Does Public Health Insurance Provide Effective Protection? Evidence on Financial Exposure and Depressive Symptoms Among Poor Older Adults in India

Abstract

India's government-financed health insurance programmes cover inpatient care; however, they do not adequately cover outpatient services, medications, or mental health support. Whether this gap is associated with financial protection and depressive symptom trajectories among Below Poverty Line (BPL) older adults remains unclear. We examine whether government health insurance is associated with greater financial protection and lower depressive symptoms, and whether expenditure exposure predicts subsequent depressive symptom trajectories. Linking the Longitudinal Ageing Study in India (LASI) Wave 1 (N=73,408) with the LASI-Diagnostic Assessment of Dementia (LASI-DAD) panel (N=4,048), we compare BPL-insured and uninsured individuals using overlap weighting (OW) and augmented overlap weighting (AOW), with analysis of covariance (ANCOVA), change-score specifications, bootstrap inference, and state fixed effects (FEs). Insurance was associated with higher hospitalisation, out-of-pocket expenditure (OOPE), and catastrophic health expenditure (CHE) at 10% and 40% thresholds, but not psychiatric care uptake. Higher OOPE predicted greater depressive symptoms; insurance was associated with higher follow-up symptoms among BPL beneficiaries, with no corresponding overall-sample association. These findings suggest that hospital-centric insurance may not ensure effective financial or mental-health protection, especially among vulnerable older adults, supporting the need for broader outpatient, pharmaceutical, and mental-health coverage.

Keywords: financial risk protection; out-of-pocket health expenditure; depressive symptoms; older adults; public health insurance; Below Poverty Line

1. Introduction

Universal Health Coverage (UHC) continues to be one of the most ambitious goals of global health policy. Yet financial protection from health spending remains elusive for large segments of the global population despite decades of reform. OOPE leads to financial hardship for around 800 million people worldwide each year, pushing about 100 million of them into poverty (Kieny et al., 2017). Sustainable Development Goal (SDG) 3 particularly focuses on protecting nations from financial risk in healthcare. Still, progress remains uneven, especially in Low- and Middle-Income Countries (LMICs), where public health funding is limited, and systems must contend with rapidly changing demographic and epidemiological pressures (World Health Organisation, 2024). These pressures have been exacerbated by population ageing and the growing prevalence of non-communicable diseases (NCDs), such as depression, the leading cause of disability globally. This raises a question that goes beyond simple coverage expansion: does government insurance, as actually designed and implemented, provide its target population with effective health and financial protection? This is especially severe for older adults living in poverty in LMICs, where there is the greatest disparity between nominal enrolment and meaningful financial protection, and where insufficient coverage extends beyond financial hardship to sustained mental health deterioration (van Hees et al., 2019). India, home to the world's largest publicly funded health insurance scheme and one of the rapidly ageing LMIC populations, provides a relevant policy-centric environment to evaluate this question.

2. Background

2.1. Healthcare Financing and the Elderly Poor

India has a particularly important healthcare financing crisis. OOPE remains one of the major sources of funding for healthcare in the country, accounting for 39.4% of total health expenditure (THE). By 2050, the share of Indians over 60 would have nearly doubled from 10.5% in 2022 to roughly 20.8%, or 347 million older adults (National Health Accounts Estimates for India 2021–22; United Nations Population Fund, 2023). India’s older population is expected to exceed children aged 0-14 by 2046 for the first time, with the 80+ cohort, the generation most in need of care, growing by around 279% between 2022 and 2050. This shift is additionally shaped by feminisation, regional inequality, and, critically, is occurring before the nation has become wealthy. This demographic shift substantially increases demand for healthcare services and troubles financing systems already characterised by high private spending.

More than 40% of India's elderly live in the poorest wealth quintile, with 18.7% having no income, severely blocking access to healthcare as health needs intensify (United Nations, 2019; WHO, 2025). About three-quarters of elderly Indians live with at least one chronic condition, many face functional disability, and depression is common but under-recognised (LASI, 2020). Yet very few have meaningful insurance or an adequate pension, leaving care overwhelmingly OOPE and informally delivered, compounded by the gradual erosion of traditional family-based support systems.

These pressures are most acute among BPL older adults, at the intersection of economic deprivation, physical morbidity, and mental health burden. Depressive symptoms affect nearly 30% of India's elderly, yet treatment gaps exceed 80%, concentrated among those with low income, no pension, and rural residence, the socioeconomic profile of BPL households (Tiwari et al., 2012; Perianayagam et al., 2022). For these households, a single hospitalisation can trigger catastrophic financial distress, since drugs and outpatient care, largely outside insured benefits, dominate OOPE with no savings cushion (Ahmad & Mohanty, 2024; Singh, 2019). Poor households are caught in a self-reinforcing cycle of illnesses, financial hardship, and psychological difficulties, which is an important risk factor for depressive symptoms (Ridley et al., 2020). Less than 2% of the national health budget is allocated to mental health treatments, despite the estimated 150 million Indians who need them.BPL older adults who have no private options especially bear the brunt of this shortfall (Rathod et al., 2017).

2.2. Public Insurance Expansion and Financial Protection

Recent reforms have been implemented to address these hardships. The Ayushman Bharat-Pradhan Mantri Jan Arogya Yojana (AB-PMJAY), which came in 2018, expanded inpatient coverage to the bottom 40% of the population, nominally containing 10 mental health packages. The Mental Healthcare Act 2017 emphasised insurance support for mental illnesses. The most clinically acceptable treatments for depression are outpatient counselling, psychiatric medication, and psychotherapy; yet, coverage is still limited to hospitalisation (Ghosh, 2021). An inpatient-only system provides insufficient protection for a population whose main unmet demand is inexpensive outpatient and pharmaceutical care. Studies show that hospitalisation increased after PM-JAY and Rashtriya Swasthya Bima Yojana (RSBY), although there is minimal evidence of decreased OOPE or CHE. (Karan et al., 2017; Parmar et al., 2023). Similar patterns are seen in private insurance, with OOPE in private institutions being several times higher than in public hospitals (Nandi et al., 2017; Prinja et al., 2019; Garg et al., 2022), reflecting that insurance expansion may improve utilisation without supporting significant financial protection.

2.3. Literature Gaps and Contribution

There remain a couple of important gaps in the literature. The majority of existing studies look at utilisation or financial protection separately (Garg et al., 2022; Ahmad & Mohanty, 2024), seldom focusing on the joint relationship between insurance and hospitalisation, CHE, psychiatric care use, and mental health trajectories, the various outcome dimensions that collectively determine welfare for older adults. Existing evaluations also disproportionately concentrate on the overall population and rarely break down by poverty status (Garg et al., 2024; Dubey et al., 2023), leaving BPL older adults largely under-studied. While international longitudinal evidence indicates public insurance significantly influences older adults' mental health trajectories (Thuong et al., 2020; Liao et al., 2025; Wang, 2024), comparable panel-based evidence in India is still lacking. The large reliance on cross-sectional designs further limits the identification of longitudinal health dynamics (Sarkodie, 2021; Sun et al., 2025). To our knowledge, no Indian study has systematically examined how government health insurance relates to mental health among BPL older adults using longitudinal data, despite well-documented depression prevalence, large treatment gaps, and acute financial hardship in this population (Perianayagam et al., 2022; Ridley et al., 2020).

Using nationally representative longitudinal data from LASI and the LASI-DAD panel, this study tries to fill these gaps. We evaluate whether government health insurance is linked to financial risk protection and lower follow-up depressive symptoms among BPL older adults, and, where protection seems to be limited, whether financial risk is associated with depressive trajectories. The results show a paradox: insurance coverage was linked with worse follow-up depressive symptoms despite higher healthcare utilisation, alongside higher OOPE and CHE, while higher OOPE was also independently associated with worse mental health in the overall insured sample. These results imply that financial toxicity can be a significant factor linked to insurance and mental health outcomes.

3. Theoretical Foundation

3.1. The Stress Process Model

This study draws on the Stress Process Model (Pearlin et al., 1981), which shows that mental health outcomes reflect the interplay between external stressors and the protective resources available to buffer their effects. Within this framework, primary stressors such as financial hardship and chronic diseases produce direct and immediate effects on depressive

symptoms, while secondary stressors act more gradually, compounding distress over time. Structural disadvantage further limits access to economic and institutional resources, which in turn heightens both exposure to stressors and vulnerability to their psychological consequences (Krause, 1987; Mirowsky & Ross, 1991).

