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The In-patient Protection Paradox: Is Expansion of Government Health Insurance Coverage Sufficient to Suppress Private Sector Reliance in High Metabolic Burden Districts?

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ABSTRACT

Introduction: Public health insurance models in low- and middle-income countries often restrict benefits to inpatient department services, overlooking outpatient department requirements. This study evaluated whether expanding IPD-only government health insurance penetration effectively insulates Indian households against out-of-pocket expenditures driven by chronic metabolic diseases. **Methods:** A cross-sectional secondary data analysis was conducted across 715 districts utilising national-level survey data. Ordinary least squares multiple linear regression evaluated the relationship between public health insurance penetration, a district's "Metabolic Index" (elevated blood sugar prevalence), and the private-to-public service utilisation ratio (a proxy for financial vulnerability). A microeconomic constrained optimisation framework and spatial analysis mapped regional variations in structural protection efficiency. **Results:** Public health insurance significantly reduced private sector reliance in low-burden environments (B = -0.037, p<0.001). However, a highly significant positive interaction term (B = 0.015, p<0.001) confirmed that this financial protection degrades systematically as a district's Metabolic Index rises. Spatial analysis identified hot spots of financial vulnerability clustered across the Southern Peninsula and North-western Borderlands. The regression model explained $97.7% of the variance in private-to-public service flight (Adjusted R^2 = 0.977). **Conclusion:** The financial protection of current public insurance is non-uniform and epidemiology-dependent. In high-metabolic load districts, overloaded public OPD infrastructures trigger private sector outpatient flight. Because chronic metabolic conditions require lifelong maintenance, cumulative outpatient OOPE insidiously drives catastrophic health expenditures despite active inpatient coverage. Public health insurance architectures must transition from historical IPD-only frameworks to integrated, comprehensive IPD-OPD management packages to achieve true financial protection.

Keywords: Catastrophic Health Expenditure, Metabolic Diseases, Out-of-Pocket Expenditure, Health Insurance, Universal Health Coverage.

Key Message: While expanding inpatient public health insurance reduces private sector reliance in low-burden settings, it systematically fails to protect households from catastrophic out-of-pocket expenditures in districts with high chronic metabolic disease burdens.

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Introduction

The roots of modern public health insurance date back to 1883 in Germany. Chancellor Otto von Bismarck introduced the world's first social health insurance system.[1] This pioneering model established a structured relationship between four core pillars. These pillars are the insured consumer, the sponsor, the insurer, and the healthcare provider. In a classic social health insurance framework, the mechanics are well-defined.[2] The consumers are individual citizens and their family members. The insurer manages the centralized financial pool. The sponsor funds the system. This sponsorship can be solely government-driven, such as Ayushman Bharat Pradan Mantri Jan Arogya Yojna (AB-PMJAY).[3] It can also operate as a joint contributory framework, such as

the Employees' State Insurance (ESI) scheme.[4] Finally, the providers are the public or private health facilities that deliver the actual medical care.

A major structural feature of many public health insurance models is the strict limitation of service coverage. Benefits are mostly restricted to inpatient department (IPD) services. Daily outpatient department (OPD) care is widely excluded from these frameworks.[5] This architectural design creates a massive policy blind spot when facing epidemiological shifts. Inpatient caps protect households against sudden, acute health shocks. However, they do not account for the continuous financial strain of non-communicable diseases.[6]

India currently faces one of the highest burdens of chronic metabolic diseases globally.[7] Diabetes alone is responsible for a massive loss of 1.5 lakh Disability Adjusted Life Years (DALYs) across the population.[8] Data from the National Family Health Survey (NFHS-6, 2023–'24) highlights a severe escalation. Diabetes prevalence surged by 5.3% in adult males and 4.3% in adult females compared to the previous survey round. [9,10] Chronic metabolic diseases do cause severe acute complications. Conditions like stroke and myocardial infarction frequently require hospital admission. Yet, the mainstay of managing them remains lifelong, continuous care. This effective chronic management relies on routine, non-hospitalised services.[11] These include monthly outdoor consultations, regular laboratory investigations, daily medications, and long-term rehabilitation services. When public insurance excludes these outpatient expenses, a compounding financial crisis occurs. Over time, routine daily costs cumulatively overwhelm traditional inpatient expenditures.[12] This ongoing financial drain pushes households directly toward catastrophic health expenditure (CHE).[13] Ultimately, families suffer deep financial distress driven by the chronic metabolic disease care burden. This occurs despite holding active public health insurance coverage. This structural failure gives rise to a critical mismatch between insurance design and patient needs. [12, 13]

Thus, this study addresses a critical health policy question: Is an increase in government health insurance penetration, which structurally covers only IPD expenses, sufficient to financially insulate households against the out-of-pocket expenditures (OOPE) driven by chronic metabolic diseases in India? This study aimed to assess the effectiveness of current government health insurance penetration in financially insulating households against metabolic disease-related OOPE across Indian districts.

