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Cost determinants and financing of health expenditure: Evidence from India

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***Abstract*---**Despite achieving sustained economic growth, India continues to face challenges in public health financing and outcomes. India's public health spending, at just 2–3% of GDP, lags global norms and contributes to persistent gaps in healthcare infrastructure and access. This study analyses annual data from 1991–2022 to examine the determinants of per capita public and private health expenditures. Using the autoregressive distributed lag (ARDL) model with FMOLS & DOLS for robustness, results confirm stable long-run relationships. Per capita public expenditure is strongly influenced by out-of-pocket spending, urbanization, and population, while per capita private expenditure responds more to life expectancy and demographic change. The findings shed light on India's dual health financing structure.

***Keywords*---**Health Expenditure, Per Capita Public & Private, Per capita out-of-Pocket spending, Demographic and Socioeconomic.
JEL Classifications: H50, H51, I11, I13 & I15.

1. Introduction

Health expenditure is widely acknowledged as both a key driver of health outcomes and a vital investment in sustainable development (Baltagi & Moscone, 2010a; Sachs, 2002). Cross-country evidence consistently demonstrates that higher health spending is associated with improvements in longevity and reductions in child mortality, though the magnitude and efficiency of this relationship vary (Filmer & Pritchett, 1999; Ray & Linden, 2020). In low- and middle-income regions, additional public expenditure often translates into

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significant health gains, whereas in high-income countries marginal benefits tend to diminish (Bein & Coker-Farrell, 2020).

India presents a particularly challenging case. Government health expenditure has historically remained low, averaging only 2–3% of GDP, far below both the global average and the 5% benchmark often observed in developing economies (Jakovljevic & Milovanovic, 2015). Consequently, households finance a large share of health costs directly: nearly 60–70% of total health expenditure is borne out-of-pocket (Mohd Nasir et al., 2021). This dependence on private spending exposes households to financial risks and perpetuates inequalities in access to essential services (Mohanty & Behera, 2020). Studies of Indian states confirm that higher public health spending can improve health indicators such as infant and child mortality, but outcomes also depend on efficiency, governance, and distributional equity (Mohanty & Behera, 2020).

This paper addresses these gaps by analysing India's healthcare cost function through two separate models of per capita public and private health expenditures over 1991–2022. Using the ARDL bounds testing approach (Pesaran et al., 2001) and robustness checks with FMOLS (Fully Modified Ordinary Least Squares) and DOLS (Dynamic Ordinary Least Squares), we examine the long- and short-run effects of demographic, socioeconomic, and supply-side variables; population, per capita out-of-pocket expenditure, life expectancy, hospital beds (proxy variable used to replace number of hospitals), and urbanization (% of population in urban areas) on per capita health spending. By disentangling the determinants of public and private expenditure, this paper contributes to the literature on financing dynamics in South Asia and informs ongoing efforts to reduce India's out-of-pocket burden while strengthening public healthcare.

2. Literature Review

The Commission on Macroeconomics and Health led by emphasized that better health is not only a consequence of economic growth but also a critical driver of it (Sachs, 2002). Among the multiple determinants of healthcare expenditure, national income remains one of the most influential. Early cross-country analyses by (Baltagi & Moscone, 2010b) established that per capita GDP explains most of the variance in health spending between nations, with Newhouse reporting that income alone accounted for over 90% of the observed cross-national differences. Later research refined this association through income elasticity estimates. While early cross-sectional findings classified healthcare as a "luxury" good (elasticity greater than one), subsequent panel data analyses placed elasticity near or below unity, confirming that healthcare behaves as a necessity in more mature systems. Evidence from Malaysia supports this: (Khan et al., 2016) estimated an elasticity of 0.99, whereas (Mohd Nasir et al., 2021) found 0.69, indicating that health spending tends to rise roughly in proportion to income. In lower-income economies, however, expenditure often grows faster than GDP in the early stages of development as governments attempt to bridge service gaps before stabilizing alongside income trends.

