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Impact of Health Insurance Coverage on Out-of-Pocket Healthcare Expenditure and Equity in India

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Abstract

This study examines the effect of health insurance coverage on household out-of-pocket healthcare expenditure (OOPE) and assesses the equity of healthcare financing in India, using nationally representative unit-level microdata from the 80th round of the National Sample Survey (NSS), Household Social Consumption: Health (January–December 2025). Analysis is based on 650,842 individuals (139,732 households) after cleaning. A binary logistic regression identifies the socio-economic determinants of insurance enrolment, and one-to-one nearest-neighbour Propensity Score Matching (PSM) with caliper restriction is used to reduce observable selection bias when estimating the causal effect of insurance on OOPE. Equity in healthcare financing is assessed using the Concentration Index, the Gini coefficient, and the Kakwani Progressivity Index.

Age, education, household size, monthly per-capita consumption expenditure (MPCE), religion, and social group are all significant predictors of insurance enrolment. Matching achieved excellent covariate balance (mean absolute standardized mean difference falling from 0.102 to 0.007). On the matched sample, insured individuals incurred approximately 29.8% higher out-of-pocket expenditure than comparable uninsured individuals ($\beta = 0.2609$, $p < 0.001$), suggesting that insurance is associated with greater healthcare utilization rather than a reduction in direct payments. The Concentration Index (0.274) and Gini coefficient (0.291) indicate that OOPE and consumption are both concentrated among relatively better-off households, while a small negative Kakwani Index (−0.017) indicates that healthcare financing is mildly regressive, close to proportional, but still imposing a marginally larger relative burden on poorer households.

Coverage is overwhelmingly publicly financed: the two large public schemes, AB-PMJAY and the state health insurance schemes, together account for 88.9% of all reported coverage. Assessed at the household level, 5.99% of households incur catastrophic health expenditure at the 10% threshold of annual consumption, and both the incidence and the intensity of these payments fall steadily as household consumption rises, so that the burden of catastrophic spending is concentrated among poorer households.

Keywords: Health Insurance, Out-of-Pocket Expenditure, Propensity Score Matching, Equity, Concentration Index, Kakwani Index, Catastrophic Health Expenditure, Financial Protection, AB-PMJAY, India, NSS 80th Round.

Introduction

Universal Health Coverage (UHC) remains a central objective of health policy in India, in line with Sustainable Development Goal (SDG) 3.8, which calls for financial risk protection alongside access to essential health services (WHO, 2010; United Nations, 2015). Despite the expansion of publicly financed health insurance schemes such as Ayushman Bharat–Pradhan Mantri Jan Arogya Yojana (AB-PMJAY), Employees' State Insurance (ESIS/ESIC), and various state government schemes, out-of-pocket expenditure continues to account for a substantial share of household healthcare spending in India (NHSRC, 2022). High OOPE can force households to cut essential consumption, deplete savings, or incur debt, and is a well-documented driver of catastrophic health expenditure and impoverishment (Wagstaff & van Doorslaer, 2003; Xu et al., 2003).

Two features of this setting motivate the analysis that follows. First, coverage under these schemes is not uniform: enrolment is spread across several distinct public, employer-based and commercial schemes that differ in whom they reach and in what they pay for, so the composition of coverage is itself informative about who is protected. Second, financial protection is measured not only by the level of out-of-pocket expenditure but by its size relative to a household's resources. A household is said to incur catastrophic health expenditure when its out-of-pocket payments absorb a large share of its total consumption, a budget-share measure embedded in Sustainable Development Goal indicator 3.8.2 and reported at thresholds of 10% and 25% of consumption. Characterising coverage by scheme and measuring catastrophic expenditure at the household level therefore complements the individual-level analysis of enrolment, expenditure and equity.

This study uses the most recently released round of India's flagship health expenditure survey - the NSS 80th round (2025) to (i) identify the socio-economic determinants of health insurance enrolment, (ii) estimate the causal effect of insurance coverage on OOPE using Propensity Score Matching, (iii) evaluate the progressivity/regressivity of healthcare financing using standard equity indices, and (iv) characterize

the composition of insurance coverage by scheme and assess financial protection directly through the incidence and intensity of catastrophic health expenditure at the household level. This analysis was constructed directly from the released government unit-level data files, following a methodology comparable to established NSS-based PSM studies in the health-economics literature (Austin, 2011; Rosenbaum & Rubin, 1983).

1.1 Literature Review

The relationship between health insurance and out-of-pocket spending has been studied extensively, both globally and within India, and the findings are notably mixed rather than uniformly supportive of a simple "insurance reduces OOPE" narrative. Internationally, one of the most methodologically influential studies is King et al. (2009), a large-scale randomised evaluation of Mexico's Seguro Popular universal health insurance programme; it found that formal insurance enrolment increased health service utilization and was associated with reduced catastrophic and impoverishing health spending in treated communities, providing experimental-quality evidence that insurance can, under the right programme design, deliver genuine financial protection. Wagstaff and van Doorslaer (2003) and Xu et al. (2003) established the now-standard conceptual and measurement framework for catastrophic and impoverishing health expenditure that much of the subsequent India literature, including the present study's equity indices, builds on.

Within India specifically, evidence on publicly financed insurance schemes has been considerably less encouraging than the Mexican experience. Selvaraj and Karan (2012), analysing repeated rounds of India's Consumer Expenditure Survey around the roll-out of the Rashtriya Swasthya Bima Yojana (RSBY) and comparable state schemes (Rajiv Aarogyasri in Andhra Pradesh, the Tamil Nadu Health Insurance Scheme), found that districts exposed to these schemes experienced a rise in real per-capita health expenditure and an increase in the incidence of catastrophic health spending relative to unexposed districts — the opposite of the schemes' stated objective. They interpreted this as evidence that India's early publicly financed schemes, which were narrowly limited to hospitalisation coverage with restricted benefit packages, induced additional utilisation without adequately capping the direct costs borne by patients. Wagstaff et al. (2009), studying a broadly comparable rural cooperative medical scheme in China, similarly found that insurance expansion raised utilisation and out-of-pocket spending simultaneously, illustrating that this utilisation-driven expenditure pattern is not unique to India.

A parallel strand of Indian literature has focused less on insurance status directly and more on how households finance whatever OOPE they incur. Joe (2015), using nationally representative NSS data, documented that over 60% of rural and 40% of urban hospitalisation cases in India relied on "distressed financing" - borrowing, sale of assets, or contributions from relatives and friends to cover out-of-pocket costs, with these distress sources accounting for more than half of total inpatient OOP payments in rural areas, and found a pronounced socio-economic gradient with greater disadvantage among women, the elderly, and socially marginalised groups. Prinja et al. (2019), examining hospitalisation for injuries specifically in North Indian public-sector hospitals, similarly found substantial catastrophic OOPE even within the nominally free public system, underscoring that formal fee exemptions or insurance coverage on paper do not automatically translate into affordable care in practice. O'Donnell et al. (2008) provided the applied health-equity toolkit including the Concentration Index and Kakwani Index methodology used in Section 3.6 of this study that has become the standard approach for quantifying exactly this kind of financing regressivity across the literature just described.