Methodology

Study Design & Data Source: This cross-sectional secondary data analysis used data from the sixth round of the National Family Health Survey (NFHS-6), conducted in 2023–'24. NFHS-6 was a nationally representative survey carried out by the International Institute of Population Sciences (IIPS), Mumbai. The project was supervised by the Ministry of Health and Family Welfare (MoHFW), Government of India. Due to operational constraints, the survey covered all Indian states and Union Territories except Manipur. The survey used a stratified random cluster sampling design. In total, it covered 6,79,238 households. For rural areas, villages served as the primary sampling units (PSUs). For urban areas, Urban Frame Survey (UFS) blocks from the National Statistical Survey Organization (NSSO) served as the PSUs. The household schedule collected information across multiple domains, including health insurance coverage. For biomarker evaluation, researchers measured the random blood sugar of men and women aged 15 years or older using capillary blood. The dataset is available to the public. It can be accessed online through the following web link: (https://www.nfhsiips.in/ nfhsuser/ assets)[9]. The final unit of analysis for this study was districts (N= 715).

Study Variables: The dependent variable was 'Private-to-public service utilisation ratio'. It was calculated as the ratio of households in a district utilising private healthcare facilities to those utilising public healthcare facilities. It was used to indicate financial vulnerability to the risk of catastrophic health expenditures. The independent variables were as follows:

1. The proportion of adult males and females in a district with elevated blood sugar was used to depict the burden of chronic metabolic disease. It was defined as random blood sugar ≥200 mg/dl.[9] The average of the proportions of adult males and females in a district was treated as 'Metabolic Index'.

2. The health insurance coverage in a district depicts the proportion of households with at least one member covered under any public, state, or union government-sponsored health insurance framework.

Other independent variables considered to control for confounding factors were-

The proportion of the geriatric population (aged 60 years or above) in a district because older individuals are more prone to develop chronic metabolic diseases.[14] The proportion of births taking place in the public institution in a district indicates the utilization of public health services. The proportion of the population in a district that belonged to the highest wealth quintile and/or resided in an urban area. Both were considered because people with higher incomes and people from urban areas are more prone to utilise private healthcare services. [15-17] It is also worth noting that private healthcare sectors are significantly more common in urban areas in comparison to rural areas.[9] Lastly, female literacy was considered because existing literature shows that an increase in female education is associated with a higher preference towards private healthcare. [18]

Research Hypothesis: Hypotheses considered in this study were as follows-

- ***Null Hypothesis (H_0):*** An increase in IPD-only government health insurance penetration provides uniform financial protection, irrespective of chronic metabolic disease prevalence in a district.
- ***Alternative Hypothesis (H_A):*** The financial protection offered by IPD-only government health insurance is non-uniform and highly dependent on the chronic metabolic disease prevalence in the district.

The formal mathematical derivations and structural equations detailing how this operational dependency functions are compiled in the Supplementary File.

Data Analysis & Software Use: To assess the predictors of private-to-public service utilization, an ordinary least squares (OLS) multiple linear regression was conducted using SPSS software version 16. To assess multicollinearity between the independent variables, the variance inflation factor (VIF) was used, and a VIF value less than five indicates the absence of multicollinearity. Model fitness was assessed by F-statistics. Total variance of the dependent variable was explained using the adjusted R^2 value. A p-value of < 0.05 was considered significant.

$$Y_i = \beta_0 + \beta_1(MI_i) + \beta_2(HI_i) + \beta_3(MI_i \times HI_i) + \sum \beta_k (X_{ki}) + \epsilon_i$$

Where:

- Y_i is the Private-to-Public Service Utilisation Ratio for district ***i***
- MI_i represents the Metabolic Index.
- HI_i represents the Public Health Insurance Penetration.
- X_{ki} represents the vector of other adjusted district-level covariates
- ϵ_i represents the stochastic error term.