Demographic and technological factors further shape this income–expenditure relationship. Aging populations are frequently cited as a major cost driver because older individuals consume more medical care, and international evidence links a higher elderly share with greater spending. Yet (Breyer & Felder, 2006) contend that once end-of-life expenditures are controlled for, the pure impact of aging on costs is modest—an argument often referred to as the “red herring” hypothesis. Conversely, technological advancement consistently emerges as a dominant force behind long-run cost escalation. (Chandra & Skinner, 2012) attribute a substantial share of historical health expenditure growth in high-income economies to innovations in diagnostics, medical procedures, and pharmaceuticals, which improve outcomes but also expand the intensity and scope of care provision.

The financing structure of healthcare also plays a decisive role. (Ahmad and Hasan, 2016)confirmed this view for Malaysia, showing that higher public allocations combined with low corruption levels significantly improve long-run health outcomes through cointegration between expenditure, income, and governance indicators. These studies collectively highlight that while funding matters, its impact depends critically on how effectively and equitably it is deployed.

The direction of causality between health expenditure and economic growth varies by development stage. As (Erdil & Yetkiner, 2009) showed, in low- and middle-income economies, the relationship typically runs from GDP to health spending, reflecting income-driven fiscal expansion. In contrast, high-income countries often experience bidirectional causality, as healthier and more productive populations contribute to economic output. Sustainability thus becomes a crucial consideration. (Asteriou et al., 2021)demonstrated that excessive public debt in Asian economies constrains growth and limits fiscal space for health. (Khandelwal, 2015) observed similar dynamics in India, where GDP growth and energy-intensive development correlate with higher health spending but persistent fiscal deficits restrict long-term public investment.

(Murthy & Okunade, 2016), analysing U.S. data (1960–2012) using a time series framework, confirmed cointegration between income, aging, and medical technology, with income elasticity below unity—reinforcing the classification of healthcare as a necessity. (Behera et al., 2024) used segmented ARDL models to show that fiscal transfers boost health expenditure while public debt constrains it. Recent empirical work continues to broaden this understanding. (Pandey, 2024) found no long-run cointegration between health spending and infant mortality across Indian states, suggesting regional policy heterogeneity. (Vyas et al., 2023) linked GDP growth and air pollution to higher health costs, emphasizing environmental and demographic pressures. Similarly, (Ruzima & Veerachamy, 2023) identified a positive long-run relationship between government health spending and India’s Human Development Index, while education spending showed an unexpected negative effect. (Mohapatra et al., 2022) reinforced the demographic argument by demonstrating that aging and income are key long-run drivers of healthcare expenditure, with unidirectional causality running from aging to spending. Collectively, these studies illustrate that while income remains central, demographic, environmental, and institutional forces jointly define the trajectory of health expenditure in emerging economies like India.

3. Methodology and Data

The theoretical foundation of this study is rooted in the health capital model developed by (Grossman, 1972), It conceptualizes health as a durable form of capital that depreciates with age but can be enhanced through investments in healthcare, nutrition, and education. In this framework, health is treated as both a consumption good, valued for its contribution to well-being, and as an investment good, enhancing productivity and economic output. The Welfare and Financing Theory of Health Economics, rooted in (Arrow, 1978), argues that healthcare cannot rely solely on market forces because of uncertainty, inequality, and externalities. It justifies government intervention, insurance mechanisms, and public investment to ensure fairness, efficiency, and universal access. Formally, per capita health expenditure (Public & Private) can be expressed as a function of multiple socioeconomic and demographic inputs:

$$HE_t = F(X_t)$$

where HE_t represents per capita public & private health expenditure at time t, and X_t includes determinants such as population, per capita out-of-pocket expenditure, life expectancy, hospital beds (proxy variable used to replace number of hospitals), and urbanization (% of population in urban areas).

