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RESEARCH ARTICLE

IMPACT OF DETERMINANTS OF HEALTHCARE EXPENDITURE IN INDIA: THE ARDL BOUNDS TESTING APPROACH

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Abstract

Despite achieving stable economic growth in the last few decades, India continues to face challenges in healthcare financing, consistently low public health expenditure, and a disproportionately high out-of-pocket burden on households. This study analyses the impact of determinants of per capita out-of-pocket healthcare expenditure and per capita total healthcare expenditure in India from 1991 to 2023.Annual time-series data is analysed using the Autoregressive Distributed Lag Bounds Testing Approach along with co-integrating regression models for robustness check. The results confirm that per capita income, secon dary education enrolment, urbanization, inflation rate, life expectancy and per capita total health expenditure have a significant impact both on per capita total health expenditure and per capita out-of-pocket health expenditure in long run. In case of per capita total health expendi ture life expectancy and education have the negative impact but in case of per capita out of pocket expenditure inflation rate, per capita income and urbanization have the negative impact. These findings underscore the dualistic nature of India's health financing system and the need for policy intervention that enhance public funding to ease household financial pressure.

Introduction:-

Globally, health expenditure reached 8.3 trillion dollars near about 10 percent of world GDP in 2018. Public financing accounts for about 59 percent of total health spending(Logarajan et al., 2022) but low& middle-income countries still rely heavily on private out-of-pocket spendingwith over 40 percent of health spending in low& middle-income countries.Consequently, reliance on out-of-pocket health spending in many low& middle-income countries experience high, raises serious equity concerns, on the other hand, healthcare in high-income countries is mainly financed through public funding.About 80 percent of the world's population living in low & middle-income countries accounts for only about 20 percent of global health spending(Bein, 2020a). Empirical evidence showed thatincreasing out-of-pocket expenditure forced households into debt and poverty(Haque & Mohd, 2025). Conversely, many evidence showed higher public healthcare expenditure improved health outcomes such as increased life expectancy and lower child mortality(Filmer & Pritchett, 1999; Ray & Linden, 2020).However, the

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efficiency of spending varies from different income group countries,increased public expenditure leads to significant health outcomes in developing countries (low & middle income), whereas returns diminish in high-income countries(Bein, 2020b). These trends show that increasing health expenditure is not sufficient, but also how it is utilized.

In India, Government health expenditure has historically remained around 3 to 4 percent of GDP(Jakovljevic & Milovanovic, 2015) far below global norms and the 5 percent benchmark for developing countries. Therefore, households beararound 60 to 70 percent of total health costs out-of-pocket, one of the highest out-of-pocket shares globally (World Bank). This heavy reliance on households private spending causehouseholds to financial risk and worsens inequalities in access to care. Empirical studies on Indian states indicate that greater public health spending can improve outcomes like infant mortality& life expectancy although these results depend on spending efficiency and equity in distribution. India's low public expenditure and high out-of-pocketexpenditure reflect a dual financing structure that continues gaps in infrastructure and coverage(Logarajan et al., 2022). Recent health policies in India emphasizes increasing public health expenditure (India's National Health Policy 2017 set a target of 2.5 percent of GDP) and expanding financial protection, however the progress remainedslow.

Despite a rich global literature on health expenditure determinants, there is a research gap in country-specific analyses that integrate both public and private healthcare expenditure in a unified framework(Buchanan et al., 2025; Pandey, 2024). In India's case, most existing studies either focus on aggregate health expenditure or examine public spending impacts on health outcomes (Behera et al., 2024; "Public Health Expenditure, Governance and Health Outcomes in Malaysia," 2016) and it remains unclear that whether an increase in public health expenditure tends to crowd out or increase out-of-pocket expenditure in India. To address this gap, we have explicitly modelled the interrelationship between per capita total health expenditure and per capita out-of-pockethealth expenditureusing annual data from 1991 to 2023.We employ the ARDL bounds testing approach for cointegration, which is well-suited for limited sample sizes and mixed integration orders(Murthy & Okunade, 2016). To check the robustness of long-run coefficient estimates we used FMOLS, DOLS, and CCR models(Murthy & Okunade, 2016; Pandey, 2024). Our analysis estimates two cointegrating models; one for per capita total health expenditure and one for per capita out-of-pocket health expenditure, each including the same set of explanatory variables (LE, BED, PCI, IR, SE, UP) and the other expenditure component (per capita out-of-pocket health expenditure or per capita total health expenditure) to capture financing interaction. By separating the determinants of public versus private health spending in India, this study offers new insights into how socioeconomic and demographic factors affect health financing. (Ray & Linden, 2020).

Literature Review:-

Globally, health expenditure has grown to around 10 percent of world GDP but this average is different for different income group countries. High-income countries spend roughly 8 percent of GDP on health whereas lower-middle-income countries like India spend only around 4–5 percent. Such underinvestment in poorer economies corresponds with persistently worse health outcomes. Cross-country evidence indicates that increasing health spending tends to improve life expectancy and reduce mortality, though with diminishing returns at higher income levels. (Bein, 2020b)observe that additional health expenditure yields significant gains in low-income settings but much smaller benefits in wealthy countries.

A large body of research has identified income as the foremost determinant of health expenditure. Newhouse's classic analysis showed that richer countries spend more on health per capita(Samadi & Homaie Rad, 2013). Subsequent panel studies confirm GDP per capita as a dominant driver(Baltagi & Moscone, 2010) found a long-run income elasticity below unity for OECD countries, implying healthcare is a necessity rather than a luxury good. Similarly,(Samadi & Homaie Rad, 2013) reported that in ECO countries health spending is cointegrated with GDP and other factors like demographics and physician density, with income elasticity also under 1.