Two gaps in this literature motivate the present study. First, almost all of the India-specific evidence above predates the major post-2018 expansion of AB-PMJAY and is therefore silent on whether the more recent, larger-benefit-package generation of publicly financed schemes has altered the utilisation/cost-shifting dynamic that Selvaraj and Karan (2012) documented for the earlier RSBY-era schemes; this study's use of the newly released NSS 80th round (2025) directly addresses that gap. Second, much of the existing Indian literature estimates a single aggregate OOPE effect and does not separate the extensive-margin utilisation response from the intensive-margin conditional-payment response precisely the distinction this study's scheme-wise margin analysis (Section 3.7) is designed to draw, and which turns out to matter substantially for the interpretation of the results (Section 4).

2. Data and Methodology

2.1 Data Source

Data are drawn from the unit-level records of the NSS 80th Round, "Household Social Consumption: Health" survey (Schedule 25.0) (NSO, 2025), conducted by India's National Statistical Office over January–December 2025. The survey employs a multi-stage stratified sampling design, with villages/urban blocks (or sub-units thereof) as First Stage Units and households as Ultimate Stage Units, both selected by simple random sampling without replacement. A total of 139,732 households (76,296 rural; 63,436 urban) and 651,732 individuals were canvassed nationally.

Seven linked data files corresponding to Blocks 1–2 & 5 (household), Block 3A/3B (demographics), Block 4 (deceased members), Blocks 6–7 (in-patient hospitalisation and expenditure), and Blocks 8–9 (out-patient ailment spells and expenditure) were merged at the household × person level using the FSU, sample, sector, state, second-stage-stratum, and household-serial identifiers, together with the household/person

serial numbers.

2.2 Variable Construction

Treatment variable - Health insurance coverage: A binary variable equal to 1 if the individual reported coverage under any health financing scheme (AB-PMJAY, state health insurance, ESIS/ESIC, CGHS/other central government scheme, employer-provided scheme, or privately purchased commercial insurance; Block 3, column 17), and 0 if explicitly recorded as "not covered." As in the source survey, only a single (primary) scheme is recorded per individual.

Outcome variable - Out-of-pocket expenditure (OOPE): The net direct payment made by the individual/household for healthcare, computed as total reported expenditure minus the amount reimbursed by insurance or employer, summed across (a) in-patient hospitalisation episodes during the last 365 days (Blocks 6–7) and (b) out-patient ailment spells during the last 15 days (Blocks 8–9). The dependent variable in the regression models is ln(OOPE + 1), to correct for the strongly right-skewed distribution of expenditure (Manning & Mullahy, 2001).

Covariates: age (years), sex, highest educational level attained (ordinal code, 1 = not literate to 13 = post-graduate and above), household size, log of monthly per-capita consumption expenditure (MPCE, computed as household usual monthly consumer expenditure divided by household size), religion, and social group (caste category) all recorded at Block 3 (person) or Block 5 (household) level.

After removing records with missing or logically invalid values on the treatment or covariates, the final analytical sample comprised 650,842 individuals.

Although the treatment variable used in the matching analysis is binary, the underlying survey item records the specific scheme under which each covered individual is enrolled, across eight distinct categories (Block 3, column 17). We exploit this additional detail to characterise the composition of coverage descriptively in Section 3.7. Because the item is administered as a single-response question, individuals enrolled in more than one scheme are recorded under one only (NSO, 2025). Reported scheme shares therefore describe primary reported affiliation rather than total enrolment and are not directly comparable with scheme-level administrative records, which permit multiple simultaneous enrolments. For this reason the scheme-wise results are presented as a descriptive characterisation of the insured population and are not used in the matching, treatment-effect or equity analyses.

2.3 Logistic Regression

A binary logistic regression model was estimated to identify the determinants of health insurance enrolment: $\text{logit}[\Pr(\text{Insured}=1)] = \beta_0 + \beta_1\text{Age} + \beta_2\text{Female} + \beta_3\text{Education} + \beta_4\text{Household Size} + \beta_5\ln(\text{MPCE}) + \text{Religion fixed effects} + \text{Social Group fixed effects}$ (Hosmer et al., 2013).

2.4 Propensity Score Matching (PSM)

Since insurance enrolment is not randomly assigned, a direct comparison of OOPE between insured and uninsured individuals is subject to selection bias (Rosenbaum & Rubin, 1983). Propensity scores (Rosenbaum & Rubin, 1983) the predicted probability of being insured given observed covariates, were estimated from the logistic regression above. Individuals were matched one-to-one, without replacement, using nearest-neighbour matching on the logit of the propensity score, subject to a caliper of 0.2 standard deviations of the logit propensity score (Austin, 2011), a widely used rule of thumb that minimises matching bias while retaining adequate sample size. Covariate balance was assessed before and after matching using standardized mean differences (SMD), with $|\text{SMD}| < 0.10$ taken as the threshold for acceptable balance.

2.5 Average Treatment Effect on the Treated (ATT)

On the matched sample, the treatment effect was estimated via an outcome regression of ln(OOPE + 1) on insurance status and the full set of covariates, with heteroskedasticity-consistent (HC1) robust standard errors (Imbens, 2004).

2.6 Equity Analysis

Three standard equity measures were computed over the full analytical sample, using MPCE as the measure of household living standard (ability to pay) (O'Donnell et al., 2008): (i) the Concentration Index of OOPE, ranking individuals by MPCE (Wagstaff et al., 1991); (ii) the Gini coefficient of MPCE (Gini, 1912); and (iii) the Kakwani Progressivity Index (Kakwani, 1977), defined as the Concentration Index of OOPE minus the Gini coefficient of MPCE. A positive Kakwani Index indicates progressive healthcare financing (richer households bear proportionally more of the burden); a negative value indicates regressive financing.

2.7 Catastrophic Health Expenditure and Financial Protection

Financial protection is inherently a household-level concept, since healthcare payments are borne from shared household resources (Wagstaff & van Doorslaer, 2003; Xu et al., 2003). Catastrophic health expenditure was therefore estimated at the household level, and all 139,732 sample households were included. Household out-of-pocket expenditure was measured net of reimbursement, that is, total reported expenditure less any amount reimbursed by an insurer or employer, across inpatient episodes (365-day recall) and outpatient spells (15-day recall). Insurance premiums were not included. Episodes attributed to deceased former household members, which account for 7.84% of aggregate household spending, were retained, since those payments were in fact incurred by the household. The denominator is total household consumption (Block 5, item 12), a monthly figure annualised by multiplying twelve to match the inpatient recall period.

Following SDG indicator 3.8.2, a household was classified as incurring catastrophic health expenditure where its out-of-pocket payments met or exceeded 10% or 25% of annual household consumption (WHO

& World Bank, 2023). For each threshold, we report two quantities: the headcount, the share of households at or above the threshold, which measures incidence; and the mean positive overshoot, the average amount by which affected households exceed the threshold, which measures intensity (O'Donnell et al., 2008).

Because the inpatient and outpatient modules use different reference periods, the numerator is constructed in two variants. Variant A, the hospitalisation-based measure, counts inpatient payments only; its 365-day reference period matches the annualised denominator exactly, and it is treated as the primary estimate. Variant B, the annualised measure, additionally incorporates outpatient payments, scaled from the 15-day recall to a full year by a factor of 365/15. Because this scaling assumes that short-recall outpatient spending is representative of the whole year, Variant B tends to overstate the burden and is treated as an alternative, upper specification rather than a preferred one. The conventional 40% capacity-to-pay threshold (Xu et al., 2003) could not be constructed because Schedule 25.0 collects no food expenditure from which to derive subsistence spending.