Table 1 :Choice of Variables

	Name of Variable
LPUHE	Log Per capita public health expenditure
LPVHE	Log Per capita private health expenditure
LPOP	Log Population
LOOP	Log Per capita out-of-pocket expenditure
LLE	Log Life expectancy
LBED	Log Hospital bed capacity
LUPOP	Log Urban population

Following extensions of the model in empirical literature e.g. (Breyer & Felder, 2006; Filmer & Pritchett, 1999; Mohd Nasir et al., 2021), we respecify the framework by explicitly including population as a key input, reflecting its central role in financing the production of health:

$$HE_t = F(PoP_t, X_t)$$
$$HE_t = \beta_0 + \beta_1 \, LPOP_t + \beta_2 \, X_t + \mu_t$$

In the present study, however, the dependent variables are not direct health outcomes but healthcare cost functions in India, represented by per capita public health expenditure (LPUHE) and per capita private health expenditure (LPVHE). Thus, two separate models are estimated to capture how socioeconomic and demographic variables shape public versus private financing patterns (all the variables are taken in log form). The general cost function is defined as:

$$LPUHE_t = \beta_0 + \beta_1 \, LPOP_t + \beta_2 \, LOOP + \beta_3 \, LLE + \beta_4 \, LBED + \beta_5 \, LUPOP + \mu_t$$
$$LPVHE_t = \beta_0 + \beta_1 \, LPOP_t + \beta_2 \, LOOP + \beta_3 \, LLE + \beta_4 \, LBED + \beta_5 \, LUPOP + \mu_t$$

Based on the literature, population (LPOP) is expected to exert upward pressure on per capita public health spending (Murthy & Okunade, 2016), while urbanization (LUPOP) is anticipated to increase both public and private health expenditure due to rising healthcare utilization (Mohapatra et al., 2022). Per capita out-of-pocket expenditure (LOOP) is hypothesized to be negatively associated with public spending, indicating substitution effects, but may positively relate to private spending (Logarajan et al., 2022). Life expectancy (LLE), reflecting aging and epidemiological transition, is expected to raise health costs, consistent with (Breyer & Felder, 2006). Hospital beds (LBED) capture supply-side capacity, with mixed effects reported across contexts (Lin & Wang, 2020).

The study uses annual data from 1991–2022, compiled from the World Bank (life expectancy, urban population, total population, out-of-pocket expenditure), the Economic Survey of India (public and private health expenditure), and supplementary sources including the Ministry of Health and EPW (hospital beds). All the variables are transformed to logarithms, its helps in stabilizing the variance and analysis was conducted using EViews 12 Student version for descriptive, unit root, and econometric tests. The summary of descriptive statistics for the variables used in the analysis is presented in Table 1.

Table 2: Descriptive Statistics

Statistic	**Mean**	**Median**	**Maximum**	**Minimum**	**Std. Dev.**	**Skewness**	**Kurtosis**	**Jarque-Bera**	**Probability**
LPUHE	2.86	2.85	3.70	2.05	0.39	0.12	2.74	0.16	0.92
LPVHE	6.69	6.73	7.15	6.14	0.35	-0.10	1.60	2.66	0.27
LPOP	20.83	20.85	21.06	20.56	0.15	-0.22	1.84	2.05	0.36
LOOP	2.45	2.46	2.93	1.82	0.27	-0.34	2.65	0.80	0.67
LLE	4.17	4.17	4.25	4.07	0.06	-0.15	1.77	2.14	0.34
LBED	14.15	14.58	14.65	13.32	0.51	-0.32	1.28	4.49	0.11
LUPOP	19.63	19.64	20.04	19.20	0.25	-0.05	1.79	1.97	0.37

Table 1 shows the descriptive statistics for the variables taken in our models. The results show that all series exhibit relatively low standard deviations, indicating stability over the sample period, with skewness values close to zero and kurtosis near the normal range. The Jarque–Bera probabilities confirm that most variables are approximately normally distributed, making them suitable for ARDL & OLS models.