Demographic and social factors play a significant role as well. Aging populations drive higher health costs, as observed in Europe where an increasing elderly share correlates with rising expenditures(Awais et al., 2021). Urbanization and healthcare capacity (e.g. more physicians or hospitals per capita) are associated with greater health spending, reflecting higher utilization and supply-side effects(Samadi & Homaie Rad, 2013).(Akca et al., 2017)found that in OECD countries, besides income, life expectancy and the age dependency ratio were key predictors of health spending levels. Technological progress and medical price inflation (Baumol's cost disease) are also cited as drivers of expenditure growth in high-income countries.

Health financing patterns are particularly crucial in developing countries. Many low- and middle-income countries rely heavily on out-of-pocket spending due to limited public expenditure. In India, about 60–70% of total health expenditure is paid out-of-pocket by households, which puts many at risk of financial hardship. Studies show that boosting public health spending can improve outcomes and reduce such risks.(Mohanty & Behera (2020), n.d.)analysed Indian states, found that higher per capita total expenditure significantly reduced infant mortality and improved life expectancy. Conversely, heavy out-of-pocket burdens can worsen health outcomes, a time-series study in Malaysia showed that greater out-of-pocket spending was associated with higher child mortality, whereas changes in public or privately insured spending had no significant effect(Logarajan et al., 2022). These findings underscore the importance of a strong health financing safety net (public funding or insurance) for better health results.
Economic and fiscal conditions also shape health spending. Periods of robust economic growth and higher government revenues generally enable greater health expenditure(Behera & Dash, 2019).

In a panel of Indian states, higher tax revenue was found to increase health budget allocations, while heavy reliance on borrowing constrained health spending in the long run. (Behera et al., 2024)observed that the structural changes around the early 2000s (such as increased central transfers) led to shifts in health spending patterns in India(Behera et al., 2024). (Awais et al., 2021)noted that personal remittance inflows can positively affect health spending in developing countries, while environmental factors like pollution may indirectly suppress health expenditure. Many researchers have used advanced econometric timeseries methods like ARDL and cointegration models to capture long run and short run relationships among the determinants(Samadi & Homaie Rad, 2013). (Murthy & Okunade, 2016) used an ARDL approach in African countries and confirmed income along with external aid as key drivers of health spending.

Prior literature shows that health spending is mainly influenced by a mix of economic strength, population changes, and the quality of the health. However, most prior studies focus on aggregate national spending. Few have disaggregated public versus private health expenditures, especially in India's case of low public funding and high out-of-pocket burdens. The present study addresses this gap by examining the distinct determinants of India's per capita public and out-of-pocket spending, contributing new insights to the health financing literature.

Methodology and Data:-

The paper draws upon the foundational framework of the health capital model introduced by (Grossman, 1972), which views health as both an investment and consumption good, accumulated through expenditures on healthcare, education, and nutrition, and depreciating with age. (Arrow, 1978) welfare theory emphasizes that healthcare markets fail under uncertainty and information asymmetry, necessitating state intervention. Additionally (Mushkin, 1962) posited health as a form of human capital essential for economic productivity, while(Barros et al., 2000) underscored the social returns to health investment. Together, these perspectives justify a dual analysis of public and private health spending in shaping long-term welfare. This study specifies the models as below:

Model 1$PCOOPE_t = F(BED_t, IR_t, LE_t, PCI_t, PCTHE_t, SE_t, UP_t)$

Model 2$PCTHE_t = F(BED_t, IR_t, LE_t, PCI_t, PCOOPE_t, SE_t, UP_t)$

Where PCOOPE(per capita out-of-pocket health expenditure)refers to out-of-pocket expenditure done by each household on health goods and services each year.

PCTHE (per capita totalhealth expenditure at time t) can be defined as total publicexpenditure done on healthcare services per person each year.
BED (number of hospital beds) refers to the total count of available inpatient beds in public and private hospitals in a country each year, it represents the physical capacity of the healthcare system (i.e. infrastructure).
IR (inflation rate) can be defined as the increased price of goods and services annually in an economy can be reflected as loss in purchasing power of money, it captures the variations in the cost of medical care, diagnostics, and healthcare services that can influence overall per capita total health expenditure.

LE (life expectancy at birth)can be measured as the average number of years an individual would live under prevailing mortality conditions and it serves as a summary measure of population health.
PCI (per capita income) measures average economic output of nation or income per person. Higher per capita income means better living conditions.

SE (secondary education enrolment) can be defined as total number of individuals enrolled in secondary education regardless of their age

UP- (urban population) can be defined as the total population living in urban areas. Urbanization influences health factors like infrastructure, healthcare access, and environmental condition of urban areas.
Data cover annual observations from 1991 to 2023, collected from official sources. Life expectancy, urban population, per capita income, out-of-pocket, secondary enrolment, and inflation ratetaken from the World Bank Data. Hospital bed counts are obtained from the EPW &Ministry of Health and supplementary reports. Population data collected from census. Analysis is conducted in EViews 12 Student version. Using the data two empirical models specified study how India's per-capita out-of-pocket health expenditure and per-capita total health expenditure are affected by the considered determinants.The above models have been described as below:
Model1 $PCOOPE_t = \beta_0 + \beta_1 BED_t + \beta_2 IR_t + \beta_3 LE_t + \beta_4 PCI_t + \beta_5 PCTHE_t + \beta_6 SE_t + \beta_7 UP_t + \mu_t$
Model2 $PCTHE_t = \beta_0 + \beta_1 BED_t + \beta_2 IR_t + \beta_3 LE_t + \beta_4 PCI_t + \beta_5 PCOOPE_t + \beta_6 SE_t + \beta_7 UP_t + \mu_t$

Based on the literature, higher supply capacity measured by hospital beds may increase both out-of-pocket spending and health care expenditure(Sakshi, S., & Sharma, J. N. (2025), n.d.), as seen in panel studies on developing economies that link urbanization and supply indicators to health expenditure levels. Evidence from ECO countries points to significant long-run relationships between per-capita total health spending and income, demographic structure, and urbanization, underscoring similar channels for India. (Samadi & Homaie Rad, 2013). For inflation, recent OECD analysis highlights how high inflation complicates health financing and raises cost pressures on public budgets, suggesting that inflation should positively influence measured spending (OECD, 2023). Income is a core driver of health spending across ARDL studies, including U.S. evidence where per-capita income and technology showed long-run positive effects on health expenditure. (Murthy & Okunade, 2016). The inclusion of per capita out-of-pocket health expenditure in the per capita public spending equation and vice versa is motivated by the financial protection literature. Recent panel work finds that high out-of-pocket burdens in developing settings create major financial hardship, heightening the importance of understanding interactions with public financing(Sofi & Yasmin, 2024).