All catastrophic-expenditure estimates are survey-weighted using the multiplier supplied with the unit-level data. Weighting is essential here rather than optional, because the survey's second-stage stratification deliberately over-samples households that contain a hospitalised member; unweighted headcounts overstate prevalence roughly fivefold and, as shown in Section 3.8, conceal the socio-economic gradient entirely. The weighted estimates represent 294.8 million households. Household insurance status is defined as coverage of any member under any scheme (63.1% of households), a household-level construct that differs from the individual-level treatment variable used in Sections 2.3 to 2.5. Households were ranked by monthly per capita consumption and grouped into survey-weighted quintiles.

3. Results

This section proceeds in three parts. Section 3.1 describes the analytical sample. Sections 3.2 to 3.6 report on the unweighted individual-level matched analysis of the effect of insurance on out-of-pocket expenditure, following the methods in Sections 2.3 to 2.6. Sections 3.7 and 3.8 use the full survey-weighted sample to describe the composition of coverage and to measure financial protection at the household level. Because these parts differ in unit, weighting, and scale, they are complementary rather than directly comparable, and Section 4 draws them together.

3.1 Descriptive Statistics

Table 1 presents a descriptive analysis. The average age was 30.6 years (SD = 20.6), reflecting the full population age distribution captured by the household roster. The mean household size was 5.71, and the mean MPCE was ₹3,531 (SD = ₹2,224). 47.1% of individuals in the sample reported coverage under some form of health financing scheme or insurance, and 52.9% were uninsured (Figure 1). This shows a substantially higher coverage rate than found in earlier NSS rounds, consistent with the continued expansion of AB-PMJAY and state health schemes.

Average OOPE (combining hospitalisation and outpatient spells) was ₹5,848, but the distribution is extremely right skewed with the median of ₹0, reflecting that most individuals reported no healthcare spending in the recall period, while a small share incurred very large expenses (maximum ₹4.46 million; Figure 2).

Table 1. Descriptive Statistics of the Analytical Sample (N = 650,842)

Variable	Mean	SD	Median	Min	Max
age	30.62	20.62	28	0	110
educ	4.97	3.43	5	1	13
hhsz	5.71	2.52	5	1	30
mpce	3531.27	2223.86	3005.64	140	81433
oope_hosp	5667.46	35838.37	0	0	4456000
oope_outp	180.32	1284.97	0	0	185000
oope	5847.78	36081.56	0	0	4456000

Source: Authors' calculations from NSS 80th Round (Schedule 25.0), NSO.

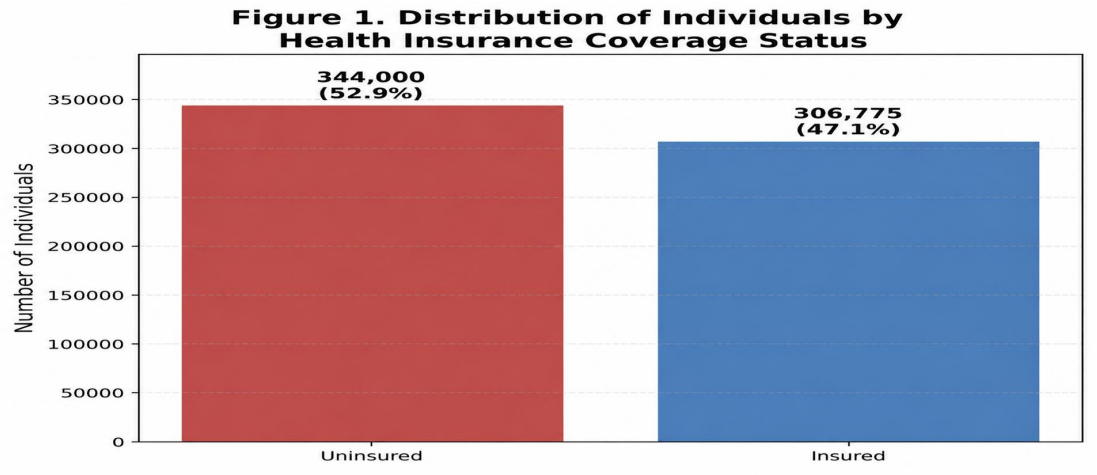


Figure 1. Distribution of Individuals by Health Insurance Coverage Status

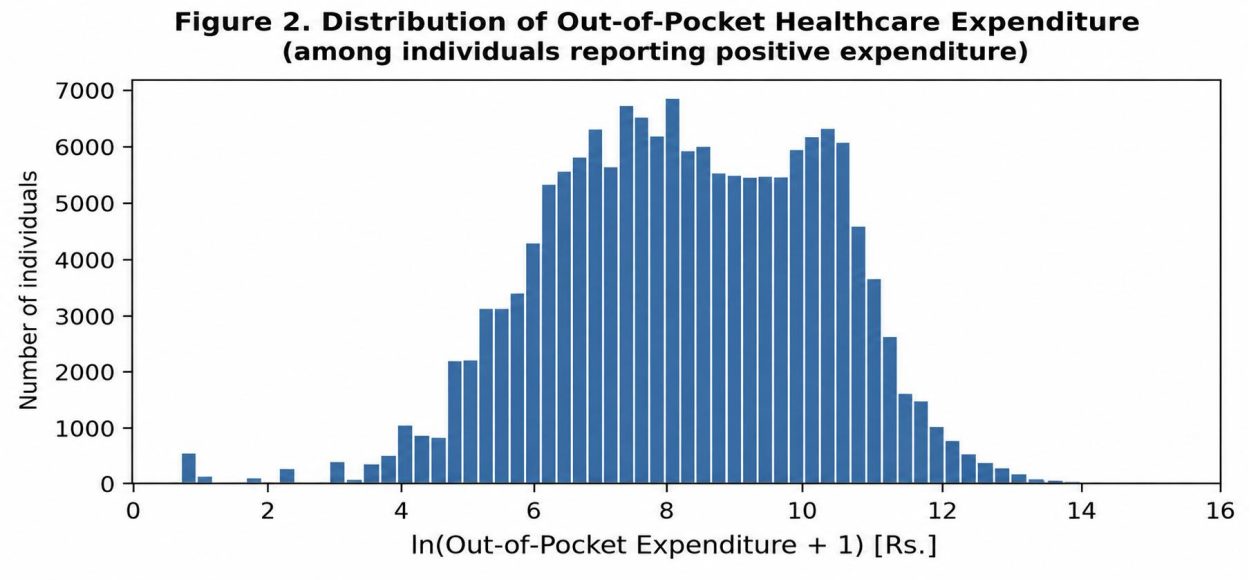


Figure 2. Distribution of Out-of-Pocket Healthcare Expenditure (log scale, individuals with positive OOPE only)

3.2 Comparison of Characteristics by Insurance Statusof Characteristics by Insurance Status

Table 2 compares insured and uninsured individuals. Insured individuals were significantly older (35.7 vs. 26.1 years), more educated, and had higher MPCE (₹3,733 vs. ₹3,351) than uninsured individuals, but lived in smaller households (5.48 vs. 5.92 members) - all differences significant at $p < 0.001$. Insured individuals also reported higher raw (unmatched) OOPE on average (₹6,675 vs. ₹5,110), consistent with greater healthcare utilization rather than reduced spending. Insurance coverage also differed significantly by religion and social group (both χ^2 $p < 0.001$), but not by sex ($p = 0.25$). These systematic differences confirm the presence of selection bias and justify the use of Propensity Score Matching before estimating a treatment effect.