Given the presence of both stationary and non-stationary variables in the dataset, the Autoregressive Distributed Lag (ARDL) model emerges as an appropriate methodological choice. As developed by, (Pesaran et al., 2001) the ARDL model has bound testing for cointegration which provides the long-run relationships among variables irrespective of their integration order (0/1). The ARDL model is suitable for small sample sizes, making it ideal for the current dataset comprising 32 annual observations from 1991 to 2022.

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{j=1}^{k} \sum_{m=0}^{q_j} \beta_{jm} X_{j,t-m} + \varepsilon_t$$

Accordingly, two separate ARDL specifications are estimated for per capita public and private health expenditure cost functions. To capture dynamics, we estimate an ARDL model of the form (3,3,1,1,3,3) & (3,3,3,2,3,3)

Equation 1: $LPUHE_t = \alpha_0 + \alpha_1 LPUHE_{(t-1)} + \alpha_2 LPUHE_{(t-2)} + \alpha_3 LPUHE_{(t-3)} + \beta_{10} LPOP_t + \beta_{11} LPOP_{(t-1)} + \beta_{12} LPOP_t + \beta_{20} LOOP_{(t)} + \beta_{30} LLE_t + \beta_{40} LBED_t + \beta_{41} LBED_{(t-1)} + \beta_{42} LBED_{(t-2)} + \beta_{50} LUPOP_t + \beta_{51} LUPOP_{(t-1)} + \beta_{52} LUPOP_{(t-2)} + \beta_{53} URBANPO + \mu_t$

Equation 2: $LPVHE_t = \alpha_0 + \alpha_1 LPUHE_{(t-1)} + \alpha_2 LPUHE_{(t-2)} + \alpha_3 LPUHE_{(t-3)} + \beta_{10} LPOP_t + \beta_{11} LPOP_{(t-1)} + \beta_{12} LPOP_t + \beta_{20} LOOP_{(t)} + \beta_{30} LLE_t + \beta_{40} LBED_t + \beta_{41} LBED_{(t-1)} + \beta_{42} LBED_{(t-2)} + \beta_{50} LUPOP_t + \beta_{51} LUPOP_{(t-1)} + \beta_{52} LUPOP_{(t-2)} + \beta_{53} URBANPO + \mu_t$

In these equations, the $\propto$ coefficients reflect the long-run relationships, while the β terms capture short-run dynamics, with α_0 as the constant and μ_t as the error term. The first step is to test for long-run equilibrium using OLS and the F-statistic from the Wald test under the following hypothesis:

H_0 $\quad \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$ (No cointegration)
H_a $\quad \beta_1 \neq 0, \beta_2 \neq 0, \beta_3 \neq 0, \beta_4 \neq 0 \; \& \; \beta_5 \neq 0$ (Cointegration)
The ECM representation is

Equation 3: $\Delta LPUHE_t = \alpha_1 \Delta LPUHE_{t-1} + \alpha_2 \Delta LPUHE_{t-2} + \beta_1 \Delta LPOP_t + \beta_2 \Delta LPOP_{t-1} + \beta_3 \Delta LPOP_{t-2} + \beta_4 \Delta LOOP_t + \beta_5 \Delta LLE_t + \beta_6 \Delta LBED_t + \beta_7 \Delta LBED_{t-1} + \beta_8 \Delta LBED_{t-2} + \beta_9 \Delta LUPOP_t + \beta_{10} \Delta LUPOP_{t-1} + \beta_{11} \Delta LUPOP_{t-2} + \gamma ECM_{t-1} + \varepsilon_t$