Above models have to be specified in the long-run ARDL form as described below:

$$PCOOPE_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i\ PCOOPE_{t-i} + \sum_{j=0}^{q_1} \beta_j\ BED_{t-j} + \sum_{k=0}^{q_2} \beta_k\ \mathrm{IR}_{t-k} + \sum_{l=0}^{q_3} \beta_l\ \mathrm{LE}_{t-l} + \sum_{m=0}^{q_4} \beta_m\ \mathrm{PCI}_{t-m} + \sum_{n=0}^{q_5} \beta_n\ PCTHE_{t-n} + \sum_{O=0}^{q_6} \beta_O\ SE_{t-O} + \sum_{P=0}^{q_7} \beta_P\ UP_{t-P} + \varepsilon_t$$

$$PCTHE_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i\ PCTHE_{t-i} + \sum_{j=0}^{q_1} \beta_j\ BED_{t-j} + \sum_{k=0}^{q_2} \beta_k\ \mathrm{IR}_{t-k} + \sum_{l=0}^{q_3} \beta_l\ \mathrm{LE}_{t-l} + \sum_{m=0}^{q_4} \beta_m\ \mathrm{PCI}_{t-m} + \sum_{n=0}^{q_5} \beta_n\ PCOOPE_{t-n} + \sum_{O=0}^{q_6} \beta_O\ SE_{t-O} + \sum_{P=0}^{q_7} \beta_P\ UP_{t-P} + \varepsilon_t$$

The ECM representation of the ARDL model is given below:

$$\Delta PCOOPE_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i\ \Delta PCOOPE_{t-i} + \sum_{j=0}^{q_1} \beta_j\ \Delta BED_{t-j} + \sum_{k=0}^{q_2} \beta_k\ \Delta\mathrm{IR}_{t-k} + \sum_{l=0}^{q_3} \beta_l\ \Delta\mathrm{LE}_{t-l} + \sum_{m=0}^{q_4} \beta_m\ \Delta\mathrm{PCI}_{t-m} + \sum_{n=0}^{q_5} \beta_n\ \Delta PCTHE_{t-n} + \sum_{O=0}^{q_6} \beta_O\ \Delta SE_{t-O} + \sum_{P=0}^{q_7} \beta_P\ \Delta UP_{t-P} + \lambda ECM_{t-1} + \varepsilon_t$$

$$\Delta PCTHE_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i\ \Delta PCTHE_{t-i} + \sum_{j=0}^{q_1} \beta_j\ \Delta BED_{t-j} + \sum_{k=0}^{q_2} \beta_k\ \Delta\mathrm{IR}_{t-k} + \sum_{l=0}^{q_3} \beta_l\ \Delta\mathrm{LE}_{t-l} + \sum_{m=0}^{q_4} \beta_m\ \Delta\mathrm{PCI}_{t-m} + \sum_{n=0}^{q_5} \beta_n\ \Delta PCOOPE_{t-n} + \sum_{O=0}^{q_6} \beta_O\ \Delta SE_{t-O} + \sum_{P=0}^{q_7} \beta_P\ \Delta UP_{t-P} + \lambda ECM_{t-1} + \varepsilon_t$$

The complete ARDL models can now be described as below:

$$\Delta PCOOPE_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \; PCOOPE_{t-i} + \sum_{j=0}^{q_1} \beta_j \; BED_{t-j} + \sum_{k=0}^{q_2} \beta_k \; \mathrm{IR}_{t-k} + \sum_{l=0}^{q_3} \beta_l \; \mathrm{LE}_{t-l} + \sum_{m=0}^{q_4} \beta_m \; \mathrm{PCI}_{t-m} + \sum_{n=0}^{q_5} \beta_n \; PCTHE_{t-n} + \sum_{O=0}^{q_6} \beta_O \; SE_{t-O} + \sum_{P=0}^{q_7} \beta_P \; UP_{t-P} + \sum_{i=1}^{p} \alpha_i \; \Delta PCOOPE_{t-i} + \sum_{j=0}^{q_1} \beta_j \; \Delta BED_{t-j} + \sum_{k=0}^{q_2} \beta_k \; \Delta \mathrm{IR}_{t-k} + \sum_{l=0}^{q_3} \beta_l \; \Delta \mathrm{LE}_{t-l} + \sum_{m=0}^{q_4} \beta_m \; \Delta \mathrm{PCI}_{t-m} + \sum_{n=0}^{q_5} \beta_n \; \Delta PCTHE_{t-n} + \sum_{O=0}^{q_6} \beta_O \; \Delta SE_{t-O} + \sum_{P=0}^{q_7} \beta_P \; \Delta UP_{t-P} + \lambda ECM_{t-1} + \varepsilon_t$$