This framework is directly applicable to BPL older adults in India, a population sitting with multiple sources of disadvantage: poverty, limited education, rural residence, multimorbidity, and precarious income. In the absence of adequate savings or financial safety nets, OOPE and CHE function as acute financial shocks that link health emergencies to financial hardship and psychological distress (Ridley et al., 2020; Wang et al., 2023). Therefore, it is possible to conceptualise OOPE as a major financial stressor linked to healthcare utilisation and mental health trajectories in this group

3.2. The Financial Toxicity Framework

The stress process model is further supported by the financial toxicity framework, which shows how OOPE leads to psychological damage. It first emerged in oncology to measure both objective financial burden and the subjective distress linked to treatment costs (Zafar & Abernethy, 2013). Since then, it has been expanded to low-income populations and chronic illness (Altice et al., 2017; Witte et al., 2019). It contains a subjective component that captures the ensuing hardship and an objective component that measures OOPE in relation to household resources. Costs that are unforeseen, ongoing, and borne by households with little savings, conditions that are common among many BPL older persons in India, cause the most harm.

When applied here, the framework shows that financial vulnerability and distress may continue if insurance coverage is linked to increased healthcare utilisation without a corresponding decrease in OOPE. Greater utilisation may raise exposure to unforeseen costs because coverage primarily targets inpatient treatment, leaving outpatient, pharmaceutical, and mental health services under-covered. This illustrates how people perceive financial threat, which causes spending shocks to result in long-term distress and depression. (Altice et al., 2017; Witte et al., 2019).

3.3. The Stress-Buffering Hypothesis

The circumstances in which outside resources disrupt the stress-to-distress route are outlined by the stress-buffering hypothesis (Cohen & Wills, 1985). Functional matching is necessary for effective buffering because a resource reduces distress by attenuating the degree of the stressor rather than only by raising systemic engagement. When increasing engagement

results in leftover costs that exacerbate financial toxicity, misaligned institutional resources may worsen rather than alleviate distress.

This study looks at government health insurance as the primary buffer and public pension as a secondary, interacting buffer. If effective, insurance would be expected to reduce OOPE and CHE, decreasing the connection between financial stress and depression. However, hospital-centric coverage that leaves out outpatient, pharmaceutical, and mental health care may be linked to greater utilisation without commensurate decrease in residual costs, limiting its protective role and possibly exacerbating financial toxicity. In situations where insurance protection is limited, public pensions seem to function differently. As direct income transfers, they may be linked to more stable household resources, a higher effective CHE threshold, and fewer psychological effects of financial shocks (Kim et al., 2024; Guimbeau & Menon, 2024).

4. Empirical Evidence

There is conflicting and very context-dependent evidence regarding whether public insurance provides significant financial protection. A meta-analysis of 185 studies found that community-based health insurance significantly boosted utilisation and decreased OOPE and CHE, but its effects on health outcomes were still uncertain (Eze et al., 2023). As demonstrated by Thailand's UHC delivering notable OOPE reductions (Tangcharoensathien et al., 2020) and Indonesia's JKN scheme increasing inpatient admissions by 8.2% (Eralangga et al., 2018), comprehensive benefit design can serve as financial protection in contexts with limited resources.

International evidence shows that expanding public insurance improves mental health, mostly through easier access to care and less financial burden. The important evidence comes from the Oregon Health Insurance Experiment, where Medicaid coverage increased antidepressant use and mental health treatment, eliminated CHE, and decreased depression (Finkelstein et al., 2012; Baicker et al., 2013). Subsequent analyses reflect a decrease in undiagnosed and untreated depression (Baicker et al., 2018). While private insurance and contributory pensions have been linked to improved mental health among older adults (Jun & Aguila, 2021; Kim et al., 2024), Medicaid expansion in the US also leads to improved healthcare access, decreased poor mental health days, and may have decreased suicide rates (Griffith & Bor, 2020; Winkelman & Chang, 2018; Ortega, 2023). While CHE is connected with a higher risk of depression (Wang et al., 2023), basic medical insurance and pension are linked to decreased rates of depression among older individuals in LMICs, especially in low-income and rural populations (Gu et al., 2017; Liao et al., 2025; Zhou et al., 2025). The benefits

in China include considerable reimbursement as well as outpatient and pharmaceutical coverage features that are mostly lacking in the Indian context.

There is a paradox in the Indian experience since insurance expansion increases healthcare utilisation without ensuring equal financial security. While PM-JAY increased utilisation without significantly lowering OOPE or CHE overall (Parmar et al., 2023), insurance did not lower OOPE or CHE under RSBY (Karan et al., 2017). However, one hospital-based study reported significant reductions among patients with prior CHE, indicating heterogeneity (Kanwal et al., 2024). Private insurance provides similarly limited protection, with no reduction in OOPE, substantially higher expenditures in private facilities, and CHE affecting over half of private hospitalisations irrespective of insurance status (Garg et al., 2022; Prinja et al., 2019). Mental health coverage also remains limited: 17 of 33 insurance policies lack explicit mental illness coverage, and OOPE accounts for 64.2% of mental health spending despite the Mental Healthcare Act 2017 (Avula et al., 2025). Public pensions, however, have been associated with lower depression among the elderly poor (Guimbeau & Menon, 2024). To the best of our knowledge, no study has jointly examined insurance, financial exposure, and follow-up depressive symptoms among poor older adults using nationally representative longitudinal data in India.

5. Materials and Methods

We link two LASI datasets to construct the study panel: the nationally representative LASI Wave 1 baseline survey of 73,408 adults aged ≥45 years and their spouses, covering all states and UTs (IIPS, 2020), and the Harmonized LASI-DAD panel, a longitudinal subsample for cognitive and health outcomes, with Wave 1 conducted during 2017–2020 and Wave 2 during 2022–2024, providing approximately four years of follow-up (Lee et al., 2019; Chien et al., 2022). Records were linked using a unique person identifier.

To classify poverty status, household ration-card records were extracted from the LASI household file and linked to individual respondents via the primary key. Consistent with India's Public Distribution System, households holding Antyodaya Anna Yojana (AAY) or Priority Household (PHH) ration cards were classified as BPL (NFSA, 2013).

We employ two complementary designs: longitudinal panel models estimating associations between baseline insurance status and follow-up depressive symptoms, extended to hospitalisation, CHE, log outpatient OOPE, and log total OOPE, with supplementary insurance–pension interaction tests and cross-sectional baseline models examining insurance's associations with utilisation and financial risk protection. We assess whether government

health insurance is associated with financial exposure at baseline, and whether such exposure is associated with worse depressive symptoms at follow-up.