While macro-level district variations are evaluated by this equation, the underlying microeconomic constrained optimization framework validating this structural relationship is elaborated within the Supplementary File. Lastly, a simple slopes analysis was conducted in R software version 4.3.2, at the mean ± 1 standard deviation (SD) of the district adult blood sugar distributions to visualize a significant moderation effect.

Ethical Consideration: This study used de-identified district-level secondary data from a publicly available nationally representative study. Thus, this study did not require any ethical approval from the institutional ethics committee.

***Data Availability Statement*:** This study was based on data from NFHS-6 Factsheet. It is available on public domain and could be accessed using the following link: (https://www.nfhsiips.in/nfhsuser/assets)

***AI Use Declaration*:** The authors declare that AI technology was not used during any stage of this work.

Results

Among the 715 surveyed districts, on average, private surface utilization was 2.4 times higher than public healthcare services. The mean household penetration of health insurance was (61.79 ± 10.79) % among these districts. On average, (18.17 ± 3.38) % of the population had elevated blood sugar **(Table-1).**

Table -1: District-level distribution of variables (n = 715)

Variables	Mean ± SD	Minimum	Maximum
Household Health Insurance Penetration (%)	61.79 ±10.79	26.55	89.4
Metabolic Index (%)	18.17 ±3.38	9.75	30.14
Geriatric population (%)	10.99 ±1.94	6.87	20.04
Public institutional birth (%)	63.64 ±11.38	31.49	96.88
Highest wealth quintile (%)	19.81 ±13.75	0	75.6
Urban area (%)	30.59 ±17.17	0	100
Female literacy (%)	70.46 ±9.0	48.16	96.79
Private-to-Public Service Utilization Ratio	2.4 ±0.6	0.58	4.06
Metabolic Index = [Men with high blood sugar (%) + Women with high blood sugar (%)]/2			

Ordinary least squares (OLS) linear regression shows that a 1% increase in health insurance penetration was associated with a 0.037 times reduction in private healthcare utilization compared to public one, and it was statistically significant (B -0.037, 95% CI: -0.037 to -0.036, p<0.001). Conversely, an increase in insurance penetration in the districts with higher chronic metabolic index caused a 0.015 times increase in the utilization of private healthcare services, and it was also statistically significant (B 0.015, 95% CI: - 0.015 to 0.016, p<0.001). The model was fit (F-statistic 380.2.245, p<0.001) and it explained 97.7% of the variance in the dependent variable (Adjusted R^2 0.977) **(Table-2)**.

Table 2: Multiple linear regression showing predictors of the private-to-public healthcare service utilization ratio across Indian districts (N = 715)