$$\Delta PCTHE_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \; PCTHE_{t-i} + \sum_{j=0}^{q_1} \beta_j \; BED_{t-j} + \sum_{k=0}^{q_2} \beta_k \; \mathrm{IR}_{t-k} + \sum_{l=0}^{q_3} \beta_l \; \mathrm{LE}_{t-l} + \sum_{m=0}^{q_4} \beta_m \; \mathrm{PCI}_{t-m} + \sum_{n=0}^{q_5} \beta_n \; PCOOPE_{t-n} + \sum_{O=0}^{q_6} \beta_O \; SE_{t-O} + \sum_{P=0}^{q_7} \beta_P \; UP_{t-P} + \sum_{i=1}^{p} \alpha_i \; \Delta PCTHE_{t-i} + \sum_{j=0}^{q_1} \beta_j \; \Delta BED_{t-j} + \sum_{k=0}^{q_2} \beta_k \; \Delta \mathrm{IR}_{t-k} + \sum_{l=0}^{q_3} \beta_l \; \Delta \mathrm{LE}_{t-l} + \sum_{m=0}^{q_4} \beta_m \; \Delta \mathrm{PCI}_{t-m} + \sum_{n=0}^{q_5} \beta_n \; \Delta PCOOPE_{t-n} + \sum_{O=0}^{q_6} \beta_O \; \Delta SE_{t-O} + \sum_{P=0}^{q_7} \beta_P \; \Delta UP_{t-P} + \lambda ECM_{t-1} + \varepsilon_t$$

The first step in the analysis is to check if there is a stable long-term relationship between the variables. This is done by using ordinary least squares (OLS) and testing the F-statistic with a Wald test under following hypothesis:

H_0: $\alpha_i = \beta_j = \beta_k = \beta_l = \beta_m = \beta_n = \beta_o = \beta_p = 0$ (No cointegration)

H_a : $\alpha_i \neq \beta_j \neq \beta_k \neq \beta_l \neq \beta_m \neq \beta_n \neq \beta_o \neq \beta_p \neq 0$ (Cointegration)

Analysis of Results and Discussions:-

The various estimated results of the study have been analysed with discussion as below:

Descriptive Statistics:

Table 1 below shows the descriptive statistics for the variables taken in the models to be estimated.

Table 1: Descriptive Statistics

Statistics	PCTHE	PCOOPE	BED	IR	LE	PCI	SE	UP
Mean	19.58066	12.24848	13.45212	7.078788	65.59542	1172.859	97328444	3.50E+08
Median	17.42186	12.02012	16.00000	6.400000	65.80300	1069.247	95306729	3.42E+08
Maximum	43.44934	20.22219	19.50000	13.90000	72.00000	2270.905	1.44E+08	5.19E+08
Minimum	7.776550	6.194022	4.900000	3.300000	59.03200	531.8984	54180391	2.18E+08
Std. Dev.	8.769288	3.429271	4.587009	3.089878	3.909198	521.4399	29480837	90252272
Skewness	1.175962	0.415212	-0.215686	0.633318	-0.079709	0.524433	0.120148	0.256155
Kurtosis	3.893158	2.737263	1.402653	2.224193	1.779201	1.998034	1.544250	1.871756
Jarque-Bera	8.702764	1.043121	3.764199	3.033586	2.084176	2.893078	2.993308	2.111167
Probability	0.12889	0.593594	0.152270	0.219414	0.352717	0.235384	0.223878	0.347989
Sum	646.1618	404.1997	443.9200	233.6000	2164.649	38704.36	3.21E+09	1.15E+10
Sum Sq. Dev.	2460.813	376.3168	673.3008	305.5152	489.0186	8700787.	2.78E+16	2.61E+17
Observations	33	33	33	33	33	33	33	33

Source: Author's calculation

The results show that all series exhibit relatively low standard deviations, indicating stability over the sample period, with positive skewness values for the variables PCTHE, PCOOPE, IR, PCI, SE and UP. In case of BED and LE, there is negatively skewed distribution. The Jarque–Bera probabilities confirm that all variables are normally distributed. The kurtosis values show heterogeneity in the shapes of distribution of variables. PCTHE shows a leptokurtic distribution, which suggest higher peak and heavier tails, whereas PCOOPE is approximately mesokurtic. On the other hand, remaining variables (BED, IR, LE, PCI, SE, UP)showed platykurtic distributions, comparatively flatter distributions with fewer extreme observations.

Correlation Analysis:
Table 2 presents the pair-wise Karl Pearson's correlation coefficients in case of all the considered variables:

Table 2 : Correlation Matrix

Variable	PCTHE	PCOOPE	BED	IR	LE	PCI	SE	UP
PCTHE	1							
PCOOPE	0.930446	1						
BED	0.319394	0.228191	1					
IR	-0.357156	-0.386113	-0.239119	1				
LE	0.742969	0.664997	0.679783	-0.381444	1			
PCI	0.856229	0.715803	0.587696	-0.360007	0.950560	1		
SE	0.777664	0.658698	0.662347	-0.333306	0.974239	0.979028	1	
UP	0.838899	0.713316	0.635470	-0.370177	0.969097	0.990744	0.990306	1

Source: Author's calculation

It is clear that per capita out-of-pocket health expenditure and per capita total health expenditure are very closely related (correlation = 0.93). Other variables like PCI, SE, LEand UP are also highly related to both health spending and each other. IR, on the other hand, tends to move in the opposite direction from all other variables.

Unit Root Test:
Table 3 and Table 4 report the estimates of unit root tests using the ADF and PP tests both at level and first difference respectively.

Table 3: Stationarity: Unit Root Tests at Level

Variables	ADF		PP	
	C	C & T	C	C & T
PCTHE	0.300 (0.974)	0.041 (0.995)	0.882 (0.993)	-0.830 (0.951)
PCOOPE	-1.686 (0.428)	-2.646 (0.264)	-1.376 (0.581)	-2.673 (0.253)
BED	-2.436 (0.140)	-2.992 (0.149)	-2.296 (0.179)	-2.966 (0.156)
IR	-3.374 (0.020)**	-3.448 (0.035)**	-3.245 (0.026)**	-3.241 (0.044)**
LE	-2.665 (0.0925)	2.279 (1.000)	-0.366 (0.903)	-4.227 (0.0111)**
PCI	2.766 (1.000)	-0.535 (0.975)	9.208 (1.000)	1.058 (0.999)
SE	0.269 (0.972)	-1.839 (0.661)	0.238 (0.970)	-1.921 (0.619)
UP	16.582 (1.000)	1.741 (1.000)	14.691 (1.000)	1.482 (1.000)
*Asterisks indicate the level of statistical significance: ** for 5%. Values in parentheses are respective prob values of the test statistic.*				

Source: Author's calculations

The Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests both check whether a time-series has a unit root. Table 3 shows results at levels PCTHE, PCOOPE, BED, PCI, SE and UP all have large p-values and relatively small test statistics, so they remain non-stationary at level. The inflation rate (IR)& life expectancy (LE)had a low p-value, indicating stationarity.