Equation 4: $\Delta LPVHE_t = \alpha_1 \Delta LPVHE_{t-1} + \alpha_2 \Delta LPVHE_{t-2} + \beta_1 \Delta LPOP_t + \beta_2 \Delta LPOP_{t-1} + \beta_3 \Delta LPOP_{t-2} + \beta_4 \Delta LOOP_t + \beta_5 \Delta LOOP_{t-1} + \beta_6 \Delta LOOP_{t-2} + \beta_7 \Delta LLE_t + \beta_8 \Delta LLE_{t-1} + \beta_9 \Delta LBED_t + \beta_{10} \Delta LBED_{t-1} + \beta_{11} \Delta LBED_{t-2} + \beta_{12} \Delta LUPOP_t + \beta_{13} \Delta LUPOP_{t-1} + \beta_{14} \Delta LUPOP_{t-2} + \gamma ECM_{t-1} + \varepsilon_t$

where ECM_{t-1} is the lagged deviation from long-run equilibrium.

4. Results and Discussion

Table 2 showed results from ADF and PP unit-root tests for each series. These results of the tests indicate that most variables are non-stationary at level but became stationarity after first differencing, which confirms their integration of order one, I(1). Overall, none of the variables is integrated of order two, thereby satisfying the requirements for ARDL bounds testing.

Table 3: Stationarity using Unit root test

Level	Augmented Dickey–Fuller		Phillips–Perron	
	Intercept	Intercept and trend	Intercept	Intercept and trend
LPUHE	-0.491	-1.483	-1.054	-2.285
LPVHE	-1.006	-3.351*	-0.986	-1.575
LPOP	-9.25***	-0.869***	-9.35***	-0.871***
LOOP	-1.531	-2.026	-2.118	-2.856
LLE	-2.269	0.450	-2.91**	-2.024
LBED	-2.148	-3.733**	-2.148	-3.744**
LUPOP	-2.503	-0.766	-2.177	-0.949

	First Difference			
LPUHE	-7.09***	-6.99***	-7.18***	-7.07**
LPVHE	-2.423	-2.512	-4.54***	-4.53***
LPOP	-1.340	-5.253***	-1.902	-5.252***
LOOP	-7.43***	-7.287***	-7.629***	-7.474***
LLE	-2.754*	-2.609	-2.72*	-3.71**
LBED	-8.33***	-8.21***	-11.345***	-13.08
LUPOP	-3.81**	-2.49**	-3.81***	-4.28**

Asterisks indicate the level of statistical significance: *** for 1%, ** for 5%, and * for 10%.

To determine the optimal lag structure for the ARDL models with 32 observations, we applied all three selection criteria, Schwarz Criterion (SC), Akaike Information Criterion (AIC), and Hannan-Quinn Criterion (HQ), consistently selected ARDL per capita public health expenditure (LPUHE)-(3,3,1,1,3,3) and per capita private health expenditure (LPVHE)- (3,3,3,2,3,3). The selection of three lags is well-supported by prior studies handling small samples. (Lin & Wang, 2020) and (Mohapatra et al., 2022) emphasized using AIC and SC for limited data to avoid overfitting. (Behera et al., 2024) and (Ruzima & Veerachamy, 2023) applied similar lag lengths using structural break tests and AIC in datasets with <35 observations. (Murthy & Okunade, 2016) also adopted short lag lengths with AIC in U.S. health spending studies.

Table 4: Lag Order Selection

Lag	**LogL**	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	290.1354	NA	1.24e-16	-19.5956	-19.3127	-19.507
1	549.3778	393.3334	2.72e-23	-34.9916	-33.0114	-34.3714
2	587.4983	42.06398	3.34e-23	-35.1378	-31.4603	-33.9861
3	678.1694	62.53178*	2.40e-24*	-38.90824*	-33.53335*	-37.22489*

Table 4 showed the results of the ARDL bounds test which confirms the presence of cointegration in both models. For Model 1 (LPUHE), the F-statistic (9.927) is well above the upper bound at the 1% level, while for Model 2 (LPVHE), the F-statistic (6.397) also exceeds the 1% critical value. This indicates a stable long-run relationship between per capita public and private health expenditures and their determinants (population, out-of-pocket spending, life expectancy, hospital beds, and urbanization).