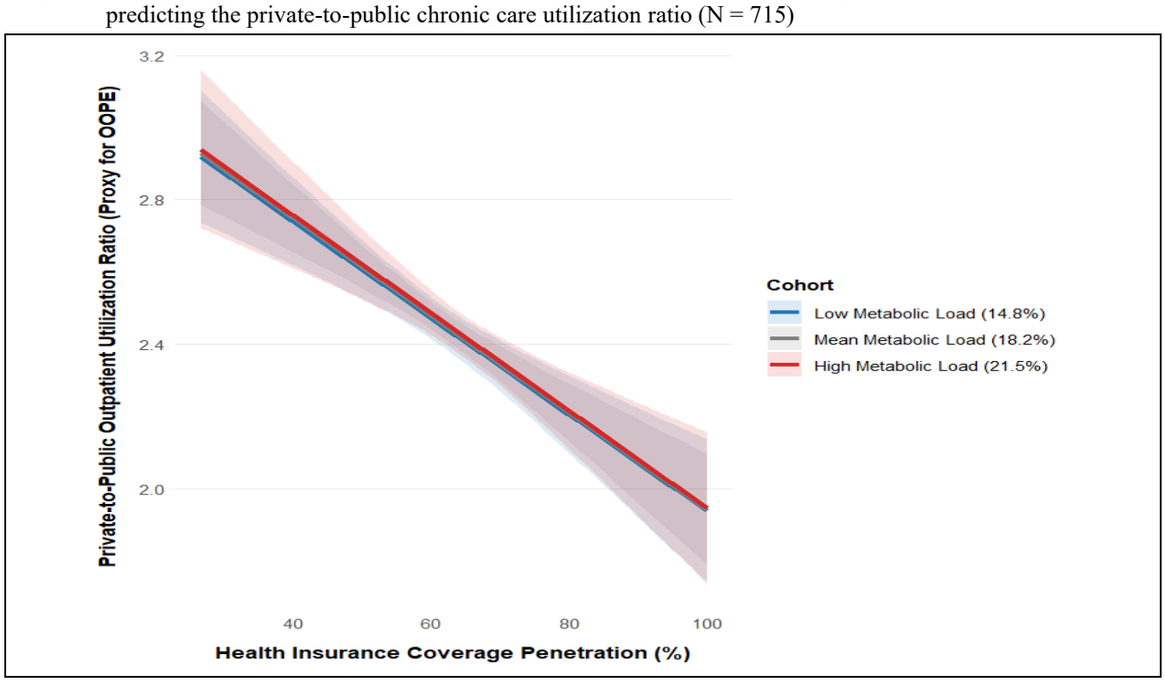
Predictors**	Unstandardized Coefficients (B)	Standard Error	Standardised Coefficients (β)	t	95% CI	p-value	VIF
Insurance coverage (%)	-0.037	0.000	-0.607	-91.719	-0.037 to - 0.036	**<0.001**	1.362
Metabolic Index^	-0.001	0.001	-0.003	-0.454	-0.003 to 0.002	0.650	1.461
Interaction $	0.015	0.000	0.963	143.59	0.015 to 0.016	**<0.001**	1.401
Geriatric proportion (%)	0.002	0.002	0.007	0.892	-0.002 to 0.007	0.373	1.722
Public institutional birth (%)	-0.001	0.000	-0.012	-1.798	-0.001 to 0.00	0.073	1.378
Highest Wealth quantile (%)	0.000	0.000	0.008	0.986	0.000 to 0.001	0.324	1.880
Urban area proportion (%)	0.000	0.000	0.004	0.609	0.000 to 0.001	0.543	1.536
Female literacy (%)	-0.002	0.001	-0.031	-4.051	-0.003 to - 0.001	**<0.001**	1.791
Constant	2.563	0.051	-	50.136	2.462 to 2.663	**<0.001**	---

** Continuous variable in ascending order (↑), F-statistics 3802.245, p-value < 0.001, Adjusted R^2 0.977

$ Interaction = (Insurance coverage * Metabolic Index), ^Metabolic Index = (Male with high blood sugar + Female with high blood sugar)/2

The simple slopes analysis to visualize a significant moderation effect of the district adult blood sugar distributions was as follows- **(Figure 1)**.

Figure-1: Simple slopes analysis of the interaction between health insurance coverage and the Metabolic Index in predicting the private-to-public chronic care utilization ratio (N = 715)



Low Metabolic Load (14.8%): In districts characterized by a lower metabolic disease burden, the slope demonstrating the protective effect of health insurance coverage penetration was steepest. Higher insurance coverage closely tracked a substantial decline in the private-to-public outpatient utilization ratio.

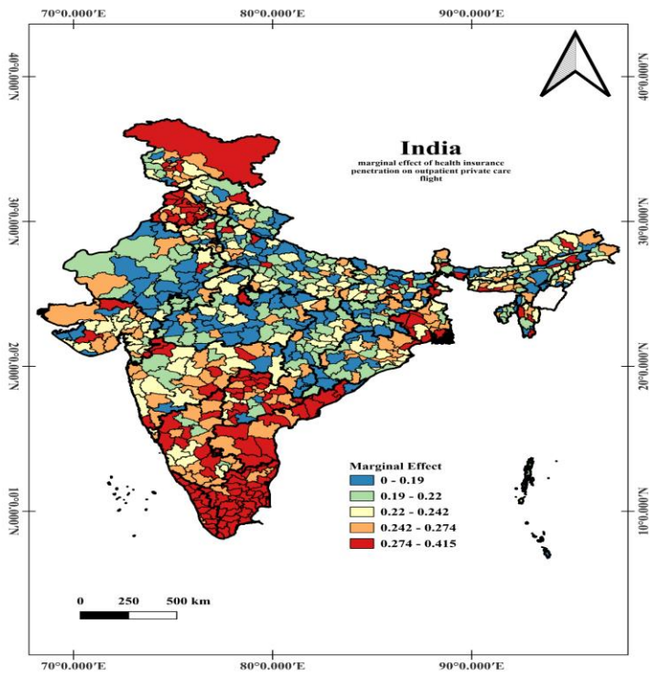
Mean Metabolic Load (18.2%): At the national average of metabolic burden, the negative slope remained prominent but began to exhibit wider parameter bounds.