Table 2. Comparison of Individual Characteristics by Insurance Status (unmatched sample; Welch's t-test)

Variable	Insured (mean)	Uninsured (mean)	t-statistic	p-value
age	35.73	26.07	194.40	< 0.001
educ	5.32	4.65	78.79	< 0.001
hhsz	5.48	5.92	-70.77	< 0.001
mpce	3733.38	3351.07	68.66	< 0.001
oope	6675.10	5110.13	17.24	< 0.001

Source: Authors' calculations from NSS 80th Round (Schedule 25.0), NSO.

3.3 Determinants of Health Insurance Enrolment

Table 3 reports the logistic regression estimates. Age (OR = 1.023, p < 0.001), education (OR = 1.041, p < 0.001), and ln(MPCE) (OR = 1.228, p < 0.001) are all positively and significantly associated with the odds of insurance coverage, confirming that older, more educated, and economically better-off individuals are more likely to be insured. Household size is negatively associated with coverage (OR = 0.970, p < 0.001). Relative to the reference religion category (Hinduism), most other religious groups show significantly lower odds of coverage, and relative to Scheduled Tribes (the reference social-group category), Scheduled Castes, Other Backward Classes, and the "Others" category all show significantly lower odds of insurance coverage. Sex shows a small but statistically significant positive association (women slightly more likely to be covered, OR = 1.017, p = 0.001).

Table 3. Logistic Regression: Determinants of Health Insurance Enrolment (Dependent variable: Insured = 1/0)

Variable	Coefficient	SE	Odds Ratio	p-value
Intercept	-1.9780	0.0481	0.138	< 0.001
Religion: Islam	-0.0195	0.0078	0.981	0.0123
Religion: Christianity	-0.2604	0.0124	0.771	< 0.001
Religion: Sikhism	-0.8739	0.0217	0.417	< 0.001
Religion: Jainism	-0.0776	0.0530	0.925	0.1432
Religion: Buddhism	-0.5275	0.0267	0.590	< 0.001
Religion: Zoroastrianism	-0.2167	0.9709	0.805	0.8234
Religion: Others	-0.0475	0.0265	0.954	0.0732
Social group: SC	-0.3859	0.0101	0.680	< 0.001
Social group: OBC	-0.6403	0.0091	0.527	< 0.001
Social group: Others	-0.5533	0.0100	0.575	< 0.001
Age (years)	0.0227	0.0001	1.023	< 0.001
Female (=1)	0.0173	0.0052	1.017	< 0.001
Education (ordinal code)	0.0399	0.0008	1.041	< 0.001
Household size	-0.0310	0.0011	0.970	< 0.001
ln(MPCE)MPCE)	0.2052	0.0058	1.228	< 0.001

Source: Authors' calculations from NSS 80th Round (Schedule 25.0), NSO.
Note: Dependent variable Insured = 1/0. Reference categories: Hinduism (religion), Scheduled Tribe (social group).

3.4 Propensity Score Matching and Covariate Balance

Propensity scores were estimated for all 650,842 individuals from the logistic model above (306,775 insured; 344,067 uninsured). One-to-one nearest-neighbor matching without replacement, with a caliper of 0.116 (0.2 SD of the logit propensity score), yielded 253,548 matched pairs (82.7% of eligible treated individuals were successfully matched), producing a matched analytical sample of 507,096 individuals.

Table 4. Matching Summary

Item	Value
Treated (insured) individuals	306,775
Control (uninsured) individuals	344,067
Caliper (0.2 SD of logit propensity score)	0.116
Matched pairs formed	253,548

Match rate (share of treated matched)	82.7%
Total individuals in matched sample	507,096

Source: Authors' calculations from NSS 80th Round (Schedule 25.0), NSO.

Table 5 and Figure 3 show that matching dramatically improved covariate balance. The mean absolute standardized mean difference across all covariates fell from 0.102 before matching to 0.007 after matching, with the maximum remaining |SMD| at just 0.045 well below the conventional 0.10 threshold. Figure 4 further confirms that the propensity score distributions of the insured and uninsured groups, which showed limited overlap before matching, are closely aligned after matching, satisfying the common support assumption required for valid causal inference.

Table 5. Covariate Balance Before and After Matching (Standardized Mean Differences)

Covariate	SMD Before Matching	SMD After Matching
Age	0.4821	0.0127
Education	0.1957	-0.0447
Household size	-0.1753	-0.0045
ln (MPCE)	0.1840	0.0158
Religion: Hindu	0.0540	0.0032
Religion: Islam	-0.0734	-0.0023
Religion: Christian	0.0435	-0.0026
Religion: Sikh	-0.0823	-0.0008
Religion: Jain	0.0123	0.0022
Religion: Buddhist	-0.0106	-0.0004
Religion: Zoroastrian	0.0014	-0.0016
Religion: Others	0.0265	0.0009
Social group: ST	0.1240	0.0036
Social group: SC	0.0037	-0.0032
Social group: OBC	-0.1215	-0.0061
Social group: Others	0.0330	0.0068

Source: Authors' calculations from NSS 80th Round (Schedule 25.0), NSO.

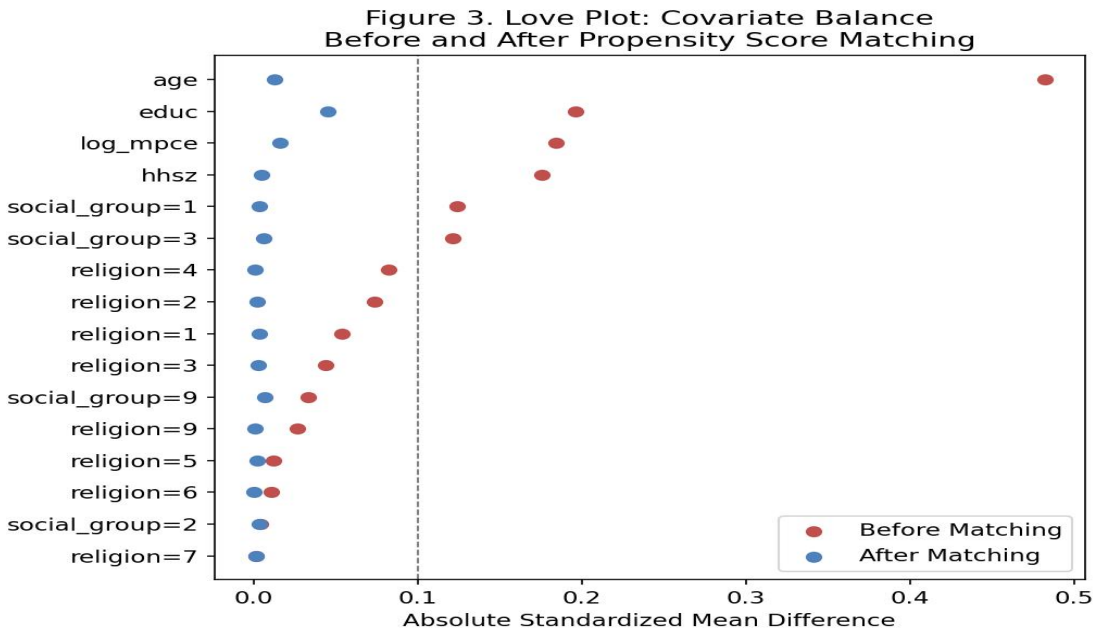


Figure 3. Love Plot — Absolute Standardized Mean Differences Before and After Matching