Table 5: Bound test (cointegration)

ARDL	**F-Statistic**	**Critical Value**	**Lower Bound**	**Upper Bound**
Dependent Variable: $LPUHE_t$ (Model 1) **(3,3,1,1,3,3)**				
Independent Variables: $LPOP_t$, $LOOP_t$, LLE_t, $LBED_t$, $LUPOP_t$	9.927	1%	3.06	4.15
Dependent Variable: $LPVHE_t$ (Model 2)				

ARDL	F-Statistic	Critical Value	Lower Bound	Upper Bound
(3,3,3,2,3,3)				
Independent Variables: $LPOP_t$, $LOOP_t$, LLE_t, $LBED_t$, $LUPOP_t$	6.397	1%	3.06	4.15

Table 5 long-run results reveal strong demographic and financial drivers of India's per capita public health expenditure. Model 1 (LPUHE) Per capita public health expenditure is statistically significant & meaningful, on the other hand, Model 2 (LPVHE) is statistically significant but not meaningful for long run estimates.
Long run coefficients from model 1 (LPUHE) suggest mix impact on per capita public health expenditure. Population size negatively influences public spending, indicating fiscal dilution under demographic pressure, consistent with (Murthy & Okunade, 2016) for the U.S. Per capita Out-of-pocket spending show a robust negative effect on public spending, household financing substituted weak public funding (Logarajan et al., 2022). Urbanization significantly raises health expenditure, aligning with (Mohapatra et al., 2022). Life expectancy & hospital beds are statistically insignificant in long run however, in short run they are positively linked, supporting (Khan et al., 2016). Fiscal management (i.e., revenue mobilization and debt sustainability) is essential to prepare a long-term strategy for health-care financing (Behera et al., 2024). These results confirm that India's fiscal response to healthcare is shaped more by demographic load and private financing gaps than by infrastructure alone. Overall, Model 2 (LPVHE) reflects no long run impact on per capita private health expenditure.

Table 6: Estimated Long Run & Short-Run Coefficients

	Long Run Estimates	
Dependent Variable:	**Model 1 ($LPUHE_t$)**	**Model 2 ($LPVHE_t$)**
LPOP	-8.37492***	-5.74342**
LOOP	-1.188248***	0.14128
LLE	5.655711	7.54651*
LBED	-0.02044	0.008845
LUPOP	4.364692**	4.099455*
C	64.38559**	12.37918
	Estimated Short-Run Coefficients from Conditional Error Correction Regression	
D(LPUHE(-1))	-0.05107**	
D(LPUHE(-2))	0.032421*	
D(LPVHE(-1))		-1.884***
D(LPVHE(-2))		-1.69818***
D(LPOP)	-20.5192***	4.934256
D(LPOP(-1))	10.06042	-68.2206***
D(LPOP(-2))	12.29613*	-19.6473**
D(LOOP)	-1.0426***	-0.04117
D(LOOP(-1))		0.032308
D(LOOP(-2))		-0.08639**

D(LLE)	5.78661***	-7.27003**
D(LLE(-1))		-13.6608***
D(LBED)	0.16381***	0.311282***
D(LBED(-1))	0.09693***	0.167497***
D(LBED(-2))	0.06049***	0.052538***
D(LUPOP)	15.58759**	19.10479**
D(LUPOP(-1))	-9.15689	53.87716***
D(LUPOP(-2))	22.742***	-45.0225***
CointEq(-1)*	-0.70433	1.136765
Asterisks indicate the level of statistical significance: *** for 1%, ** for 5%, and * for 10%.		