5.1. Study Design

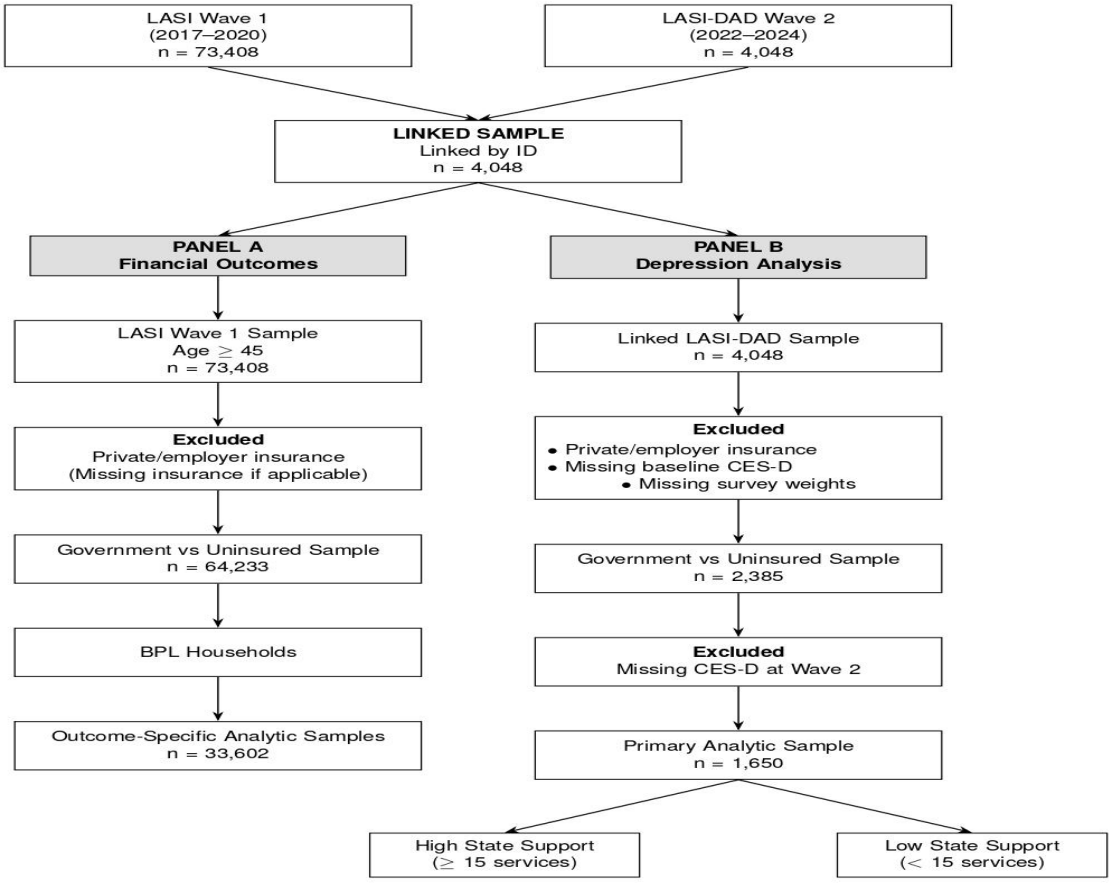


Figure 1. Construction of the Analysis Sample

5.2. Analytic Samples

Throughout, we excluded respondents with private or employer-sponsored insurance from the primary comparison and examined them separately in supplementary heterogeneity analysis (Supplementary Table A9).

Longitudinal sample

The primary longitudinal sample was restricted to respondents aged 60 years or older at baseline who were classified as either government-insured or uninsured, with non-missing baseline Center for Epidemiologic Studies Depression (CES-D) scores, baseline respondent survey weights, and Wave 2 CES-D scores. A state-support rule required at least 15

government-insured and 15 uninsured respondents per state to ensure sufficient within-state variation for models with state fixed effects (FEs). These restrictions yielded the primary analytic sample (N=1,650), with the BPL subgroup comprising 790 respondents.

Cross-sectional sample

Cross-sectional analyses included LASI baseline respondents aged ≥45. Financial-risk models were restricted to BPL households, comparing insured and uninsured respondents to reduce compositional differences, since time-invariant heterogeneity cannot be differenced out.

5.3. Exposure, Outcomes, and Covariates

Insurance status was measured at baseline (LASI Wave 1) and treated as fixed. Respondents were classified as government-insured (holding any central or state scheme, including CGHS, ESIS, RSBY, and state-sponsored plans) or uninsured, with the primary comparison focused on the BPL subsample.

The treatment indicator is baseline government insurance status:

$$T_i = 1\{\text{respondent } i \text{ reports government insurance at baseline}\}.$$

The primary longitudinal outcome is the Wave-2 CES-D-10 score (Y_{i2}); baseline CES-D-10 is denoted Y_{i1}. A secondary longitudinal outcome is CES-D change,

$$\Delta Y_i = Y_{i2} - Y_{i1}.$$

Cross-sectional pathway outcomes are hospitalisation, psychiatric medication, psychiatric treatment, inpatient $\mathrm{CHE} \geq 10\%$, total $\mathrm{CHE} \geq 10\%$, total $\mathrm{CHE} \geq 40\%$, conditional inpatient OOP ratio, and log-transformed OOP outcomes $\log(1 + \mathrm{OOP})$.

Baseline covariates used in weighted outcome models are age (linear), years of schooling, sex, rural residence, log household consumption, chronic-condition indicator, and state FEs. Propensity score models (PSM) additionally use spline age and smoking history.

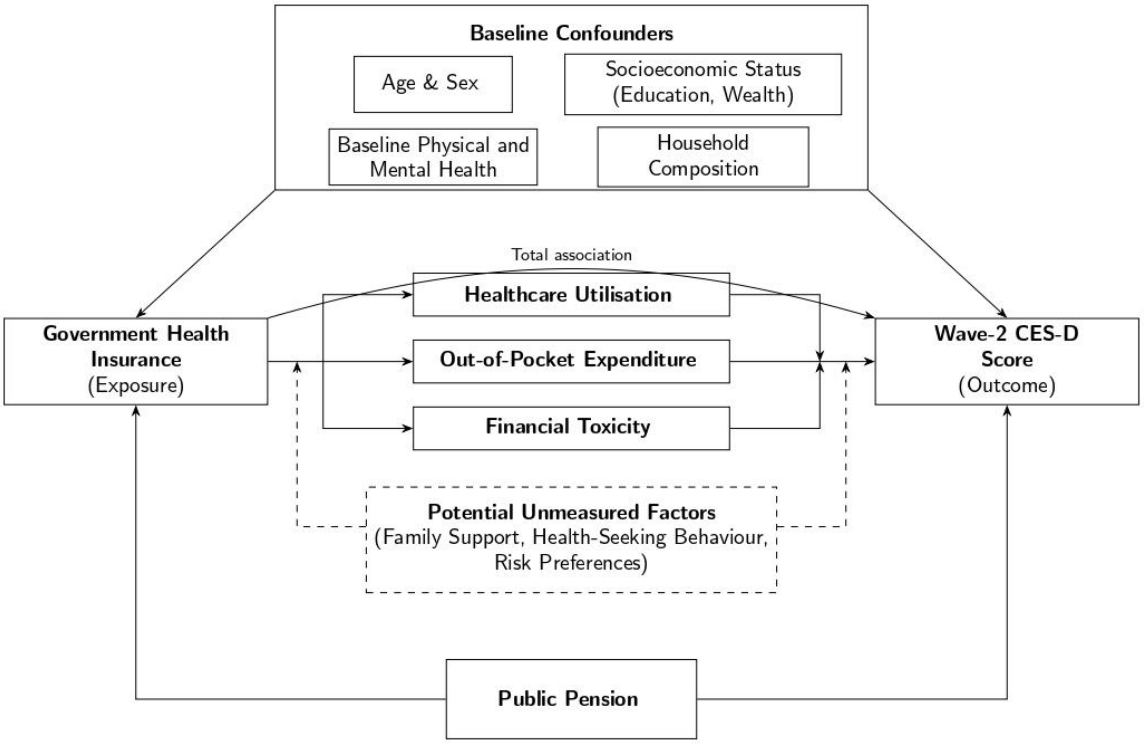


Figure 2. Conceptual Framework

5.4. Estimand and weighting strategy

Since insurance enrolment is non-random, we target the ATO, which emphasises respondents with comparable treatment propensity and reduces leverage from extreme scores (Li, Morgan, & Zaslavsky, 2018; Li, Thomas, & Li, 2019). Let i index respondents; $X_i$denote baseline covariates for treatment assignment; $Z_i$denote baseline covariates for retention; $s_i$denote baseline survey weight; and $s(i)$denote state.

PS are estimated as:

$$e_i = P(T_i = 1 \mid X_i), \text{logit}(e_i) = \alpha_0 + X_i'\alpha. \qquad (1)$$

Overlap weights are:

$$w_i^{OW} = \begin{cases} 1 - e_i, & T_i = 1 \\ e_i, & T_i = 0 \end{cases} \qquad (2)$$

Survey-weighted ow are:

$$w_i^{OWS} = w_i^{OW} \times s_i. \qquad (3)$$

To address differential follow-up into Wave-2 CES-D, we use stabilised inverse-probability-of-censoring weights (SIPCW) to reweight inference toward the retained pseudo-population under observed covariates (Robins et al., 2000; Wen et al., 2022). Let $R_i = 1$, If Wave-2 CES-D is observed:

$$\pi_i = P(R_i = 1 \mid Z_i), \text{logit}(\pi_i) = \eta_0 + Z_i'\eta. \qquad (4)$$

$$sw_i^{IPCW} = \frac{P(R = 1)}{\pi_i}. \qquad (5)$$

For the ANCOVA and change-score models, the final longitudinal analysis weights are:

$$w_i^{final} = \left(w_i^{OWS} \times \text{sw}_i^{IPCW}\right), \qquad (6)$$

The AOW estimator used the survey weight × SIPCW as the base weight, with OW incorporated internally.

Cross-sectional models use w_i^{OWS}(without IPCW).