High Metabolic Load (21.5%): In districts facing an elevated chronic metabolic disease burden, the trajectory of the slope was altered. The robust 95% confidence bounds widened significantly, indicating a degradation in the uniform protective capacity of insurance coverage as healthcare utilization patterns diverged.

Lastly, the geographical distribution of these statistical dependencies across the 715 studied districts is presented in the spatial distribution map. The calculated marginal effect of public health insurance penetration on private care flight was non-uniform across the country. It showed a marked regional clustering **(Figure 2).**

The lowest marginal effect categories (0 to 0.19 and 0.19$ to 0.22) were localized heavily within central and parts of western India. It covers most districts throughout Gujarat and the northern and western administrative divisions of Maharashtra, as well as the expansive northern and eastern districts of Bihar and sections of eastern Uttar Pradesh within the Indo-Gangetic Belt.

Figure -2: Spatial distribution map of India showing district-level variations in the calculated marginal effect of health insurance penetration on outpatient private care flight (N=715).



In contrast, the highest marginal effect categories (0.242 to 0.274 and 0.274 to 0.415) clustered heavily across the southern peninsula, north-western borders, and selected districts of the northern plains. The first major hot spot spans the Southern Peninsula, forming a continuous geographical belt across almost all districts of Kerala and Tamil Nadu, and extending into southern Andhra Pradesh and coastal Karnataka. These territories correlate with states that have reached an advanced stage of epidemiological transition, characterized by a high prevalence of chronic metabolic diseases alongside a historically dominant and deeply utilized private healthcare sector. A second highly pronounced, contiguous high-coefficient cluster is visible across the North-western Border and Northern Plains, covering the entirety of Punjab, Haryana, and the union territories of Jammu & Kashmir and Delhi. This pattern of vulnerability runs directly eastward into the fertile, densely populated plains of western and central Uttar Pradesh. Lastly, prominent pockets of elevated marginal dependency are visible along the Eastern Borderlands, specifically clustering across coastal Odisha and multiple localized districts of southern West Bengal.

Discussion

This secondary data analysis investigated whether expanding inpatient-only government health insurance is sufficient to protect Indian households from out-of-pocket expenditures driven by chronic metabolic diseases. Our empirical findings reveal that the financial protection offered by current public insurance is non-uniform. This protection depends heavily on the localized epidemiological burden of the district.

In districts with a low metabolic disease burden, public health insurance demonstrates its intended protective effect. In these low-burden settings, the public healthcare infrastructure faces fewer operational bottlenecks. This translates into shorter waiting times and reduced queuing. Service delivery efficiency remains comparable to the private sector. Because public care is far less costly, consumers naturally default to public options.[4,5] This trend effectively minimises private outpatient flights.

Conversely, our study uncovers a glaring policy paradox in high-burden districts. As detailed in our regression analysis in the results section, the capacity of public health insurance to suppress private sector reliance degrades systematically as the district metabolic load increases. In regions facing high metabolic index scores, the surging demand for chronic care severely congests public facilities. To circumvent long queues and administrative delays, patients frequently seek routine outpatient care within the private sector.[19,20]

This shifting preference highlights a profound structural mismatch between insurance design and patient needs. Chronic metabolic conditions require lifelong, continuous maintenance rather than isolated hospitalizations.[21, 22] Because of this, the routine daily costs of outpatient care cumulatively overwhelm traditional inpatient expenditures over time.[6,12] Hospitalizations are less frequent than monthly check-ups and routine laboratory investigations. Therefore, this ongoing outpatient drain slowly pushes households toward catastrophic health expenditure.[13, 23] This financial crisis happens insidiously over time, even when families hold active public health insurance.