Table 5 also showed short-run results, almost all variables are statistically significant for both the models. Population had a negative coefficient, showing fiscal adjustments to demographic surges similar to findings by (Behera et al., 2024) on India's fiscal health policy. Per capita out-of-pocket expenditure negative coefficient exerts immediate upward pressure reflecting substitution effects noted in Malaysia (Logarajan et al., 2022). Life expectancy and hospital bed availability exhibit strong but lagged short-run effects, consistent with (Vyas et al., 2023) on India's health expenditure–infrastructure relationship.

Importantly, the error-correction term is significant, confirming convergence towards equilibrium, as also emphasized in (Ruzima & Veerachamy, 2023). These patterns show that India's healthcare financing adjusts quickly to shocks but remains highly sensitive to demographic and household-level pressures, underscoring the challenge of fiscal stability in the short run.

Table 7: Estimated Long Run Coefficients from FMOLS & DOLS

	Model 1 (LPUHE)		**Model 2 (LPVHE)**	
Dependent Variable:	FMOLS	DOLS	FMOLS	DOLS
LPOP	-1.46899***	-2.106629***	-1.8616***	-2.07681***
LOOP	-1.018577***	0.993826***	-0.00132	0.067704
LLE	-10.5447***	-5.111531	11.92534***	14.06319***
LBED	-0.03841	-0.308183***	0.017357	0.19715***
LUPOP	3.844928***	3.517495**	-0.22817	-0.56387
Asterisks indicate the level of statistical significance: *** for 1%, ** for 5%, and * for 10%.				

The FMOLS and DOLS estimations reinforce the evidence of long-run relationships between healthcare expenditure and its determinants while extending the ARDL findings. In the public expenditure model (LPUHE), both estimators indicate that population (LPOP) exerts a strong negative effect, consistent with fiscal dilution observed in similar demographic contexts (Kofi Boachie et al., 2018). Per capita out-of-pocket expenditure (LOOP) is negative and significant suggest that private household spending continues to crowd-in public expenditure similar to findings for Sub-Saharan Africa (Ssozi & Amlani, 2015). Urbanization (LUPOP) is also positive, strengthening the evidence from ARDL model that demand pressures in urban areas stimulate public allocations. On the other hand, life expectancy (LLE) shows a negative effect under FMOLS and becomes insignificant under DOLS, reflecting the short-run adjustments where longevity initially moderates fiscal expenditures.

In the per capita private expenditure model (LPVHE), population is significant & remain negative across both estimators, while Per capita out-of-pocket expenditure (LOOP) loses significance, confirming the weaker private channel observed in the ARDL long-run. Life expectancy, however, turns strongly positive under both FMOLS and DOLS, supporting evidence from OECD countries where longevity drives greater household health spending (Kazemi Karyani et al., 2015). Urbanization is mildly negative, indicating that expanded urban healthcare systems may reduce reliance on private finance. Similar conclusions are supported by (Ray & Linden, 2020), who highlighted demographic and financial interactions as central to health expenditure dynamics globally.