The below Table 4 showsestimates of unit root tests in case of first difference. All variables except LE and IR become stationary at the 1% significance level based on both the ADF and PP tests, indicating integration of order one, I(1).

Table 4: Stationarity: Unit Root Tests at First Difference

Variables	ADF		PP	
	C	C & T	C	C & T
PCTHE (D)	-2.302 (0.0177)**	-7.004 (0.000)***	-6.697 (0.000)***	-7.090 (0.000)***
PCOOPE (D)	-7.664 (0.000)***	-7.569 (0.000)***	-7.745 (0.000)***	-7.650 (0.000)***
BED (D)	-7.837 (0.000)***	-7.765 (0.000)***	-8.439 (0.000)***	-8.644 (0.000)***
IR (D)	-7.403 (0.000)***	-7.362 (0.000)***	-7.627 (0.000)***	-7.452 (0.000)***
LE (D)	2.963 (1.000)	3.610 (1.000)	-21.318 (0.000)***	-21.345 (0.000)***
PCI (D)	-4.009 (0.004)***	-3.744 (0.037)**	-3.906 (0.005)***	-8.971 (0.000)***
SE (D)	-4.915 (0.000)***	-4.845 (0.002)***	-4.942 (0.000)***	-4.873 (0.002)***
UP (D)	0.211 (0.038)**	-3.827 (0.028)**	0.460 (0.0482)**	-3.847 (0.027)**
Asterisks indicate the level of statistical significance: *** for 1% and ** for 5%. Values in parentheses are respective prob values of the test statistic.				

Source: Author's calculations

On the basis of the observation of the estimates of unit root test, it can clearly be seen that the variables are of both I(0) and I(1) integration orders and none of the variables is I(2). So, it enables for the estimation of the ARDL model(Pesaran et al., 2001).Its ability to estimate cointegrating relationships in small samples makes it suitable for the 1991–2023 dataset. ARDL effectively captures both short and long-run dynamics.

Optimum Lag Selection

To capture dynamics, optimum lag selection procedure has been performed and the results are shown in Table 5. We estimate an ARDL model of the form (2,1,2,2,1,2,0,1) & (2,1,2,2,2,2,0,1)

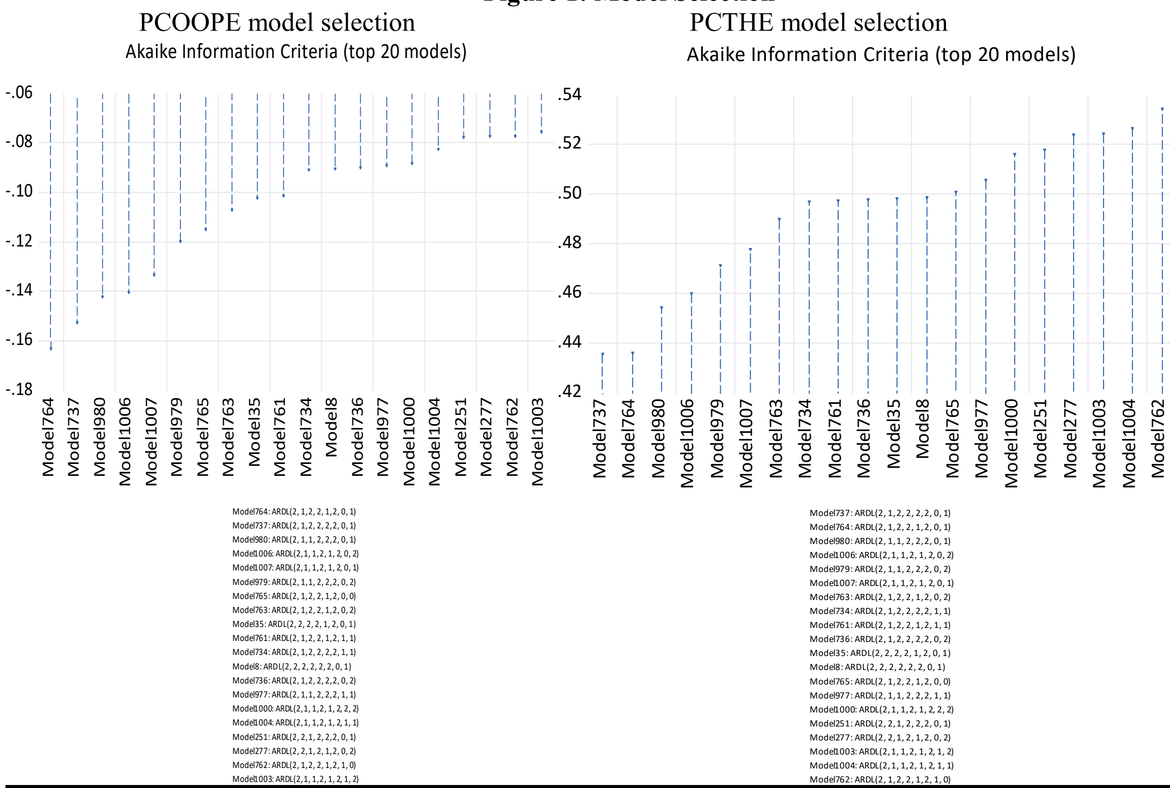
Table 5: Optimum Lag Selection

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1587.780	NA	7.12e+34	102.9535	103.3236	103.0742
1	-1298.719	410.2796	4.04e+28	88.43349	91.76404	89.51916
2	-1184.405	103.2513*	4.05e+27*	85.18743*	91.47847*	87.23815*

Source: Author's calculation

According to the Table 5, all the lag selection criteriasuggest 2 as the optimum lag length in case of both models. In this way to determine the optimal lag structure for the ARDL models with 33 observations,the Akaike Information Criterion has been used which reports the model selection results as reported below in Figure 1. Clearly, in case of PCOOPE the selected lag order is (2,1,2,2,1,2,0,1) while in case of PCTHE it is (2,1,2,2,2,2,0,1).