5.5. Longitudinal models

The primary specification is an ANCOVA model:

$$Y_{i2} = \beta_0 + \tau T_i + \rho Y_{i1} + X_i'\gamma + \lambda_{s(i)} + \varepsilon_i, \qquad (7)$$

where $\tau$is the primary treatment parameter.

The secondary change-score specification is:

$$\Delta Y_i = \theta_0 + \tau_\Delta T_i + X_i'\kappa + \lambda_{s(i)} + u_i. \qquad (8)$$

Exploratory heterogeneity is estimated via:

$$Y_{i2} = \phi_0 + \phi_1 T_i + \phi_2 BPL_i + \phi_3 (T_i \times BPL_i) + \rho Y_{i1} + X_i'\gamma + \lambda_{s(i)} + \nu_i. \qquad (9)$$

Here, $\phi_1$is the non-BPL treatment effect and $\phi_1 + \phi_3$is the BPL marginal treatment effect.

We additionally estimated an AOW specification targeting the ATO, with inference based on 500 bootstrap replications.

5.6. Cross-sectional Financial Models

For binary outcomes, we estimate OW logistic models under two specifications: a baseline treatment-only specification,

$$\text{logit}\{P(Y_i = 1)\} = \alpha + \delta T_i \qquad (10)$$

and an adjusted specification that adds prespecified covariates and state FE,

$$\text{logit}\{P(Y_i = 1)\} = \alpha + \delta T_i + X_i'\gamma + \lambda_{s(i)}. \quad (11)$$

For expenditure outcomes, we estimate OW linear models on the $\log(1 + \text{OOP})$ scale under the same two specifications:

$$\log(1 + OOP_i) = \alpha + \delta T_i \qquad (12)$$

and

$$\log(1 + OOP_i) = \alpha + \delta T_i + X_i'\gamma + \lambda_{s(i)}. \quad (13)$$

5.7. Sensitivity, Robustness and Validation Analyses

ANCOVA Model Diagnostics

To assess ANCOVA validity, post-estimation diagnostics were conducted. Homogeneity of regression slopes was evaluated by interacting insurance with each covariate (Table 7, Panel A).

Sensitivity and Power Analyses

To assess sensitivity to residual confounding, particularly given the potential for adverse selection into government insurance and unobserved health characteristics, we report coefficient stability bounds (Oster, 2019), E-values (VanderWeele & Ding, 2017), and robustness values from the omitted-variable-bias (OVB) framework of Cinelli and Hazlett (2020).

External Triangulation

As external triangulation, we use WHO-SAGE India (Wave 2: 2015; Wave 3: 2019–2020) and the Lancet Citizens' Survey (2022–2023). Because these datasets differ from LASI-LASI-DAD in exposure and outcome definitions, sampling design, and survey period, triangulation was pre-specified to assess directional and contextual consistency rather than pooled effect sizes. Primary inference is based solely on LASI-LASI-DAD, with SAGE and Lancet findings reported as supplementary descriptive evidence.

Additional sensitivity analyses evaluated robustness by re-estimating the primary longitudinal models under alternative weighting specifications, including the official LASI longitudinal weight and household-clustered standard errors (SEs). Robustness was further assessed using permutation-based inference, leave-one-state-out analyses, negative-control (placebo) outcome analyses, and alternative specifications of baseline chronic disease status: (i) a binary indicator for any chronic condition, (ii) a polymorbidity measure (0, 1, ≥2 conditions), and (iii) individual disease indicators (Supplementary Tables A4–A8). These analyses assessed robustness across weighting assumptions, inferential methods, geographic influence, residual confounding, and chronic disease operationalisation.

6. Results

Table 1. Descriptive Characteristics of the Study Sample

Variable	A3 Baseline (N = 73,408)	DAD Wave 1 linked sample (N = 4,048)
Age (years)	57.95	68.83
	(0.049)	(0.121)
Education (years)	3.93	3.38
	(0.024)	(0.070)
Life satisfaction (1–7)	4.72	
	(0.007)	—
CES-D10 (0–30)	9.68	10.09
	(0.020)	(0.087)
ADL total	0.34	0.57
	(0.005)	(0.022)
IADL total	1.01	1.59
	(0.009)	(0.036)
Female	42,265	2,181
	(57.6%)	(53.9%)
Male	31,143	1,867
	(42.4%)	(46.1%)
Rural	47,417	2,505
	(64.6%)	(61.9%)
Urban	25,991	1,543

	(35.4%)	(38.1%)
Poor health	26,387 (36.4%)	—
Good health	46,066 (63.6%)	—
Public Pension	12,553 (17.1%)	2,164 (53.4%)
Insurance-BPL (Government, age ≥ 45 gov/uninsured sample)	8,460 (25.15%)	—
Insurance-BPL (Uninsured, age ≥ 45 gov/uninsured sample)	25,183 (74.85%)	—
Insurance – Uninsured	56,049 (77.2%)	3,157 (78.9%)
Insurance – Government	14,685 (20.2%)	761 (19.0%)
Insurance – Private/Other	1,056 (1.5%)	66 (1.6%)
Insurance – Employer	227 (0.3%)	6 (0.1%)
Insurance – Mixed/Multiple	567 (0.8%)	10 (0.2%)

Notes:(i) Column A3 includes all LASI Wave 1 baseline respondents; the DAD column includes linked respondents aged ≥60 with non-missing baseline CES-D and complete baseline covariates (N=4,048). (ii) Continuous variables show survey-weighted means (SEs). (iii) Categorical variables show unweighted counts (percentages). (iv) BPL insurance rows use the age ≥45 BPL insured-versus-uninsured comparison sample from Table 4.

Table 1 presents baseline characteristics across analytic samples. The LASI A3 sample (N=73,408) has a mean age of 57.95 years, 3.93 years of schooling, 57.6% women, and 64.6% rural residents; the linked LASI-DAD Wave 1 sample (N=4,048) is older (68.83 years), slightly less educated (3.38 years), 53.9% women, and 61.9% rural. A3 health indicators include 36.4% reporting poor health, mean ADL/IADL scores of 0.34/1.01, CES-D10 of 9.68, and life satisfaction of 4.72 (1–7 scale). Public pension receipt is 17.1% (A3) versus 53.4% (DAD), reflecting the latter's older profile. Insurance coverage is similarly limited across samples: 77.2% (A3) and 78.9% (DAD) uninsured, with government insurance at 20.2% and 19.0%, respectively. Of the government versus uninsured comparison group (age ≥45), 74.85%(N=25,183) do not have government insurance, while 25.15% (N=8,460) do.

Table 2. Covariate Balance Before and After Weighting

Variable	BPL–Government	BPL–Uninsured	BPL–Gov vs BPL–Unins (Unadj.)	BPL–Gov vs BPL–Unins (Adj.)
Age in years	58.84 (9.95)	59.88 (10.86)	0.100	0.010
Years of Education	2.97 (3.89)	2.85 (4.10)	0.029	0.030
Male (%)	47.1	45.6	0.032	0.014
Rural (%)	78.8	73.0	0.137	0.007
Log consumption	11.73 (0.73)	11.83 (0.77)	0.128	0.011
Any chronic condition (%)	30.8	32.0	0.027	0.004
State FE (max |SMD|)	—	—	0.411	0.022
Maximum |SMD| (all covariates including state FE)	—	—	0.411	0.030
N	8,460	25,183		

Notes: SMD = Standardised Mean Difference. AAY and PHH ration card holders make up the "BPL Govt Insured vs BPL-Uninsured" group. (i) Sample: BPL respondents who are at least 45 years old who have either no insurance at all or baseline government insurance; private or employer-sponsored coverage is not included. (ii) ATO overlap weights from PSM (spline age, education, sex, rural residence, log consumption, chronic conditions, and state FEs) are used in covariate balance. (iii) Binary: percentages; continuous: mean (SD). (iv) Adjusted SMD adheres to ATO weighting; SMD is absolute.

Before and after OW, the covariate balance between BPL government-insured and uninsured respondents is shown in Table 2. State composition (maximum SMD=0.411), rural residence (0.137), log consumption (0.128), and age (0.100) were the main areas of pre-weighting imbalance. Balance significantly improved after ATO: the highest adjusted SMD for all covariates was 0.030, and within the state FE block it was 0.022, both of which were below the traditional 0.10 threshold, showing robust post-weighting comparability. (Tables A1, A2, and Figures A1–A3 provide comprehensive balance statistics, longitudinal panels, and figures.) Longitudinal estimates of the relationship between baseline government insurance and subsequent depression symptoms are shown in Table 3, which represents our main analysis.