Table 8: Model Diagnostics

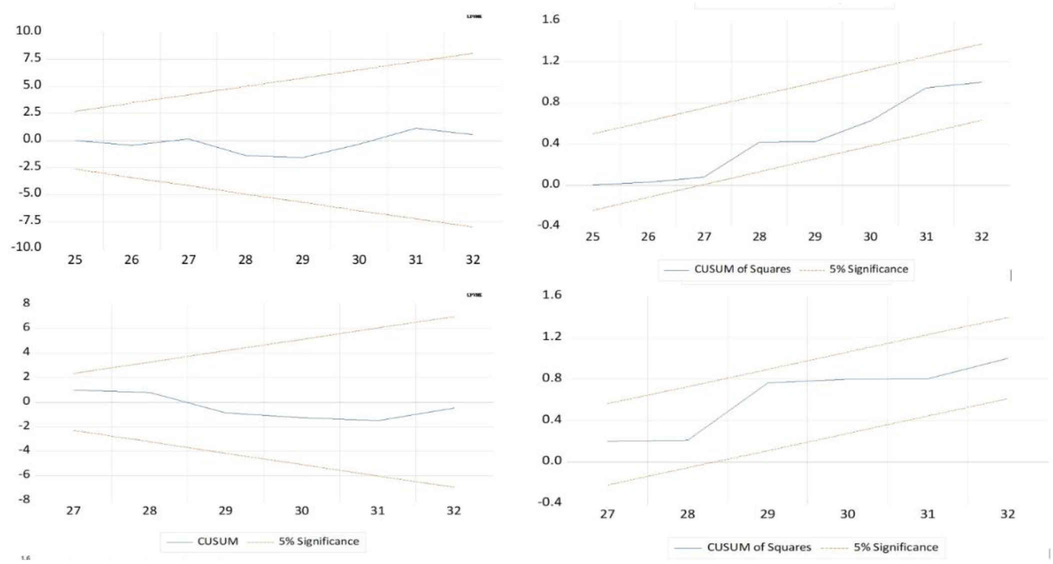
	Test	F-stat	P-value	H_0	Conclusion
Residual Diagnostics	Normality (Jarque-Bera)	$(0.102)^1$ $(17.2)^2$	$(0.949)^1$ $(0.18)^2$	Residuals are normally distributed	Normally distributed errors
	Heteroskedasticity (Breusch-pagan test)	$(0.436)^1$ $(0.728)^2$	$(0.939)^1$ $(0.732)^2$	The residuals are homoscedastic.	No-Heteroscedasticity
	Serial Correlation (Breusch-godfrey test)	$(3.688)^1$ $(2.77)^2$	$(0.08)^1$ $(0.175)^2$	There is no-second order serial Correlation in the residuals.	No autocorrelation
Stability Diagnostics	Ramsey RESET Test	$(1.332)^1$ $(1.86)^2$	$(0.281)^1$ $(0.230)^2$	Model is correctly specified	No omitted variables & no non-linearities

Values indicated with superscript 1 correspond to Model 1 (LPUHE), while those with superscript 2 correspond to Model 2 (LPVHE)

The diagnostic tests confirm that both models are statistically reliable. To check normally distributed residuals Jarque–Bera test has been applied for Model 1 and 2 with p-values (0.94 & 0.18). To check heteroskedasticity Breusch–Pagan test was applied, result shows no evidence of with p-values (0.939 & 0.732), and the Breusch–Godfrey test confirms the absence of serial correlation for both the models at 5 % significance with p-values (0.08 & 0.175). Finally, the Ramsey RESET test validates correct model specification, suggesting no omitted variables or functional form misspecification. Overall, both models are stable and well-fitted.

Figure 1: 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-run are valid throughout observed years.



5. Conclusion

All three models used in the paper (ARDL, FMOLS, DOLS) confirm a robust long-run cointegration between per capita public health expenditure and its determinants in India from 1991 to 2022. On the other hand, for model 2 per capita private health expenditure results are significant but not meaningful for long run. Results from model 1 shows population, per capita out-of-pocket expenditure, and urbanization each exert significant effects in long run and all variables are significant in short run, with diagnostic tests indicating well-specified models. These findings align with evidence that per capita public health expenditure is strongly driven by demographic and economic factors across contexts(Saleh et al., 2023; Younsi et al., 2024). In India's case, increasing population underscores the need for greater public investment to expand health infrastructure and service capacity. Rapid urbanization further amplifies healthcare demand, necessitating expanded medical facilities and broader coverage in growing metro cities. The prominence of per capita out-of-pocket expenditure in our results highlights the heavy financial burden on households; high per capita out-of-pocket spending is known to impoverish families and hinder equitable access. To reduce this household financial risk, our findings call for substantially boosting public health funding and risk-pooling mechanisms (e.g., insurance), consistent with evidence that stronger tax-based financing improves financial protection(Sofi & Yasmin, 2024).

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