This systemic erosion of financial protection is completely validated by the microeconomic optimization frameworks detailed in our supplementary material. Under current insurance architectures, allocating all public funding exclusively to inpatient packages triggers diminishing health returns. The microeconomic model proves that the current inpatient-only resource allocation operates at structural inefficiency. By shifting funding away from resource-intensive hospitalisations toward baseline outpatient prevention, health systems can achieve a substantial net gain in health benefits within a fixed budget.

Furthermore, our spatial analysis highlights the real-world impact of this structural flaw. As shown in the mapping results, prominent hot spots of vulnerability cluster heavily across the Southern Peninsula and the North-western Borderlands. These regions correlate with territories in advanced stages of epidemiological transition.[24] They combine a high prevalence of chronic metabolic diseases with historically dominant private healthcare sectors. Ultimately, these findings argue for an immediate shift in India’s universal health coverage strategy.[3,4] To achieve true financial risk protection, public health insurance models must evolve from their historical inpatient-only frameworks and actively integrate comprehensive inpatient-outpatient management packages.

Conclusion

Current public health insurance in India faces a critical policy mismatch. Expanding inpatient-only coverage reduces private sector reliance in low-burden districts. However, it systematically fails to protect households in high metabolic burden areas. Chronic conditions like diabetes require lifelong, continuous outpatient care. They do not just require isolated hospitalizations. Over time, routine daily costs cumulatively overwhelm traditional inpatient expenditures. This ongoing outpatient drain insidiously drives families toward catastrophic health expenditure. This financial crisis occurs despite families holding active public insurance. Regression and spatial analyses confirm that financial protection degrades as a district's Metabolic Index rises. Prominent hotspots of financial vulnerability cluster heavily across the Southern Peninsula and Northwestern Borderlands. Therefore, India's public health insurance architectures must evolve. True financial insulation requires a transition from historical inpatient-only frameworks to integrated, comprehensive inpatient-outpatient management packages.

Mathematical Derivation

Mathematical Derivation: The combined OPD-IPD insurance model is cost-effective to an IPD-only model at a fixed budget equilibrium. The constrained optimisation model is as follows-

Variables considered were-

- ***N*** was the total population of metabolic disease patients in a district.
- ***p*** was the probability of a patient of chronic metabolic disease developing a severe complication requiring tertiary hospitalisation (IPD admission).
- ***x*** was the government's investment in outpatient department (OPD) care per patient (routine diagnostics, blood sugar monitoring, and maintenance drugs).
- C_H was the fixed cost of a single tertiary hospitalization (IPD event),
- C_M was the fixed cost of managing an outpatient.
- The probability of hospitalization is a decreasing function of outpatient investment: ***p(x)***, where $\frac{dp}{dx} < 0$ (as OPD investment increases, the risk of hospitalization drops).

Scenario Zero (Status Quo): Under the current IPD-only Model, no money is spent on prevention ($x = 0$). The baseline probability of acute crisis was p_0. The total cost spent by the government matches the budget cap

$$B_0 = N \cdot p_0 \cdot C_H$$

Scenario One: Under the Proposed Combined IPD-OPD Model, the government invests a specific amount $x^* > 0$ into outpatient care per patient, which reduces the hospitalization probability to $p(x^*)$. The new balanced budget equation is:

$$B_0 = N \cdot p(x^*) \cdot C_H + N \cdot x^* \cdot C_M$$

Since the total budget B_0 is identical in both scenarios, we equate the two resource allocations to see how money is saved and redirected

$$N \cdot p_0 \cdot C_H = N \cdot p(x^*) \cdot C_H + N \cdot x^* \cdot C_M$$

$$p_0 \cdot C_H = p(x^*) \cdot C_H + x^* \cdot C_M$$

$$[p_0 - p(x^*)] \cdot C_H = x^* \cdot C_M$$

Where, $[p_0 - p(x^*)]$ or Δp was the absolute reduction in the rate of hospitalization (or hospitalization prevented) due to implementation of the proposed IPD-OPD model

$[p_0 - p(x^*)].C_H$ was the total cost saved from the prevented hospitalisations.

$x^* \cdot C_M$ was the total cost required to provide OPD services under the proposed IPD-OPD model

For the combined model to be viable within the same budget B_0, the marginal savings from averted hospitalizations must equal or exceed the marginal cost of running the outpatient program:

$$\Delta p \cdot C_H \geq x^* \cdot C_M$$

Because tertiary metabolic hospitalizations in India e.g., stroke ICU care, dialysis, amputations, are highly expensive relative to daily maintenance drugs, i.e. metformin/statins, $C_H \gg C_M$. Thus, even a small reduction in Δp yields substantial cost savings,

proving that the combined model absorbs less structural waste per unit of money spent.