6.1. Main Longitudinal Effects

Table 3. Longitudinal Effect of Government Insurance on Depression

Variable	(1) ANCOVA	(2) Change score	(3) AOW
Panel A: BPL			
Government insurance (treated)	0.926***	0.838*	0.925***
	(0.342)	(0.473)	(0.350)
Baseline CES-D (W1) included	Yes	No	Yes
Covariates included	Yes	Yes	Yes
State FEs	Yes	Yes	Yes
Weights (survey / AOW)	Yes	Yes	Yes
N	790	790	790
Panel B: Full Sample			
Government insurance (treated)	0.274	−0.063	0.273
	(0.252)	(0.327)	(0.260)
Baseline CES-D (W1) included	Yes	No	Yes
Covariates included	Yes	Yes	Yes
State FEs	Yes	Yes	Yes
Weights (survey / AOW)	Yes	Yes	Yes
N	1,650	1,650	1,650

Notes: SEs are reported in parentheses. The AOW estimator's SEs are obtained from 500 bootstrap replications. The sample consists of LASI-DAD panel respondents who are at least 60 years old. Panel A (N=790) shows estimates for the BPL subsample comparing baseline government-insured and uninsured individuals, whereas Panel B (N=1,650) shows estimates for the full sample. Columns (1), (2), and (3) display the ANCOVA, change-score, and AOW specifications, respectively. While column (2) lacks baseline CES-D (Wave 1), columns (1) and (3) do. Every model makes use of survey weights: The final analysis weight (Wave 1 respondent survey weight × SIPCW × OW) is used by ANCOVA and change-score models; the Wave 1 respondent survey weight is used by the AOW estimator. *p<0.10, **p<0.05, ***p<0.01.

Government insurance was positively linked to follow-up depressive symptoms using all three estimation techniques in the BPL subsample (Panel A; N=790). In the ANCOVA model, the estimated treatment effect was 0.926 (SE=0.342, $p<0.01$); in the change-score model, it was 0.838 (SE=0.473, $p<0.10$); and in the AOW specification, it was 0.925 (SE=0.350, $p<0.01$). The results are consistent across different estimating techniques, based on the direction, magnitude, and statistical significance. The estimated treatment effects for the entire government-insured sample (Panel B; N=1,650), on the other hand, were significantly smaller and statistically insignificant in all models (ANCOVA: 0.274, SE=0.252; change-score: −0.063, SE=0.327; AOW: 0.273, SE=0.260), suggesting that there was no significant association between government insurance and follow-up depressive symptoms in the overall sample. Sensitivity analyses using the official LASI-DAD longitudinal participant weight and household-clustered SEs produced substantively similar results, indicating that the primary findings were not materially affected by the choice of weighting strategy or variance estimation (Table A7). The findings were also robust to alternative specifications of baseline chronic disease status, including a binary chronic disease indicator, a multimorbidity measure, and

individual chronic disease indicators, with the estimated coefficients remaining similar in magnitude and statistical significance across specifications (Table A8).

To examine whether the insurance–depressive symptoms association differed by public pension receipt, we estimated exploratory interaction models between government insurance and public pension receipt (Table A3), suggesting the insurance–depressive symptoms association may be attenuated among pension recipients. However, none of the interaction terms reached statistical significance in either sample, providing no statistical evidence of effect modification. Given the relatively small sample sizes within interaction strata, these analyses should be interpreted as exploratory, with limited power to detect interaction effects.

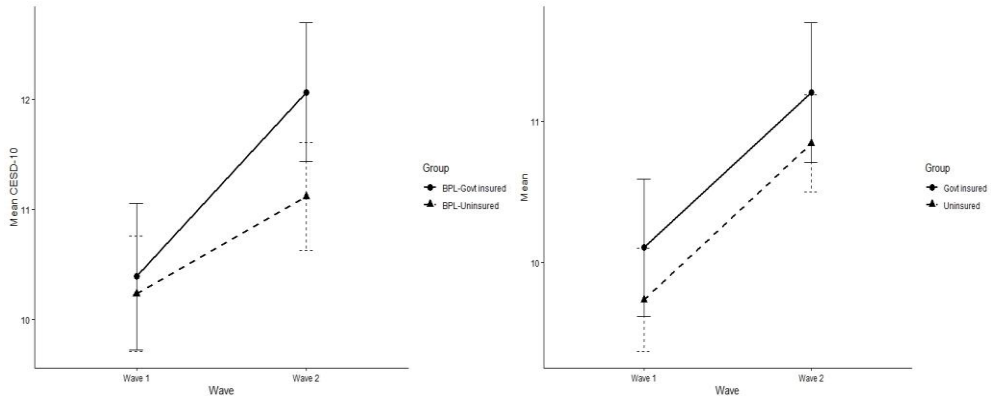


Figure 3. Weighted Depressive Symptom Trajectories

Figure 3 presents weighted mean CES-D-10 scores across the two survey waves by baseline government insurance status for the BPL subsample and full sample. In the BPL subsample, depressive symptoms increased in both groups but more markedly among government-insured older adults, yielding greater separation at follow-up; although 95% CIs overlapped, trajectories were consistent with the regression results. In the full sample, depressive symptoms also increased over time, with only modest differences between groups and substantial CI overlap, indicating limited visual evidence of differential change. These figures provide descriptive evidence on depressive symptom trajectories between Wave 1 (2017–2020) and Wave 2 (2022–2024).

6.2. Financial Protection and Expenditure Exposure

Although government insurance was associated with higher follow-up depressive symptoms among BPL older adults, longitudinal analyses do not explain utilisation or financial burden. We therefore examine cross-sectional patterns of both.

Table 4. Cross-Sectional Associations: BPL Government-Insured vs. Uninsured

Outcome	(1) Weighted	N	(2) Fully Adjusted	N
Any hospitalisation	1.318*** [1.153, 1.507]	32,501	1.333*** [1.163, 1.528]	32,501
Inpatient CHE ≥ 10%	1.185 [0.891, 1.577]	2,142	1.113 [0.814, 1.521]	2,142
Total CHE ≥ 10%	1.379*** [1.213, 1.568]	32,515	1.411*** [1.236, 1.612]	32,515
Total CHE ≥ 40%	1.484** [1.092, 2.018]	32,515	1.495** [1.095, 2.041]	32,515
Inpatient OOP Ratio (Conditional)	−0.050* [−0.101,0.000]	2,028	−0.065*** [−0.107, −0.022]	2,028
Log Total OOP Amount	0.532*** [0.390, 0.674]	32,515	0.534*** [0.403, 0.666]	32,515
Log Inpatient OOP	0.108*** [0.030, 0.186]	32,515	0.109*** [0.032, 0.185]	32,515
Log Outpatient OOP	0.505*** [0.366, 0.643]	32,555	0.505*** [0.375, 0.634]	32,555
Log Medicine OOP	0.023 [−0.072,0.117]	32,555	0.023 [−0.069, 0.114]	32,555
Psychiatric Medication	1.217 [0.605, 2.445]	32,536	1.217 [0.601, 2.462]	32,536
Psychiatric Treatment	0.737 [0.372, 1.461]	32,534	0.742 [0.369, 1.491]	32,534

Notes: Sample: BPL LASI Wave 1 respondents aged ≥45, comparing government-insured and uninsured individuals; those with private or employer-sponsored insurance were excluded. (ii) Estimates represent overlap-weighted ATO contrasts using the primary survey-weighting strategy. (iii) Column (1) reports OW models; Column (2) additionally adjusts for prespecified covariates and state FEs. (iv) Odds ratios (95% CIs) are reported for binary outcomes; regression coefficients (95% CIs) for continuous outcomes. (v) Financial outcomes are estimated on the log (1+OOP expenditure) scale. (vi) All models use Wave 1 respondent survey weight × OW. *p<0.10, **p<0.05, ***p<0.01.