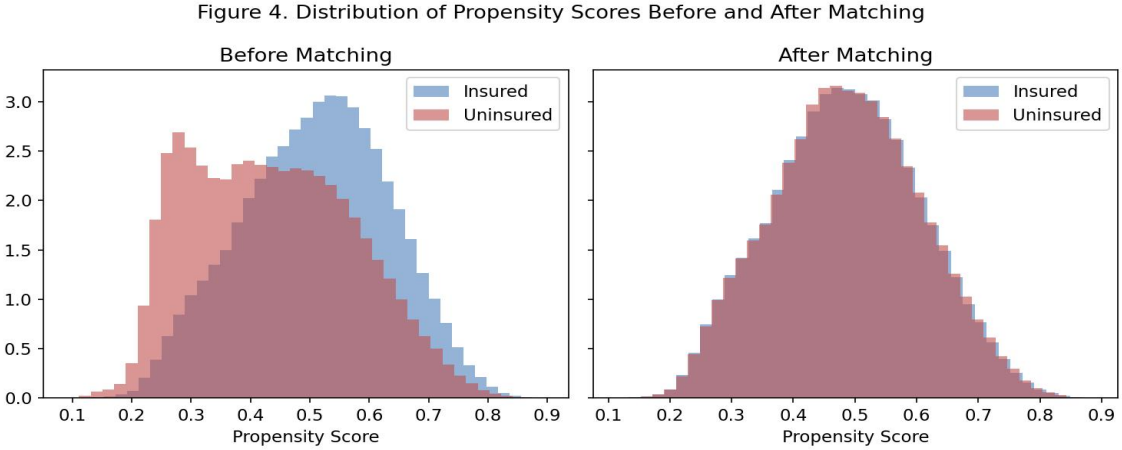


Figure 4. Distribution of Propensity Scores Before and After Matching

3.5 Average treatment Effect of Insurance on OOPE

On the matched sample, the simple (unadjusted) difference in mean OOPE between insured and uninsured individuals was small and slightly negative (−₹238), reflecting the extreme right-skew of raw expenditure and a small number of very high-cost uninsured cases. However, once the outcome is log-transformed and covariates are controlled for in the outcome regression, insurance coverage shows a positive and highly significant association with OOPE: the coefficient on insurance is 0.2609 (robust SE = 0.010, $p < 0.001$), which — since the dependent variable is in logarithmic form — implies that insured individuals incur approximately 29.8% higher out-of-pocket healthcare expenditure than observably comparable uninsured individuals.

Table 6. ATT Regression Results on Matched Sample (Dependent variable: ln(OOPE + 1); HC1 robust standard errors)

Statistic	Value
Insurance coefficient (β, log scale)	0.2609
Robust SE (HC1)	0.01
p-value	< 0.001
Implied % change in OOPE	29.80%
Matched-sample mean OOPE, insured (Rs.)	5962.8
Matched-sample mean OOPE, uninsured (Rs.)	6200.8

Naive (unadjusted) mean difference (Rs.)	-237.9

Source: Authors' calculations from NSS 80th Round (Schedule 25.0), NSO.

This finding is consistent with the broader literature: rather than eliminating direct medical payments, health insurance appears to increase healthcare utilization (more hospitalizations, more diagnostic tests, greater willingness to seek treatment), some of which still involves co-payments, non-covered services, or spending on care not fully reimbursed by the scheme (King et al., 2009; Wagstaff et al., 2009).

3.6 Equity in Healthcare Financing

Equity indices were computed over the full analytical sample using MPCE as the measure of living standards. The Concentration Index of OOPE (ranked by MPCE) is 0.274, indicating that out-of-pocket healthcare spending is concentrated among relatively wealthier households in absolute terms. The Gini coefficient of MPCE is 0.291, indicating a moderate degree of consumption inequality in the sample. The Kakwani Progressivity Index, the difference between the two, is 0.017, a small negative value indicating that healthcare financing in this sample is mildly regressive: poorer households devote a marginally larger share of their resources to healthcare than richer households, even though richer households pay more in absolute rupee terms.

Table 7. Equity Indices for Healthcare Financing

Index	Value
Concentration Index of OOPE (ranked by MPCE)	0.2737
Gini Coefficient of MPCE	0.2909
Kakwani Progressivity Index	-0.0171

Source: Authors' calculations from NSS 80th Round (Schedule 25.0), NSO

3.7 Composition of Coverage and Out-of-Pocket Expenditure by Scheme

Although the treatment variable in the matched analysis is binary, the survey data records the specific scheme under which each covered individual is enrolled. This section uses that record for two purposes: to characterise the composition of coverage, and to decompose the difference in expenditure between insured and uninsured individuals into its extensive and intensive margins, a distinction that bears directly on how the treatment effect in Section 3.5 should be read.

Insurance coverage is overwhelmingly publicly financed. Table 8 disaggregates the 306,775 insured individuals in the analytical sample by reported scheme. The two publicly financed schemes account for most of all coverage. AB-PMJAY covers 56.0% of insured individuals, and State health insurance schemes cover 32.9%, so that together they constitute 88.9% of all reported coverage and 41.9% of the full analytical sample. Applying the survey multipliers, these two schemes alone extend to an estimated 289.6 million and 205.9 million persons, respectively, or 41.1% of the population.

All remaining categories are small by comparison. Privately purchased commercial insurance covers 4.0% of insured individuals (2.1% of the population). The five employer-linked and government-employee schemes, namely ESIS/ESIC, CGHS/ECHS and other central government schemes, state government medical reimbursement, PSU employer coverage, and other employer-provided insurance, together account for 7.1% of the insured and 3.2% of the population. None of these five exceeds 2.3% of insured individuals on their own, and PSU-provided coverage is reported by only 1,525 individuals (0.5%). Estimates for these categories are correspondingly imprecise and are reported for completeness rather than as a basis for scheme-level comparison.

The composition observed here is consistent with the policy trajectory of the past decade, in which the expansion of nominal coverage in India has been driven almost entirely by tax-financed public schemes rather than by growth in contributory or commercial insurance (Selvaraj & Karan, 2012).

Table 8. Composition of Health Insurance Coverage by Scheme (NSS 80th Round)

Code	Scheme	N	% of insured	% of sample	Wtd % of pop.	Wtd persons (m)
01	AB-PMJAY	171,862	56.02	26.41	24.00	289.6
02	State Health Insurance Scheme	100,948	32.91	15.51	17.06	205.9
10	Only privately purchased	12,258	4.00	1.88	2.14	25.8

	commercial					
05	State govt. medical reimbursement [a]	6,878	2.24	1.06	0.78	9.4
04	CGHS/ECHS/ other Central Govt.[a]	5,650	1.84	0.87	0.71	8.6
07	Other employer insurance [a]	4,138	1.35	0.64	0.91	11.0
03	ESIS/ESIC [a]	3,516	1.15	0.54	0.62	7.5
06	PSU as employer [a]	1,525	0.50	0.23	0.18	2.1
	All insured	306,775	100.00	47.14	46.41	560.0
19	Not covered (reference)	344,067	n/a	52.86	53.59	646.5

Source: Authors' own Calculation. Scheme codes from Block 3, column 17; codes 08 and 09 undefined in the codebook. Single-response item, so individuals in multiple schemes are counted once. [a] Marked categories each under 2.3% of the insured; estimates imprecise and not further disaggregated (together 7.08% of the insured, n = 21,707).

