothesis is rejected. There is strong evidence of a long-run cointegration relationship among the variables in the model.

3. The short-run ARDL designates that a unit increase in the change of health expenditure decreases the short-run growth of life expectancy by (0.02) units, possibly due to delayed effects. The first Difference of Health Expenditure indicates that the Coefficient (0.01) t-Statistic (3.57) (p = 0.00). The lagged short-term effect of health expenditure on life expectancy is not statistically significant. The previous changes in life expectancy strongly influence its current changes. Immediate changes in health expenditure negatively affect life expectancy in the short run, but lagged effects are insignificant.

4. The long-run ARDL (Autoregressive Distributed Lag) model indicates that the lagged value of the dependent variable (LHEXP (-1)) has a positive and statistically significant effect (p < 0.05) on the dependent variable in the long run. For every one-unit increase in LHEXP (-1), the dependent variable increases by (0.11) units in the long run. The constant term is statistically significant, indicating that the dependent variable will have a baseline value of (1.10) when all other variables are zero. Both variables have p-values of (0.00), indicating they are statistically significant at a 1% level.

5. The Serial Correlation Test (Breusch-Godfrey LM Test) indicates no evidence of serial correlation in the model's residuals up to 2 lags. The absence of serial correlation suggests that the model is correctly specified regarding lag structure. F-statistic is (0.11), with a probability (p-value= 0.90).

6. Heteroskedasticity Test (ARCH Test) indicates no significant heteroscedasticity in the residuals. Obs*R-squared = (0.39) with a p-value (0.53) supports the conclusion of homoscedasticity. The F-statistic and chi-square test results indicate that the model does not suffer from heteroscedasticity.

7. The relationship between infant mortality rate (IMR) and health expenditure shows the coefficient of LHEXP (-0.58) shows an increase in health expenditure is associated with a significant decrease in infant mortality rate.

8. The Bound Test and Long-run Relationship between IMR and Health Expenditure exists a long-run cointegration relationship. The calculated F-statistic (7.09) exceeds the upper bound values across all significance levels. This indicates that the null hypothesis is rejected. There is strong evidence of a long-run cointegration relationship among the variables in the model. The variables share a common trend in the long run, validating the existence of a stable long-run equilibrium relationship.

9. The Long-Run ARDL (Autoregressive Distributed Lag) model suggests that the lagged value of the dependent variable (LHEXP (-1)) has a negative and statistically significant effect (p < 0.02) on the dependent variable in the long run. The Coefficient of LHEXP (-1) indicates a 1-unit increase in lagged LHEXP, which is associated with a (0.38) unit decrease in LIMR in the long run. The Coefficient is statistically significant at the 5% level. The lagged LHEXP significantly negatively affects LIMR in the long term. This model suggests a negative relationship between the lagged dependent variable in the long run.

10. The short-run ARDL model shows that the Coefficient (-0.02) is negative, as expected in an error-correction model. This implies that about 2% of the disequilibrium from the previous period's shock is corrected each period. The p-value (0.03) indicates marginal significance, which is significant at 5%. Δ (LIMR (-1) indicates that a 1-unit increase in the lagged first difference of LIMR leads to a (0.70) unit increase in LIMR in the short run. The change in LHEXP and its lagged difference do not significantly affect LIMR in the short run (p-values = 0.40 and 0.77, respectively). R-squared (0.94) indicates that the model explains 94% of the variation in the dependent variable (ΔLIMR). The short- run dynamics indicate that the lagged dependent variable has a significant effect, but LHEXP and its lagged values have no immediate impact.

11. The Serial Correlation Test (Breusch-Godfrey LM Test), F-statistic is (10.65) with a p- value (0.91) is much higher than (0.05), so we fail to reject the null hypothesis. This suggests that no significant serial correlation exists in the residuals up to 2 lags. Obs*R-squared (14.60) with Prob. (0.77) indicates that the test statistic has no serial correlation. The F-statistic and p-value suggest that no serial correlation exists in the residuals.

12. The Heteroskedasticity Test (ARCH Test) evaluates whether the variance of the residuals is constant (homoscedasticity) or whether it varies (heteroscedasticity). F- statistic = (0.00) with p-value

(0.92). This indicates that there is no significant heteroscedasticity in the residuals. Obs*R-squared = (0.01), the chi-square test p-value (0.91) supports the conclusion of homoscedasticity. The F-statistic and chi-square test results indicate that the model does not suffer from heteroscedasticity. The variance of the residuals is consistent over time.

CONCLUSION

The Health spending has a positive impact on India's GDP. Additionally, it comes to light that the correlation between health spending and health outcomes like- LEB, IMR, is significant and Positive for life expectancy at birth and negative for infant mortality rate. The short-run impact on life expectancy with health expenditure is positive and significant, while there is a negative impact of IMR with health expenditure in long-run. This study also concluded that economic growth (GDP) causes health expenditure and vice-versa. more awareness of the health of the people is necessary if sustainable growth is pursued; Since health disparities are essential in explaining differences in economic growth rates between states, the government must integrate health investment as a macroeconomic policy instrument. This suggests that health investment boosts economic growth.