Figure 1: Model Selection



Bound Test

Table 6 reports the estimates of the Bound tests:

Table 6: Bound Test (Cointegration)

Test Statistic	PCOOPE	PCTHE		
F-Statistic	11.3557	12.6821		
K	7	7		
	ARDL	Critical Value	Lower Bound, I(0)	Upper Bound, I(1)
Dependent Variable: $PCOOPE_t$ (Model 1) (2,1,2,2,1,2,0,1)				
Independent Variables: BED_t, IR_t, $LE_t PCI_t$, UP_t, SE_t, $PCTHE_t$		1%	2.96	4.26
Dependent Variable: $PCTHE_t$ (Model 2) (2,1,2,2,2,2,0,1)				
Independent Variables: BED_t, IR_t, $LE_t PCI_t$, UP_t, SE_t, $PCOOP_t$		1%	2.96	4.26

Source: Author's calculation

Table 6, the bounds test cointegration,clearly shows that both models exhibit strong long-run cointegration as the F-statistics for PCOOP (11.36) and PCTHE (12.68) lie far above the 1% upper bound of 4.26. This confirms that per capita out-of-pocket health expenditure and per capita total health-expenditure dynamics in India are not drifting randomly but are tied together through a stable long-run equilibrium. The high F-values also validate the chosen lag structures, indicating that short-run adjustments eventually converge to meaningful long-run relationships.

Long-Run ARDL Model

The estimates of long-run form of the ARDL models have been reported in Table 7.

Table 7: Estimates of Long-Run ARDL Model

	Model 1 (PCOOPE)			Model 2 (PCTHE)		
Variable	Coefficient	Std. Error	Prob.	Coefficient	Std. Error	Prob.
BED	0.0307	0.018828	0.1286	-0.0345	0.025205	0.1980
IR	-0.0849***	0.021048	0.0017	0.1088***	0.027711	0.0024
LE	1.5406***	0.069047	0.0000	-1.9700***	0.106701	0.0000
PCI	-0.0040***	0.000810	0.0003	0.0059***	0.001415	0.0014
PCTHE	0.7700***	0.029505	0.0000	-	-	-
PCOOPE	-	-	-	1.3091***	0.051376	0.0000
SE	1.68E-07***	2.38E-08	0.0000	-2.10E-07***	2.59E-08	0.0000
UP	-1.33E-07***	1.14E-08	0.0000	1.65E-07***	1.28E-08	0.0000
*Note: ***-significant at 1% level.*						

Source: Author's calculation

Table 7 shows the long-run ARDL estimates which align with Grossman's health capital theory according to which economic and demographic factors drive health spending. Both IR and PCI have negative significant impact on PCOOPE and positive significant impact on PCTHE, reflecting its status as a normal good. LE has a positive effect on PCOOPE , consistent with population aging and higher health investment(Grossman, 1972; Kofi Boachie et al., 2018). The effect of IR indicatesincreasing cost pressures both on public and out-of-pocket expenditures. By contrast, hospital capacity BED has no significant long-run effect on both the health expenditures. Conversely,SE have opposite effects across both expenditures, more secondary school enrolment lower per capita out-of-pocket burdens but can increase overall public health spending. Similar results can be seen for UP,opposite effects across both expenditures, as population in urban areas increases leads to crowd out-of-pocket expenditure and increases public health expenditure. These results suggest an improved public provision(Kazemi Karyani et al., 2015; Ssozi & Amlani, 2015). Finally, greater investment public health expenditurecan reduce out-of-pocket expenditure in low & middle-income countries, confirming a substitution effect in health financing (Logarajan et al., 2022).

Short-Run ARDL Model

Table 8 shows the short-run ARDL results which reveal dynamic adjustment patterns in health spending.

Table 8: Estimated Short Run Coefficients

Model	Model 1 (PCTHE)			Model 2 (PCOOPE)		
Variable	Coefficient	Std. Error	Prob.	Coefficient	Std. Error	Prob.
C	127.23***	9.901135	0.0000	-91.5660	7.6733	0.0000
D(PCOOPE(-1))				0.4060***	0.065747	0.0000
D(PCTHE(-1))	0.4059***	0.061380	0.0000			
D(BED)	0.0650***	0.012089	0.0002	-0.0450***	0.009104	0.0003
D(IR)	0.0740***	0.022927	0.0080	-0.0456**	0.017471	0.0227
D(IR(-1))	-0.0323	0.020132	0.1366	0.0261	0.015003	0.1065
D(LE)	-0.8740***	0.092282	0.0000	0.7952***	0.044526	0.0000
D(LE(-1))	1.1497***	0.129084	0.0000	-0.7585***	0.084545	0.0000
D(PCI)	0.0026**	0.000972	0.0189	-0.0018**	0.000720	0.0262
D(PCI(-1))	-0.0046**	0.001861	0.0290			
D(PCOOPE)	1.3351***	0.024663	0.0000			
D(PCOOPE(-1))	-0.5722***	0.088307	0.0000			
D(PCTHE)				0.7373***	0.013170	0.0000
D(PCTHE(-1))				-0.2966***	0.045947	0.0000
D(UP)	8.36E-08**	3.06E-08	0.0193	-8.47E-08***	1.87E-08	0.0007
CointEq(-1)*	-0.8375***	0.101568	0.0000	-0.9383***	0.110759	0.0000
*Asterisks indicate the level of statistical significance: *** for 1%, ** for 5%.*						