Government insurance was associated with significantly higher odds of hospitalisation (survey-weighted: OR=1.318, 95% CI: 1.153–1.507, p<0.01; fully adjusted: OR=1.333, 95% CI: 1.163–1.528, p<0.01). It was also associated with higher odds of total CHE at the 10% threshold (survey-weighted: OR=1.379, 95% CI: 1.213–1.568, p<0.01; fully adjusted: OR=1.411, 95% CI: 1.236–1.612, p<0.01) and the 40% threshold (survey-weighted: OR=1.484, 95% CI: 1.092–2.018, p<0.05; fully adjusted: OR=1.495, 95% CI: 1.095–2.041, p<0.05), whereas no significant association emerged for inpatient CHE at the 10% threshold. Government insurance was further associated with higher total OOPE (survey-weighted: β=0.532; fully adjusted: β=0.534), inpatient OOPE (survey-weighted: β=0.108; fully adjusted: β=0.109), and outpatient OOPE (survey-weighted: β=0.505; fully adjusted: β=0.505), all significant at 1%, while medicine OOPE showed no significant association. Compared with

uninsured BPL households, insured households had a significantly lower inpatient OOP ratio among those with inpatient expenditure (survey-weighted: β=−0.050, p<0.10; fully adjusted: β=−0.065, p<0.01), indicating a smaller share of hospitalisation costs paid out of pocket. However, insured households also incurred significantly higher absolute inpatient OOPE, suggesting increased utilisation outweighed the reduced cost share. These findings indicate partial financial protection without eliminating OOPE. No significant associations were observed for psychiatric medication use or treatment; findings were robust across alternative specifications.

Table 5. Cross-Sectional Associations- Government Insured vs Uninsured

Outcome	(1) Weighted	N	(2) Fully Adjusted	N
Any hospitalisation	1.297*** [1.167, 1.440]	63,480	1.305*** [1.172, 1.453]	63,480
Any outpatient spending	1.239*** [1.172, 1.309]	63,617	1.265*** [1.194, 1.340]	63,617
CHE ≥ 10%	1.251*** [1.130, 1.385]	63,541	1.269*** [1.142, 1.410]	63,541
CHE ≥ 40%	1.288** [1.005, 1.651]	63,541	1.292** [1.006, 1.660]	63,541
Psychiatric Medication	1.318 [0.770, 2.257]	63,585	1.319 [0.772, 2.253]	63,585
Psychiatric Treatment	0.954 [0.551, 1.652]	63,582	0.960 [0.551, 1.671]	63,582
Log Outpatient OOP (Conditional)	0.007 [−0.051,0.065]	32,639	0.010 [−0.042, 0.062]	32,639

Notes: (i) Sample: LASI Wave 1 respondents aged ≥45, comparing government-insured and uninsured individuals; those with private or employer-sponsored insurance were excluded. (ii) Estimates represent OW ATO contrasts using the primary survey-weighting strategy. (iii) Column (1) reports OW models; column (2) additionally adjusts for prespecified covariates and state FEs. (iv) Odds ratios (95% CIs) are reported for binary outcomes; regression coefficients (95% CIs) for continuous outcomes. (v) The outpatient expenditure model is conditional on positive outpatient expenditure. (vi) All models use Wave 1 respondent survey weight × OW. *p<0.10, **p<0.05, ***p<0.01.

Table 5 reports the associations between government insurance and healthcare utilisation, financial risk protection, and mental healthcare outcomes. Government insurance was associated with higher odds of hospitalisation (survey-weighted: OR=1.297, 95% CI: 1.167–1.440, p<0.01; fully adjusted: OR=1.305, 95% CI: 1.172–1.453, p<0.01), outpatient spending (survey-weighted: OR=1.239, 95% CI: 1.172–1.309, p<0.01; fully adjusted: OR=1.265, 95% CI: 1.194–1.340, p<0.01), and CHE at both the 10% threshold (survey-weighted: OR=1.251, 95% CI: 1.130–1.385, p<0.01; fully adjusted: OR=1.269, 95% CI: 1.142–1.410, p<0.01) and the 40% threshold (survey-weighted: OR=1.288, 95% CI: 1.005–1.651, p<0.05; fully adjusted: OR=1.292, 95% CI: 1.006–1.660, p<0.05).

In contrast, no significant association was observed for conditional outpatient OOPE (survey-weighted: β=0.007; fully adjusted: β=0.010), suggesting that, among individuals with outpatient expenditure, insurance did not significantly affect the amount paid per episode. Combined with higher odds of outpatient spending and CHE, this suggests insurance was associated with greater utilisation rather than lower costs per outpatient episode. No significant associations were observed for psychiatric medication use (survey-weighted: OR=1.318; fully adjusted: OR=1.319) or psychiatric treatment (survey-weighted: OR=0.954; fully adjusted: OR=0.960). Overall, government insurance was associated with greater healthcare utilisation and higher odds of CHE, but not with lower conditional outpatient OOPE or greater mental healthcare utilisation.

6.3. Financial Exposure and Depressive Symptoms

Table 3 shows that government insurance is associated with higher follow-up depressive symptoms among Below Poverty Line (BPL) older adults. Tables 4 and 5 examine associations between insurance and healthcare utilisation, and between insurance and financial burden. Table 6 examines whether hospitalisation and financial exposure indicators (any hospitalisation, CHE ≥10%, log outpatient OOPE, log total OOPE) are associated with follow-up depressive symptoms, alongside the observed insurance–depressive symptoms association. Analyses use the ANCOVA specification, supplemented by AOW and Partially Linear Residual (PLR) models.

Table 6. Financial Vulnerability and Depressive Symptoms

Variable	(1) ANCOVA	(2) AOW / PLR
Panel A. BPL		
Any hospitalisation	0.468	0.510
	(0.595)	(0.630)
CHE ≥ 10%	−0.514	−0.519
	(0.553)	(0.590)
Any OOPE spending	−0.126	−0.123
	(0.337)	(0.324)
Log outpatient OOPE	−0.018	−0.015
	(0.042)	(0.042)
Log total OOPE	0.000	0.004
	(0.041)	(0.039)
Baseline CES-D (Wave 1)	Yes	Yes
Covariates included	Yes	Yes
State FEs	Yes	Yes
Weights (Survey/AOW)	Yes	Yes
N	790	790
Panel B. Full Sample		

Any hospitalisation	1.250***	1.380***
	(0.417)	(0.438)
CHE ≥ 10%	0.749*	0.747
	(0.418)	(0.458)
Any OOPE spending	0.535**	0.531**
	(0.242)	(0.240)
Log outpatient OOPE	0.059*	0.059*
	(0.030)	(0.031)
Log total OOPE	0.089***	0.090***
	(0.030)	(0.029)
Baseline CES-D (Wave 1) included	Yes	Yes
Covariates included	Yes	Yes
State FEs	Yes	Yes
Weights (Survey/AOW)	Yes	Yes
N	1,650	1,650

Notes: SEs are reported in parentheses; for augmented estimators, SEs use 500 bootstrap replications. Samples: LASI-DAD respondents aged ≥60 (BPL subsample N=790; full sample N=1,650), varying by outcome exposure availability. Column (1): ANCOVA. Column (2): AOW (targeting the average treatment effect in the overlap population) for binary exposures, PLR for continuous exposures. Baseline CES-D10 included in both. Models use Wave 1 respondent survey weight, SIPCW, and exposure-specific OW where applicable. *p<0.10, **p<0.05, ***p<0.01.

In the BPL government-insured subsample (Panel A; N=790), estimated associations between hospitalisation and financial burden indicators and follow-up depressive symptoms were generally modest, with none reaching conventional statistical significance. Hospitalisation, CHE ≥10%, any OOPE spending, log outpatient OOPE, and log total OOPE were not significantly associated with follow-up depressive symptoms in either the ANCOVA or corresponding AOW/PLR specification. Although several estimates were directionally consistent with the full sample, the relatively small BPL subsample may have had limited power to detect modest associations.

In the full government-insured sample (Panel B; N=1,650), evidence was more consistent. Hospitalisation was positively and significantly associated with follow-up depressive symptoms in both the ANCOVA (β=1.250, SE=0.417, p<0.01) and AOW (β=1.380, SE=0.438, p<0.01) models. CHE ≥10% was also positively associated, reaching marginal significance in ANCOVA (β=0.749, SE=0.418, p<0.10), while the AOW estimate was similar in magnitude (β=0.747, SE=0.458) but not conventionally significant. Any OOPE spending was positively and significantly associated with follow-up depressive symptoms in both ANCOVA (β=0.535, SE=0.242, p<0.05) and AOW (β=0.531, SE=0.240, p<0.05). Log total OOPE was positively and significantly associated in both ANCOVA (β=0.089, SE=0.030, p<0.01) and PLR (β=0.090, SE=0.029, p<0.01). Likewise, log outpatient OOPE showed a

positive, marginally significant association in both ANCOVA (β=0.059, SE=0.030, p<0.10) and PLR (β=0.059, SE=0.031, p<0.10). These findings are consistent with financial toxicity as a factor possibly associated with government insurance and poorer follow-up mental health outcomes.