REFERENCES

1. Balaji, B. (2011). "Causal Nexus Between Public Health Expenditure and Economic Growth in Four Southern Indian States." *The IUP Journal of Public Finance, 9(3), 7-22.*
2. Elmi, Z. M., and Sadeghi, S. (2012). Health Care Expenditures and Economic Growth in Developing Countries: Panel Co-Integration and Causality. Middle-East Journal of Scientific Research, 12(1), 88-91.
3. Mehrara, M., & Musai, M. (2011). "The causality between health expenditure and economic growth in Iran." *Int. j. eco. res*, *2*(4), 13-19.
4. Mehrara, M., and Musai, M. (2011). "Granger causality between Health and Economic Growth in oil exporting countries." *Interdisciplinary Journal of Research in Business, 1(8), 103-108*
5. Amiri, A., and Ventelou, B. (2010). "Causality test between health care expenditure and GDP in the US: comparing periods (No. halts-00520326)."
6. Hooda, S. K. (2014). *Changing pattern of public expenditure on health in India: Issues and challenges*. ISID-PHFI Collaborative Research Centre, Institute for Studies in Industrial Development.
7. Reeves A, Basu S, McKee M, Meissner C, Stuckler D. Does investment in the health sector promote or inhibit economic growth? Global Health. (2013) 9:1–12. doi: 10.1186/1744-8603-9-43
8. Ilori I, Olalere SS, Babatola MA. An empirical analysis of public health expenditure on life expectancy: evidence from Nigeria. BJEMT. (2017) 17:1– 17. doi: 10.9734/BJEMT/2017/31783
9. Karim D. Health expenditure and economic growth nexus: an ARDL-type analysis for Nigeria. Imp J Interdisc Res. (2016) 2:516–29.
10. Sen A. (2014), The Globalization and Development Reader: Perspectives on Development and Global Change. Hoboken: John Wiley & Sons p. 525.
11. Albulescu C, Oros C, Tiwari AK. Is there any convergence in health expenditures across EU countries? Econ Bull. (2017) 37:2095–101.
12. Raghupathi V, Raghupathi W. Healthcare expenditure and economic performance: insights from the United States Data. Frontiers in Public Health. (2020) 8:156. doi: 10.3389/fpubh. 2020.00156
13. Karaman S, Urek D, Demir IB, Ugurluoglu O, Isik O (2020). The impacts of healthcarespending on health outcomes: new evidence from OECD countries. Erciyes Med J. 42:218 -23.
14. Christopoulos K, Eleftheriou K. The fiscal impact of health care expenditure: Evidence from the OECD countries. Econ Anal Policy. (2020) 67:195–202. doi: 10.1016/j.eap.2020.07.010
15. Kim TK, Lane SR. Government health expenditure and public health outcomes: a comparative study among 17 countries and implications for US health care reform. Am Int J Contemp Res. (2013) 3:8–13.
16. Onofrei M, Vatamanu A-F, Vintila˘ G, Cigu E. Government health expenditure and public health outcomes: a comparative study among EU developing countries. Int J Environ Res Public Health. (2021) 18:10725. doi: 10.3390/ijerph1820 10725.
17. Lippi G, Mattiuzzi C, Cervellin G. No correlation between health care expenditure and mortality in the European Union. Eur J Intern Med. (2016) 32:e13–e4. doi: 10.1016/j.ejim.2016.02.025
18. Mackenbach JP. Health care expenditure and mortality from amenable conditions in the European Community. Health Policy. (1991) 19:245–55. doi: 10.1016/0168-8510(91)90011
19. Van Baal P, Obulqasim P, Brouwer W, Nusselder W, Mackenbach J. The Influence Expenditure on Life Expectancy (2014). of Health Care Spending on Life Expectancy (2013).
20. Grossman,M.(1972)."On the concept of health capital and the demand for health." *Journal of Political Economy, 80, 223-55*
21. Baltagi, B. H., & Moscone, F. (2010). "Health care expenditure and income in the OECD reconsidered: Evidence from panel data. "*Economic modelling*, *27*(4), 804-811.
22. Shaw, J.W., Horrace, W.C., Vogel, R.J., (2005). "The Determinants of Life Expectancy: An Analysis of the OECD Health Data." *Southern Economic Journal 71, p. 768.*
23. Cutler, D., Deaton, A., Lleras-Muney, A., (2006). "The determinants of mortality." *Journal of Economic Perspectives 20 (3), p.97.*
24. Jen, M.H., Johnston, R., Jones, K., Harris, R., Gandy, A., (2010)."International Variations in Life Expectancy: A Spatio–Temporal Analysis." Tijdschrift voor Economische en Sociale Geografie 101(1), p. 73.