Mathematical Derivation: The combined OPD-IPD insurance model is superior to an IPD-only model, yielding greater health benefits in terms of total DALYs averted. The variables were as follows-

- D_{Total} was the total DALYs averted by the health system after implementation of proposed IPD-OPD model
- $U_H(B)$ was the DALYs averted by spending money on acute IPD hospitalizations.
- $U_O(B)$ was the DALYs averted by spending money on outpatient services.
- B_H was the total money spent on hospitalization or IPD care
- B_O was the total money spent on hospitalization or OPD services

[In health economics, both functions follow the law of diminishing returns: the first derivative is positive ($\frac{dU}{dB} > 0$), meaning

more money buys more health. But if the second derivative is negative ($\frac{d^2U}{dB^2} < 0$), meaning the next rupee spent on the same

service yields smaller and smaller incremental health gains.]

The government's goal is to maximize total DALYs averted subject to the budget constraint:

$$\text{Maximize } D_{Total} = U_H(B_H) + U_O(B_O) \quad \text{subject to } B_H + B_O = B_0$$

Using the Lagrangian Multiplier Method to solve this constrained optimization problem:

$$\mathcal{L}(B_H, B_O, \lambda) = U_H(B_H) + U_O(B_O) + \lambda(B_0 - B_H - B_O)$$

Taking the partial first derivatives with respect to expenditures in both sectors (B_H and B_O) and setting them to zero to find the maximum efficiency point:

$$\frac{\partial \mathcal{L}}{\partial B_H} = \frac{dU_H}{dB_H} - \lambda = 0 \Longrightarrow \frac{dU_H}{dB_H} = \lambda$$

$$\frac{\partial \mathcal{L}}{\partial B_O} = \frac{dU_O}{dB_O} - \lambda = 0 \Longrightarrow \frac{dU_O}{dB_O} = \lambda$$

Equating the two yields the Equi-Marginal Principle of Health Optimization:

$$\frac{dU_H}{dB_H} = \frac{dU_O}{dB_O}$$

Under the current system, the government allocates 100% of the budget to IPD care ($B_H = B_O$) and 0% to OPD care ($B_O = 0$). Because B_H is extremely large, the marginal health benefit of the last rupee spent on hospitalization ($\frac{dU_H}{dB_H}$) drops toward zero due to diminishing returns. Conversely, because $B_O = 0$, the marginal health benefit of the first rupee spent on basic outpatient prevention ($\frac{dU_O}{dB_O}$) is at its absolute peak.

Therefore, under the current model:

$$\frac{dU_H}{dB_H} \ll \frac{dU_O}{dB_O}$$

Since the marginal returns are unequal, the current IPD-only allocation is mathematically inefficient. By shifting a single unit of money (ΔB) away from late-stage IPD care and allocating it to baseline OPD care, the health system experiences a marginal loss in IPD health benefits that is vastly outweighed by the massive marginal gain in OPD health benefits.

Net health optimization (D_{Total}) will continuously increase until the health returns per rupee are perfectly balanced across both sectors. At the same budget cap (B_0), a combined model mathematically guarantees a higher volume of total population DALYs averted.

Connection to the Empirical Model

The equi-marginal disparity ($\frac{dU_H}{dB_H} \ll \frac{dU_O}{dB_O}$)

proven above demonstrates that when the district-level chronic metabolic burden (MI_i) is high, allocating public health insurance (HI_i) exclusively to inpatient packages results in diminishing health returns and forces households to seek private outpatient care. Mathematically, this systemic erosion of financial protection is captured in the empirical OLS regression model via the two-way multiplicative interaction term (β_3):

$$\frac{\partial Y_i}{\partial HI_i} = \beta_1 + \beta_3(MI_i)$$

Because our empirical results yield a highly significant, positive interaction coefficient ($\beta_3 = 0.015$, p-value < 0.001), it provides mathematical verification of this exact theoretical framework: the capacity of health insurance to suppress private healthcare reliance ($\beta_1 = -0.037$) degrades monotonically as a linear function of the district's metabolic index (MI_i).

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