Source: Author's calculation

Both short-run models PCOOPE and PCTHEshowed consistent and significant lagged effects. The lagged dependent variables D(PCTHE(-1)) and D(PCOOPE(-1)) are positive and highly significant, indicating strong short-run adjustment (past spending strongly influence current spending), supporting fiscal inertia in health budgets(Ray

& Linden, 2020). Life expectancy (LE) shows opposite short-run effects across models, D(LE) is negative for PCTHE and positive for PCOOPE, while D(LE(-1)) reverses sign, showing short term adjustment lags(Vyas et al., 2023), also highlighted demographic-driven fluctuations in spending.

Inflation (IR) affects the two models differently,a positive coefficient inPCTHE and negative in PCOOPE, reflecting increased public spending and decreased private spending, whereas lagged signed reverse in both the models. Similarly,urbanization (D(UP)) significantly affects both models with opposing sign, a positive coefficient for PCTHE and a negative coefficient for PCOOPE, suggesting that better public health services in urban areas(Mohapatra et al., 2024). Hospital beds (D(BED)) shows a positive& significant coefficient for PCTHE but negative PCOOPE(Kusunoki & Morita, 2025), who found that expanding health infrastructure can often shifts financial burden away from households.

Per capita income (PCI) shows opposite effects in both the models, D(PCI) is positive in PCTHE and negative in PCOOPE, while D(PCI(-1)) shows a lagged negative effect on PCTHE(Ssozi & Amlani, 2015). Finally, both models report significant and negative ECM terms (−0.8375 and −0.9383), indicating strong correction towards equilibrium(Logarajan et al., 2022).

Robustness Check

To study the robustness check of the model cointegrating regression equation have been estimated for the Fully Modified Ordinary Least Squares, Dynamic Ordinary Least Squares and Canonical (Cointegration Regression models. Results have been reported in Table 9.

Table 9: Estimates of FMOLS, DOLS and CCR

	Model 1 (PCOOPE)			**Model 2 (PCTHE)**		
Model	**FMOLS**	**DOLS**	**CCR**	**FMOLS**	**DOLS**	**CCR**
BED	-0.036058 (0.2313)	0.379437 (0.0040)***	-0.040467 (0.4136)	0.026800 (0.5366)	-0.508254 (0.0128)**	0.030898 (0.6685)
IR	-0.097646 (0.0084)***	-0.512520 (0.0034)***	-0.095751 (0.0172)**	0.137955 (0.00880***	0.699153 (0.0107)**	0.139872 (0.0199)**
LE	0.909623 (0.0000)***	0.847903 (0.0281)**	0.917013 (0.0000)***	-1.324704 (0.0000)***	-1.086127 (0.0969)*	-1.333332 (0.0000)***
PCI	-0.008831 (0.0000)***	-0.001121 (0.0712)*	-0.008669 (0.0000)***	0.013122 (0.0000)***	0.000528 (0.5029)	0.013343 (0.0000)***
PCTHE	0.664764 (0.0000)***	0.857083 (0.0016)***	0.644807 (0.0000)***			
PCOOPE				1.391993 (0.0000)***	1.166302 (0.0065)***	1.428848 (0.0000)***
SE	1.88E-07 (0.0000)***	4.47E-07 (0.0044)***	1.78E-07 (0.0006)***	-3.16E-07 (0.0000)***	-5.81E-07 (0.0127)**	-3.16E-07 (0.0000)***
UP	-7.56E-08 (0.0000)***	-1.79E-07 (0.00710***	-7.25E-08 (0.0019)***	1.28E-07 (0.0000)***	2.32E-07 (0.0248)**	1.26E-07 (0.0001)***
*Asterisks indicate the level of statistical significance: *** for 1%, ** for 5%, and * for 10%.*						

Source: Author's calculation

The above Table 9 confirms that the long-run cointegration results are stable across the models of FMOLS (Fully Modified Ordinary Least Squares), DOLS (Dynamic Ordinary Least Squares) and Canonical Cointegration Regression. Broadly,the results from these models confirm the robustness of earlier ARDL findings. Rising life expectancy and declining per capita income consistently increase PCOOPE and vice-versa. Grossman's view of health as a long-lived investment good and the income–expenditure nexus (Baltagi & Moscone, 2010; Grossman, 1972; Murthy & Okunade, 2016). Inflation has a negative and significant effect on PCOOPE, where as it has positive and significant effect on PCTHE, captures cost-push pressures on households in developing health systems (Jakovljevic & Milovanovic, 2015). There is strong two way relationship between PCTHE and PCOOPEreinforce evidence of substitution between public and private financing found for Malaysia and other middle-income economies (Logarajan et al., 2022; Samadi & Homaie Rad, 2013). Secondary school enrolment (SE) and urban population (UP) showedinverse effects between the two spending components, suggesting structural differences in access and utilisation across regions consistent with recent Indian state-level findings (Behera & Dash, 2019). Overall, the consistency across estimators strengthens the credibility of the long-run cointegration relationship in both models.