Notes: Scheme codes from Block 3, column 17; codes 08 and 09 undefined in the codebook. Single-response item, so individuals in multiple schemes are counted once. [a] Marked categories each under 2.3% of the insured; estimates imprecise and not further disaggregated (together 7.08% of the insured, n = 21,707).

Out-of-pocket expenditure also differs markedly across insurance schemes (Table 9). Survey-weighted mean combined OOPE ranges from ₹1,121 among the uninsured to ₹2,936 among individuals with privately purchased commercial insurance. Among the two major publicly financed schemes, mean OOPE is ₹1,400 for AB-PMJAY members and ₹1,345 for state-scheme members, approximately 20–25% higher than among the uninsured.

These differences across schemes should be interpreted considering the characteristics of the populations covered by each type of insurance. Private and employer-linked coverage is more concentrated among relatively wealthier and urban populations, who may face higher provider prices and make greater use of private healthcare facilities. Differences in OOPE across schemes may therefore reflect differences in the socioeconomic composition of beneficiaries, healthcare utilisation, and provider choice, in addition to differences in insurance coverage itself.

The expenditure pattern can be further understood along the two margins of expenditure: the extensive margin, which captures whether an individual incurred any OOPE, and the intensive margin, which captures the amount spent among those with positive expenditure.

On the extensive margin, insured individuals across every scheme are more likely to record positive out-of-pocket spending than the uninsured: 16.3% of AB-PMJAY members and 19.2% of state-scheme members reported positive combined expenditure, compared with 11.6% of the uninsured. The pattern changes on the intensive margin. Among individuals with positive expenditure, mean OOPE was lower for AB-PMJAY members (₹22,678) and state-scheme members (₹19,888) than for the uninsured (₹25,460). In contrast, individuals with privately purchased insurance (₹41,960) and other employer-provided coverage (₹31,542) recorded substantially higher conditional expenditure.

For the two large publicly financed schemes, the higher unconditional mean therefore appears to reflect the extensive margin primarily: members are more likely to incur healthcare expenditure, while those who incur expenditure spend less on average than uninsured individuals. This contrasts with that of private and employer-linked coverage, where expenditure is higher on both margins. Among publicly financed scheme members, the observed difference may reflect higher healthcare utilisation and improved access to care after insurance coverage. However, these descriptive comparisons alone cannot establish whether insurance caused the observed difference in utilisation.

The unweighted means in the final column of Table 9 run roughly three to five times their weighted equivalents, reflecting the survey's oversampling of households with a hospitalised member. The rank ordering of schemes is almost unchanged between the two, so only the weighted figures should be read as

population-level magnitudes.

Table 9. Out-of-Pocket Expenditure by Insurance Scheme (₹)

Scheme	Weighted mean IPD	Weighted mean OPD	Weighted mean combined	% zero OOPE	Weighted mean if > 0	Unweighted mean
AB-PMJAY	1,250	151	1,400	83.7	22,678	6,397
State Health Insurance Scheme	1,159	186	1,345	80.8	19,888	5,614
ESIS/ESIC[a]	2,272	132	2,404	82.1	25,943	7,954
CGHS/ECHS/ other Central Govt.[a]	2,166	298	2,463	77.2	23,244	8,561
State govt. medical reimbursement [a]	2,244	318	2,562	77.0	27,982	9,235
PSU as employer [a]	1,751	329	2,080	72.3	21,017	7,870
Other employer insurance[a]	1,886	259	2,145	83.0	31,542	10,412
Only privately purchased commercial	2,673	263	2,936	79.5	41,960	15,229
Not covered (reference)	1,006	115	1,121	88.4	25,460	5,110

Source: Authors' calculations from NSS 80th Round (Schedule 25.0), NSO. Median expenditure ₹0 for all schemes, omitted. Zero-expenditure percentages survey-weighted. IPD 365-day recall, OPD 15-day recall; combined expenditure mixes the two reference periods. [a] Marked categories each under 2.3% of the insured; estimates imprecise.

3.8 Incidence and Intensity of Catastrophic Health Expenditure

Table 10 reports catastrophic health expenditure at the national level and by household insurance status. Under the hospitalisation-based measure (Variant A), 5.99% of Indian households, or approximately 17.7 million, incurred out-of-pocket payments exceeding 10% of annual consumption expenditure, and 2.99% exceeded the 25% threshold. Under the broader annualised measure (Variant B), these figures rise to 23.40% and 12.60% respectively. The large difference between the two measures primarily reflects the treatment of expenditure reported over the 15-day outpatient recall period, and the two should be read as the bounds of a range rather than as competing point estimates.

Catastrophic payments, where they occur, are severe. Among households crossing the 10% threshold under the hospitalisation-based measure, out-of-pocket spending averaged ₹80,885 (median ₹46,500), which is 46.7% of annual household consumption on average, representing a mean positive overshoot of 36.7 percentage points above the threshold. Set against a weighted mean annual household consumption of ₹180,125, this indicates that affected households devoted close to half of a year's total consumption to a single episode of care.

Households with at least one insured member were more likely to incur catastrophic expenditure than fully uninsured households: 6.28% against 5.59% at the 10% threshold under the hospitalisation-based measure, and 25.72% against 20.19% under the annualised measure (Table 10). This ordering is consistent in direction with the propensity-score results reported in Section 3.5 and points to an insurance-induced utilisation effect rather than weaker financial protection alone.

A more nuanced pattern emerges in the intensity

measure. Although insured households cross the catastrophic threshold more often, they overshoot it by less: the mean positive overshoot was 0.355 among insured households against 0.387 among uninsured households at the 10% threshold, and 0.508 against 0.547 at the 25% threshold under the hospitalisation-based measure. The same contrast is observed under the annualised measure. This is consistent with existing schemes absorbing part of the cost of the largest episodes while at the same time lowering the effective price of seeking care, so that the depth of catastrophic payments falls even as their frequency does not.

Table 10. Catastrophic Health Expenditure, All India and by Household Insurance Status (survey-weighted)

Specification	Threshold	Group	Headcount (%)	Mean overshoot
Variant A (hospitalisation-based)	10%	All	5.99	0.367
		Insured	6.28	0.355
		Uninsured	5.59	0.387
	25%	All	2.99	0.523
		Insured	3.08	0.508
		Uninsured	2.86	0.547
Variant B (annualised)	10%	All	23.40	0.377
		Insured	25.72	0.366
		Uninsured	20.19	0.397
	25%	All	12.60	0.496
		Insured	14.00	0.470
		Uninsured	10.65	0.544

Source: Authors' calculations from NSS 80th Round (Schedule 25.0), NSO.
Notes: Survey-weighted. N = 139,732 households (294.8 million weighted). Mean annual household consumption ₹180,125 (median ₹157,500). Insured = at least one member covered by any scheme; n = 88,171 insured, 51,561 uninsured. Household definition differs from the individual-level treatment in Sections 2.3 to 2.5.