Table 7 summarises sensitivity, robustness, and validation analyses. Panel A reports ANCOVA diagnostics, confirming the homogeneity-of-slopes assumption. Panel B presents sensitivity analyses for the primary depression outcome and key cross-sectional outcomes (hospitalisation, CHE ≥10%), including Oster bounds, E-values, and robustness values to assess vulnerability to unmeasured confounding, including selection into government insurance. Panel C provides external triangulation using WHO-SAGE India and the Lancet Public Health Survey.

Table 7. Sensitivity, Robustness and Validation Analyses

Treatment × covariate interaction	BPL Government Insured β (SE)	p-value	Government Insured, All Eligible β (SE)	p-value
Baseline CES-D	−0.072 (0.064)	0.255	0.005 (0.049)	0.907
Age	−0.041 (0.056)	0.458	0.009 (0.043)	0.834
Education	−0.012 (0.091)	0.903	0.034 (0.057)	0.554
Log consumption	−0.346 (0.445)	0.438	0.046 (0.329)	0.887

Panel B. Sensitivity Analysis to Unmeasured Confounding

B1. BPL Government Insured

Sensitivity measure	Depression (CES-D W2)	Hospitalisation	CHE ≥10%
Treatment effect	0.926*** (0.342)	0.019*** (0.005)	0.023*** (0.005)
Oster bound (δ = 1)	[0.918, 0.926]	[0.019, 0.019]	[0.023, 0.023]
E-value	1.611	—	—
E-value, lower CI	1.259	—	—
Robustness value (RV)	0.103	0.036	0.043
Robustness value (RVα)	0.037	0.026	0.033
N	790	33,367	33,381

B2. Government Insured, All Eligible

Sensitivity measure	Depression (CES-D W2)	Hospitalisation	CHE ≥10%
Treatment effect	0.274 (0.252)	0.018*** (0.004)	0.015*** (0.003)
Oster bound (δ = 1)	[0.230, 0.274]	[0.018, 0.018]	[0.015, 0.015]
E-value	1.271	—	—
E-value, lower CI	1.000	—	—

Robustness value (RV)	0.031	0.034	0.029
Robustness value (RVα)	0.000	0.026	0.022
N	1,650	63,480	63,541

Panel C. External Triangulation

Dataset	Depression	Healthcare Utilisation	Out-of-Pocket Spending
LASI–DAD	0.926*** (0.342)	1.333*** (0.091)	0.534*** (0.073)
Lancet Public Health Survey	1.352*** (0.254)	0.491*** (0.120)	0.105 (0.103)
WHO-SAGE India	2.242*** (0.302)	—	—

Notes: Panel A reports treatment-by-covariate interaction tests for the homogeneity-of-regression-slopes assumption underlying the ANCOVA specification. Panel B reports sensitivity analyses using Oster (2019) coefficient-stability bounds, E-values (VanderWeele and Ding, 2017), and robustness values (Cinelli and Hazlett, 2020). Oster bounds are calculated assuming proportional selection with δ = 1. Panel C reports external triangulation using LASI–DAD, the Lancet Public Health Survey, and WHO-SAGE India. Standard errors are in parentheses. RV = robustness value. *$p < 0.10$, **$p < 0.05$, **$p < 0.01$.

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Panel A reports formal tests of the homogeneity-of-regression-slopes assumption underlying the ANCOVA specification. Across both the BPL government-insured subsample and the full government-insured sample, none of the interaction terms between treatment status and baseline continuous covariates (CES-D score, age, education, log household consumption) is statistically significant (all p>0.05), indicating that the relationship between baseline covariates and follow-up depressive symptoms does not vary by treatment status. This supports the validity of the ANCOVA specification used in the primary analyses.

Panel B evaluates robustness to potential unmeasured confounding using Oster coefficient-stability bounds, E-values, and robustness values. In the BPL subsample, the association between baseline government insurance and follow-up depressive symptoms remained positive and significant (β=0.926, SE=0.342, p<0.01). Oster bounds stayed entirely above zero ([0.918, 0.926]), suggesting relative robustness to omitted variable bias. The E-value (1.611; lower confidence limit=1.259) and robustness values (RV=0.103; RVα=0.037) indicate an unmeasured confounder would need only a modest association with both treatment and outcome to explain the effect. For hospitalisation (β=0.019, SE=0.005) and CHE ≥10% (β=0.023, SE=0.005), effects remained significant, though E-values were not reported (adjusted risk differences); their smaller robustness values (RV=0.036 and 0.043) suggest greater confounding sensitivity than the primary outcome. In the full sample, the insurance–depression association was positive but non-significant (β=0.274, SE=0.252). Oster bounds

([0.230, 0.274]) remained positive, while the E-value (1.271; lower confidence limit=1.000) and robustness values (RV=0.031; RVα=0.000) indicate limited robustness. Hospitalisation (β=0.018, SE=0.004) and CHE ≥10% (β=0.015, SE=0.003) remained significant, though small robustness values (RV=0.034, 0.029) indicate greater confounding susceptibility. The insurance–depression association is more robust in the BPL subsample than the full sample.

Panel C presents external triangulation using the WHO-SAGE India and Lancet Public Health Survey datasets. Despite differences in survey design, study population, outcome definitions, and exposure measurement, estimated associations were broadly directionally consistent with the primary findings, with government insurance more consistently associated with greater healthcare utilisation than with improved mental health or reduced OOP financial burden. Given these methodological differences, the analyses are interpreted as supportive contextual evidence rather than confirmatory replication. Detailed results appear in Supplementary Tables B1–B5 and Tables A4–A6. Permutation inference supported statistical reliability. Negative control falsification tests showed no significant associations, and leave-one-state-out analyses confirmed findings weren't driven by any single state.

7. Discussion

This study examines the longitudinal and cross-sectional associations of government health insurance with financial risk protection and follow-up depressive symptoms among older adults in India using linked LASI–LASI-DAD data. Cross-sectionally, government insurance was associated with greater hospitalisation, higher OOPE across multiple expenditure categories, and higher odds of CHE at both the 10% and 40% thresholds, but not with psychiatric medication use or treatment. Although insured individuals paid a lower share of inpatient costs out of pocket, indicating some financial protection, the concurrent increase in absolute OOPE and CHE suggests this protection was only partial, coinciding with greater utilisation and higher overall treatment costs. Longitudinally, government insurance was associated with higher follow-up depressive symptoms among BPL older adults, with no significant association in the broader insured sample; findings were robust to alternative weighting, variance estimation, and baseline chronic disease specifications. Consistent with this, log total and outpatient OOPE and hospitalisation were positively associated with follow-up depressive symptoms, significantly so in the full sample and directionally consistent but non-significant in the BPL subsample. Combined with evidence of only partial financial protection, these findings suggest that financial toxicity may be a relevant factor associated with insurance and mental health outcomes among vulnerable older adults.

Government insurance was associated with greater healthcare utilisation- hospitalisation, outpatient services, and medication expenditure- consistent with evidence that publicly financed schemes improve access among disadvantaged populations (Garg et al., 2022). However, increased utilisation did not translate into complete financial protection: benefit packages appear not to fully offset costs from increased service use, and residual expenditures may still trigger CHE among financially constrained households. This pattern aligns with the Stress Process Model and stress-buffering hypothesis (Pearlin et al., 1981; Cohen & Wills, 1985), and the financial toxicity framework (Zafar & Abernethy, 2013), which posit that persistent financial strain adversely affects psychological well-being.

The concentration of higher depressive symptoms among BPL older adults, who have been faced with multiple vulnerabilities, may be explained by these patterns. First, government insurance is associated with higher hospitalisation (Reshmi & Debasis, 2019), and where coverage gaps are sustained, hospitalisation may still result in residual OOPE, income loss, and caregiver burden, placing psychosocial stress on households with limited protection. Second, financial stress is consistently associated with depressive symptoms among older adults who are economically fragile (Guan et al., 2022; Song et al., 2025). This is specifically true for BPL older adults who are situated in persistent poverty, lower health literacy, informal employment, multimorbidity, functional disability, and rural residence (Perianayagam et al., 2022; Chowdhary & Goli, 2025). In line with findings that outpatient mental health care in India is still in its infancy, insurance was not linked to the use of psychiatric medication or therapy (Ghosh, 2021; Avula et al., 2025). Exploratory heterogeneity analyses revealed limited evidence of effect modification: the insurance–pension interaction term was consistently negative across ANCOVA, change-score, and AOW models but never significant, perhaps due to underpowered strata.