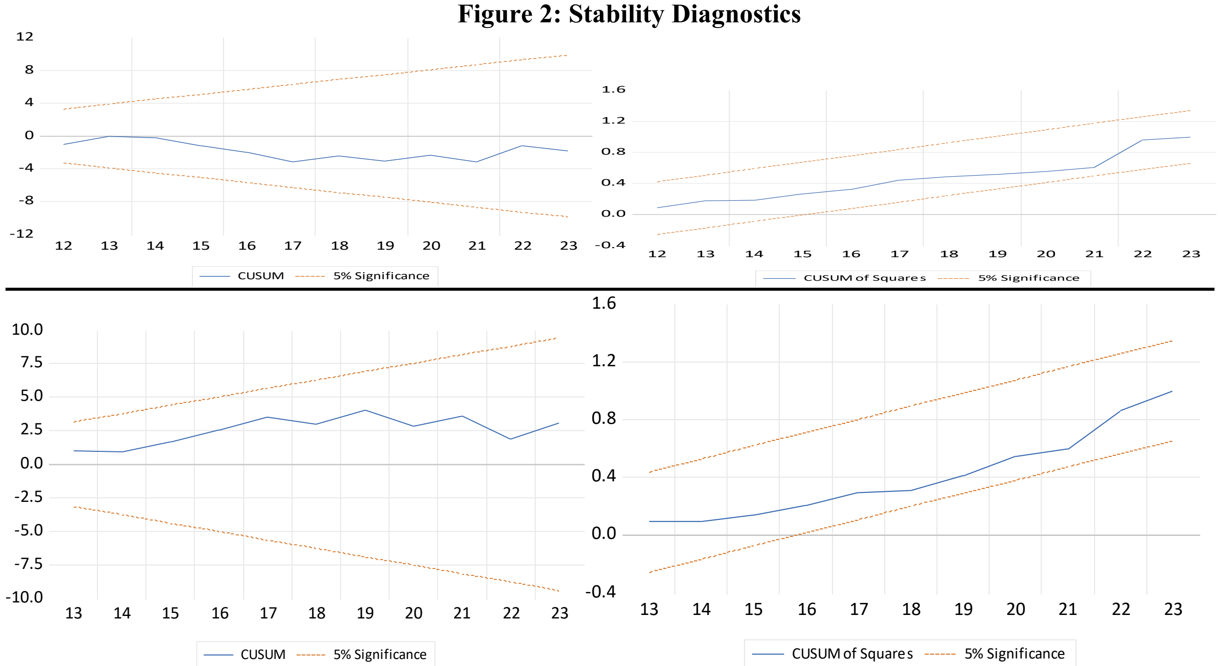
Diagnostic Tests:
Various diagnostic tests have been applied on the estimated models to see whether these models are suitable for policy making.

Table 10: Model Diagnostics

Test		F-stat	P-value	H_0	Conclusion
Residual Diagnostics	Normality (Jarque-Bera)	(0.23)[1] (0.92)[2]	(0.888)[1] (0.62)[2]	Residuals are normally distributed	Normally distributed errors
	Heteroskedasticity (Breusch-pagan test)	(0.377)[1] (0.341)[2]	(0.969)[1] (0.980)[2]	The residuals are homoscedastic.	No-Heteroscedasticity
	Serial Correlation (Breusch-godfrey test)	(2.987)[1] (1.631)[2]	(0.096)[1] (0.248)[2]	There is no-second order serial Correlation in the residuals.	No autocorrelation
Stability Diagnostics	Ramsey RESET Test	(1.029)[1] (0.034)[2]	(0.332)[1] (0.856)[2]	Model is correctly specified	No omitted variables & no non-linearities
Values indicated with superscript 1 correspond to Model 1 (PCOOPE), while those with superscript 2 correspond to Model 2 (PCTHE)					

Source: Author's calculation
The diagnostic tests confirm that both models are statistically reliable. To check whether residuals are normally distributed, Jarque–Bera test has been applied. Results show that residuals are normally distributed. To check heteroscedasticity, Breusch–Pagan Godfrey test has been applied and result shows no evidence of heteroscedasticity because null hypothesis has been accepted.In case of serial correlation, the test statistic has been found to be significant revealing that there is no evidence of serial correlation in the estimated results. Finally, the Ramsey RESET test validates correct model specification.The stability of the estimated models has been studied with the help of CUSUM and CUSUMSQ as shown in the below figures:

Figure 2: Stability Diagnostics



The CUSUM and CUSUMSQ plots demonstrate that the ARDL model remains stable across the entire study period. In both cases, the plotted cumulative residuals stay well within the 5% critical boundaries, indicating no evidence of structural instability or parameter shifts. This consistency confirms that the estimated relationships-both long-run and short-runare valid throughout observed years.

Conclusion:-

This study provides fresh evidence on the long-run and short-run dynamics of healthcare financing in India. We examined the determinants of India's per capita out-of-pocket health expenditure and per capita total health expenditure over 1991–2023 using ARDL, FMOLS, DOLS and CCR estimators, and the results showed a stable long-run relationship between health expenditures and key socioeconomic factors.Results indicate a structural reallocation of healthcare financing in India. Inflation, rising life expectancy, growing per capita income, increasing secondary school enrolment, and increasing urban population significantly shape public & private expenditures, with higher per capita total health expenditure systematically reducing per capita out-of-pocket burden on households, while greater reliance on household out-of-pocket spending increases overall public health expenditure. The opposite signs of variables across public and private expenditure confirm a strong substitution effect between the two-healthcare financing in India, whereas hospital bed capacity remains insignificant, suggesting that investment in infrastructure alone does not drive better long-term health outcomes and efficiency improvements.

As suggested by (Mushkin, 1962), health as a form of human capital essential for economic productivity and (Barros et al., 2000) underscored the social returns to health investment. The policymakers should not only focus on how muchexpenditureis done on health, but on how effectively it is allocated. Mainly toward primary care and preventive servicesto maximize health gains. Many researcher's evidence indicates that public health expenditure is more effective at improving overall population health outcomes than out-of-pocket spending(Rezapour et al., 2019) reinforcing the importance of strong public provision. A 10 percent increase in public health spending has been linked to a 1–7 percent decline in mortality though simply spending more is insufficient without strengthening service delivery(Mays & Smith, 2011). Therefore,allocating resources toward cost-effective interventions such as maternal, child health services, vaccination programs and community-based care is likely to generate better outcomes and a more equitable health system.

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