Table 11 presents catastrophic health expenditure by sector and economic status. Rural households were more exposed than urban households on both dimensions: 6.22% against 5.59% at the 10% threshold, with a higher mean overshoot (0.379 against 0.346). The gap between rural and urban households widens at the 25% threshold (3.21% against 2.61%).

The socio-economic gradient is the principal finding of Table 11. Catastrophic expenditure declines steadily across the consumption distribution: 6.56% of households in the poorest quintile incurred catastrophic payments at the 10% threshold, against 5.07% in the richest, a relative excess of 29% for the poorest quintile. The gradient is steeper still at the 25% threshold (3.51% against 2.49%, a 41% excess).

The intensity gradient runs in the same direction as the incidence gradient. The mean positive overshoot falls from 0.416 in the poorest quintile to 0.342 in the richest at the 10% threshold, and from 0.571 to 0.482 at the 25% threshold. Poorer households are therefore not only more likely to be pushed into catastrophic expenditure but are pushed further beyond the threshold when they are. This reinforces the equity findings of Section 3.6: although the Concentration Index shows that out-of-pocket payments are larger in absolute terms among better-off households, the burden relative to resources falls disproportionately on the poor, consistent with the mildly negative Kakwani Index reported there.

Table 11 also reports unweighted headcounts alongside the weighted estimates, and the contrast is instructive. Unweighted, the quintile pattern is flat and non-monotonic (29.97% in the poorest quintile and 30.34% in the richest, with the intermediate quintiles higher than both) and would suggest that catastrophic expenditure is unrelated to economic status. That conclusion would be an artefact of the survey's deliberate over-sampling of households that contain a hospitalised member. The socio-economic gradient becomes clearly apparent once the survey multipliers are applied.

Table 11. Catastrophic Health Expenditure by Sector and Economic Status (Variant A, hospitalisation-based)

Group	N (households)	CHE10 weighted (%)	CHE25 weighted (%)	Overshoot at 10%	CHE10 unweighted (%)
Sector					
Rural	76,296	6.22	3.21	0.379	30.86
Urban	63,436	5.59	2.61	0.346	31.11
MPCE quintile					
Q1 (poorest)	29,701	6.56	3.51	0.416	29.97
Q2	28,652	6.26	3.07	0.359	31.19
Q3	28,758	6.01	2.92	0.347	31.38
Q4	28,959	6.07	2.95	0.365	31.91
Q5 (richest)	23,662	5.07	2.49	0.342	30.34

Source: Authors' calculations from NSS 80th Round (Schedule 25.0), NSO.
Notes: Survey-weighted. Weighted MPCE quintile cut-points ₹2,253, ₹2,995, ₹3,915, ₹5,564 per person per month. Unweighted headcounts shown for comparison only.

Under the hospitalisation-based measure, the distribution is highly concentrated. 86.3% of households recorded no inpatient expenditure at all, and the median and 75th percentile of the health share are both zero. The distribution becomes material only in the upper tail, at 2.4% of consumption at the 90th percentile, 13.6% at the 95th, and 64.7% at the 99th. Financial burden from health payments in India is therefore highly concentrated. With a relatively small proportion of households experiencing the most severe healthcare expenditure shocks.

4. Discussion

Three main findings emerge from this analysis of the NSS 80th round data. First, insurance enrolment remains socially patterned: it rises with age, education, and economic status, and varies significantly by religion and social group, even though overall coverage (47%) has expanded considerably relative to earlier survey rounds (Joe, 2015). Second, after rigorously controlling for observable selection into insurance via Propensity Score Matching, insured individuals still incur significantly higher, not lower, out-of-pocket expenditure than comparable uninsured individuals. This is consistent with an induced-utilization effect: insurance lowers the effective price of care and encourages greater use of health services, but existing schemes evidently do not fully cover the resulting costs (e.g., diagnostics, medicines, or services outside the covered benefit package), leaving a residual direct payment burden (King et al., 2009; Prinja et al., 2019). Third, equity analysis shows that while absolute OOPE is concentrated among wealthier households (positive Concentration Index), the burden relative to household resources is close to proportional but mildly regressive (small negative Kakwani Index) — a less severe regressivity than reported in some earlier studies, plausibly reflecting the expansion of publicly-financed schemes targeted at poorer households in the years since 2017–18 (Selvaraj & Karan, 2012).

These results reinforce a now well-established finding in the health-financing literature for India: expanding insurance enrolment alone is not sufficient to achieve full financial protection (Joe, 2015). Strengthening benefit packages (particularly for out-patient care and medicines), streamlining reimbursement, and improving targeting of vulnerable groups remain necessary complements to coverage expansion.

The scheme-wise and household-level results reported in Sections 3.7 and 3.8 lend further support to this interpretation. Among members of the two large publicly financed schemes, which together account for nearly nine-tenths of all coverage, higher out-of-pocket expenditure operates entirely through the extensive margin: enrollees are more likely to incur any expenditure than the uninsured yet spend less than uninsured individuals once they spend at all. At the household level, about 6% of Indian households, some 17.7 million, incur health payments exceeding a tenth of their annual consumption, and both the incidence and the intensity of these catastrophic payments decline steadily with economic status, so that the poorest quintile is not only more exposed but is pushed further beyond the threshold when exposure occurs. Read alongside the mildly regressive Kakwani Index reported in Section 3.6, this suggests that the aggregate proportionality of health financing in India conceals a burden borne disproportionately by poorer households, and that the positive treatment effect on expenditure reflects insurance drawing previously untreated individuals into care rather than a failure of financial protection among enrollees.

5. Limitations

This analysis has several important limitations. First, PSM corrects for selection bias only on observed covariates; unobserved factors such as risk aversion, underlying health status, or awareness of entitlements may still bias the estimated treatment effect (Austin, 2011; Rosenbaum & Rubin, 1983). Second, the outcome variable combines a 365-day hospitalisation recall period with a 15-day out-patient recall period, which are not directly comparable in scale; results should be interpreted as a composite indicator of recent direct healthcare payments rather than a precisely annualized OOPE figure. Third, the analysis is unweighted at the individual level (i.e., survey design weights were not applied in the regression and matching steps, consistent with standard micro-econometric PSM practice) (Stuart, 2010), so results describe relationships within the achieved sample rather than population-level totals; population-representative aggregates would require applying the survey multiplier (mult/100) throughout. Fourth, insurance status is a single-response variable in the source survey, so individuals covered by multiple schemes are recorded under only one, which may understate the depth of coverage for some households. Fifth, as with any cross-sectional survey, the estimated relationships should be interpreted as associational rather than strictly causal in the counterfactual sense, notwithstanding the use of PSM.

Sixth, the catastrophic-expenditure analysis (Section 3.8) is survey-weighted and defined at the household level, whereas the matched analysis is unweighted and defined at the individual level, So the two sets of estimates are not directly comparable. Only the budget-share thresholds could be computed, because Schedule 25.0 does not collect food-expenditure information required for the capacity to pay measure. The hospitalisation-based and annualised measures (Variants A and B) differ roughly fourfold at the 10% threshold, a range that reflects genuine uncertainty about how to treat the 15-day outpatient recall rather than sampling error. CHE captures realized expenditure only and may not identify households that forego unaffordable care.

Seventh, the scheme-wise results (Section 3.7) are unadjusted for systematic differences in the characteristics of individuals enrolled across schemes. Consequently, the observed variation in OOPE cannot be attributed to differences in insurance coverage, as healthcare utilisation patterns, socioeconomic characteristics, and provider choice may also have contributed to these differences. Smaller scheme category estimates are less precise due to their limited sample shares.

6. Conclusion and Policy Implications

Using the most recent nationally representative government microdata (NSS 80th round, 2025), this study finds that health insurance coverage in India remains socio-economically patterned and that insured individuals incur significantly higher out-of-pocket expenditure than matched uninsured individuals, providing evidence of an insurance-induced utilization effect rather than full financial protection. CHE analysis further shows that insured households experience a higher incidence of catastrophic expenditure, but a lower depth of catastrophic expenditure among affected households. Healthcare financing remains mildly regressive overall. Policy priorities implied by these findings include: (i) expanding effective, rather than merely nominal coverage, particularly for out-patient care and medicines, which remain major sources of uncovered direct payments; (ii) simplifying and speeding up reimbursement processes; (iii) targeted outreach to older, less-educated, and socially disadvantaged households who remain under-insured; and (iv) continued monitoring of financial-protection indicators - not just enrolment counts as the primary metric of scheme effectiveness (WHO & World Bank, 2023; World Bank, 2023; National Health Authority, 2023).

Two features of the results sharpen these priorities. Because coverage is now overwhelmingly publicly financed, with AB-PMJAY and the state schemes accounting for close to nine-tenths of all enrolment, the effectiveness of these two schemes is particularly important for financial protection. Moreover, catastrophic health expenditure remains concentrated among poorer households; financial-protection indicators are most informative when disaggregated by consumption quintile rather than reported only in aggregate.

Data and Reproducibility Note

All statistics reported in this document were computed directly from the released NSS 80th round unit-level data files (hhscsL1–L7.csv), using the variable definitions in the official Data Layout and Codes documentation (NSO, 2025). Sample sizes, coefficients, and indices in this report are original computations from that data and are not reproduced from any previously published study.

An Empirical Analysis Using Unit-Level Microdata from the NSS 80th Round (January–December 2025), Household Social Consumption: Health Survey

Data source: National Statistical Office (NSO), Government of India - Unit-level records (Schedule 25.0)

References

1. Austin, P. C. (2011). An introduction to propensity score methods for reducing the effects of confounding in observational studies. Multivariate Behavioral Research, 46(3), 399–424. https://doi.org/10.1080/00273171.2011.568786
2. Gini, C. (1912). Variabilità e mutabilità. Tipografia di Paolo Cuppini.
3. Hosmer, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). Applied logistic regression (3rd ed.). John

Wiley & Sons. https://doi.org/10.1002/9781118548387
4. Imbens, G. W. (2004). Nonparametric estimation of average treatment effects under exogeneity: A review. Review of Economics and Statistics, 86(1), 4–29. https://doi.org/10.1162/003465304323023651
5. Joe, W. (2015). Distressed financing of household out-of-pocket health care payments in India: Incidence and correlates. Health Policy and Planning, 30(6), 728–741. https://doi.org/10.1093/heapol/czu050
6. Kakwani, N. C. (1977). Measurement of tax progressivity: An international comparison. The Economic Journal, 87(345), 71–80. https://doi.org/10.2307/2231833
7. King, G., Gakidou, E., Imai, K., Lakin, J., Moore, R. T., Nall, C., Ravishankar, N., Vargas, M., Téllez-Rojo, M. M., Ávila, J. E. H., Ávila, M. H., & Llamas, H. H. (2009). Public policy for the poor? A randomised assessment of the Mexican universal health insurance programme. The Lancet, 373(9673), 1447–1454. https://doi.org/10.1016/S0140-6736(09)60239-7
8. Manning, W. G., & Mullahy, J. (2001). Estimating log models: To transform or not to transform? Journal of Health Economics, 20(4), 461–494. https://doi.org/10.1016/S0167-6296(01)00086-8
9. National Health Authority. (2023). Ayushman Bharat Pradhan Mantri Jan Arogya Yojana (AB-PMJAY): Annual report 2022–23. Government of India.
10. National Health Systems Resource Centre (NHSRC). (2022). National health accounts estimates for India, 2018–19. Ministry of Health and Family Welfare, Government of India.
11. National Statistical Office (NSO). (2025). Household social consumption: Health, NSS 80th round (January–December 2025): Unit-level data, Schedule 25.0. Ministry of Statistics and Programme Implementation, Government of India.
12. O'Donnell, O., van Doorslaer, E., Wagstaff, A., & Lindelow, M. (2008). Analyzing health equity using household survey data: A guide to techniques and their implementation. The World Bank. https://doi.org/10.1596/978-0-8213-6933-3
13. Prinja, S., Jagnoor, J., Sharma, D., Aggarwal, S., Katoch, S., Lakshmi, P. V. M., & Ivers, R. (2019). Out-of-pocket expenditure and catastrophic health expenditure for hospitalization due to injuries in public sector hospitals in North India. PLOS ONE, 14(11), e0224721. https://doi.org/10.1371/journal.pone.0224721
14. Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. Biometrika, 70(1), 41–55. https://doi.org/10.1093/biomet/70.1.41
15. Selvaraj, S., & Karan, A. K. (2012). Why publicly-financed health insurance schemes are ineffective in providing financial risk protection. Economic & Political Weekly, 47(11), 60–68.
16. Stuart, E. A. (2010). Matching methods for causal inference: A review and a look forward. Statistical Science, 25(1), 1–21. https://doi.org/10.1214/09-STS313
17. United Nations. (2015). Transforming our world: The 2030 Agenda for Sustainable Development (A/RES/70/1). United Nations.
18. Wagstaff, A., Lindelow, M., Jun, G., Ling, X., & Juncheng, Q. (2009). Extending health insurance to the rural population: An impact evaluation of China's new cooperative medical scheme. Journal of Health Economics, 28(1), 1–19. https://doi.org/10.1016/j.jhealeco.2008.10.007
19. Wagstaff, A., Paci, P., & van Doorslaer, E. (1991). On the measurement of inequalities in health. Social Science & Medicine, 33(5), 545–557. https://doi.org/10.1016/0277-9536(91)90212-U
20. Wagstaff, A., & van Doorslaer, E. (2003). Catastrophe and impoverishment in paying for health care: With applications to Vietnam 1993–1998. Health Economics, 12(11), 921–933. https://doi.org/10.1002/hec.776
21. World Bank. (2023). Walking the talk: Reimagining primary health care after COVID-19. World Bank.
22. World Health Organization (WHO). (2010). The world health report 2010: Health systems financing: The path to universal coverage. World Health Organization.
23. World Health Organization (WHO), & World Bank. (2023). Tracking universal health coverage: 2023 global monitoring report. World Health Organization.
24. Xu, K., Evans, D. B., Kawabata, K., Zeramdini, R., Klavus, J., & Murray, C. J. L. (2003). Household catastrophic health expenditure: A multicountry analysis. The Lancet, 362(9378), 111–117. https://doi.org/10.1016/S0140-6736(03)13861-5