This positive insurance–depression link among BPL older adults contradicts other settings, possibly reflecting benefit design diversity. The Oregon Medicaid experiment shows that public insurance improved mental health via greater antidepressant access and reduced financial hardship (Baicker et al., 2013; Baicker et al., 2018), while Chinese evidence connects insurance reforms to lower depression among rural older adults, possibly by reducing hospitalisation expenses (Zhang et al., 2025; Zhuo et al., 2025; Zhang et al., 2024). In contrast, little outpatient, pharmaceutical, and mental healthcare is offered by India's inpatient-focused programmes. Our results corroborate previous evidence that RSBY did not lower OOPE and PM-JAY increased hospitalisation without much reduction in CHE (Karan et al., 2017; Parmar et al., 2023), suggesting utilisation without much protection is more important than cost

inflation per episode. Accordingly, China's critical illness insurance programme shows higher reimbursement and lower post-hospitalisation expenditure alongside better mental health outcomes (Zhang et al., 2025). Studies from the US and China also show insurance expansion improves mental health when benefit design includes effective financial protection and psychiatric care pathways (Griffith & Bor, 2020; Ortega, 2023; Liao et al., 2025), suggesting institutional design may underlie the contrasting findings in India.

Because insurance enrolment is not random, residual selection bias cannot be completely ruled out even though the longitudinal design, SIPCW estimation, comprehensive covariate adjustment, full-sample and BPL-subpopulation analyses, robustness checks (change-score, AOW), and external triangulation strengthen credibility. Regression adjustment addresses observed and stable unobserved differences but not time-varying unobserved factors. Although self-selection cannot be ruled out completely, there has been evidence that RSBY's modest enrolment fees, camp-based enrolment, and lack of third-party administration narrow down systematic adverse selection (Nandi et al. (2015); Prinja et al. (2017)). While Sengupta and Rooj (2019) find that insurance is still positively linked to hospitalisation after controlling for health-seeking behaviour, Azam (2018) finds that RSBY improved utilisation without lowering OOPE, indicating both moral hazard and residual adverse selection. Future randomised or quasi-experimental designs would provide more conclusive evidence, even though consistency among techniques reflects selection bias is unlikely to fully explain outcomes.

7.1. Limitations

There are some limitations that should be indicated. The study is observational, and residual confounding from unmeasured time-varying factors, such as health status changes, household income shocks, or COVID-19-related stressors during Wave 2, cannot be entirely ruled out. Although ANCOVA, change-score, and AOW models adjust for baseline depressive symptoms and rich observed covariates, and Oster's bounds, E-values, and Cinelli–Hazlett robustness values suggest moderately strong unmeasured confounding would be required to explain the primary association, residual selection bias from non-random insurance enrolment cannot be fully excluded. Causal directionality cannot be established by cross-sectional analyses. Self-reported psychiatric medication and treatment use probably understates true prevalence given India's significant mental health care gap and accompanying stigma, and the state-support rule restricts representativeness for states with extreme program penetration. Limited subgroup sizes and power may restrict longitudinal pension interaction analyses; null interactions should be taken as imprecision rather than a conclusive lack of heterogeneity.

Future studies should use quasi-experimental designs with upcoming LASI waves to take advantage of the state-level PM-JAY rollout, and its expansion to all people aged 70 and above irrespective of their socio -economic class.

7.2. Policy Implications

These findings have implications for India's UHC reforms. They highlight the need to relate benefit design with the realities of care usage, financial hardship, and ageing. The expansion of inpatient-focused schemes from RSBY to PM-JAY has left outpatient care, medicines, chronic disease management, and mental health services under-covered, leading to a paradox: insurance improves utilisation without providing consistent financial protection or better mental health outcomes. Although telehealth services are becoming widely recognised under PM-JAY, they are not successfully integrated into routine care pathways, especially for older adults who face high and rising mental health burdens linked to chronic disease. India's insurance system is still not well suited to the country's ageing population: BPL older adults encounter numerous chronic conditions, frequent outpatient needs, and long-term pharmaceutical costs, none sufficiently covered under a hospitalisation-centric approach, leaving insurance unable to function as a true financial protection umbrella. Policy priorities should move beyond expanding inpatient care toward an integrated, continuous care model, bolstering outpatient and pharmaceutical benefits, integrating mental health screening and treatment into insurance, enhancing provider accountability and cashless enforcement, and utilising teleconsultation to achieve real access. Insurance design needs to move away from episodic illness and move towards life cycle-based coverage appropriate for ageing.

Insurance reform alone cannot address delivery-side gaps in outpatient, home-based, and preventive care. In addition to a separate Department for the seniors coordinating integrated services, complementary fiscal transfers depending on the share of the senior population might support home-based care, including door-to-door assessments by ASHA employees and community volunteers.

8. Conclusion

This study gives longitudinal and cross-sectional findings on the health and financial effects of government insurance among older adults in India. The lack of a protective association in the overall insured population, together with the adverse association among BPL older adults, shows that insurance coverage does not always equate to effective financial protection. As India's ageing population is expected to rise from 104 million to 319 million by 2050, increasing enrolment without improving benefit depth risks widening the gap between

policy goals and actual outcomes. India must move from coverage breadth to coverage efficacy in order to achieve UHC. Persistent CHE among insured BPL older adults also reflects operational shortcomings, such as incomplete cashless-care enforcement and continued cost-shifting by empanelled providers, while mental health remains an unmet need despite the Mental Healthcare Act 2017. Insurance needs to change from privilege to promise for India's vulnerable older adults. India's ageing population is already in motion; the speed at which reliable, reasonably well healthcare is developed on a large scale will determine whether this is a burden or an opportunity.

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Data Availability Statement: This study uses secondary data from LASI, LASI-DAD, WHO-SAGE India, and the Lancet Citizens' Survey. The datasets are available from their respective custodians subject to applicable access requirements.
Ethics Statement: This study involved secondary analysis of existing survey data. The original survey teams obtained ethical approval and informed consent.

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Supplementary File

Table A1. Descriptive Statistics and Covariate Balance Before and After Propensity Score Weighting (Govt vs Uninsured and Private/Mixed vs Uninsured)

Covariate	Uninsured mean	Gov mean	SMD (Unadj.)	SMD (Adj.)	Uninsured mean	Private/Mixed mean	SMD (Unadj.)	SMD (Adj.)
		Gov vs Uninsured				**Private/Mixed vs Uninsured**		
Age (years)	60.030	58.918	0.110	0.018	60.030	57.449	0.236	0.042
Education (years)	4.131	3.924	0.044	0.047	4.131	7.601	0.646	0.110
Male	0.458	0.486	0.028	0.003	0.458	0.525	0.067	0.002
Rural	0.637	0.723	0.086	0.006	0.637	0.482	0.155	0.076
Log consumption	11.996	11.881	0.150	0.032	11.996	12.280	0.365	0.081
Any chronic condition	0.366	0.346	0.020	0.002	0.366	0.434	0.068	0.031
N		64,233				52,648		

Notes: SMD = standardised mean difference. (i) Sample includes LASI respondents aged ≥45, comparing (a) individuals with baseline government insurance to those without any insurance and (b) individuals with private/mixed insurance to the uninsured; categories are mutually exclusive. (ii) Covariate balance is assessed using ATO weights derived from a propensity score model including age (spline), education, sex, rural residence,

log consumption, chronic conditions, and state FEs. (iii) Continuous variables are reported as means; binary variables are proportions. (iv) SMD denotes the absolute SMD; adjusted SMD reflects balance after application of ATO weights. (v) N denotes the comparison-specific sample size used to estimate the corresponding PS and balance diagnostics.

Table A2. Longitudinal Panel Balance

Covariate	Unadjusted |SMD|	Weighted |SMD|
Age (years)	0.078	0.020
Education (years)	0.050	0.000
Male	0.082	0.004
Rural	0.143	0.020
Log consumption	0.051	0.009
Any chronic condition	0.009	0.001
Ever smoked	0.043	0.007
State FE: code 21	0.111	0.025
State FE: code 27	0.092	0.015
State FE: code 19	0.079	0.002
State FE: code 8	0.041	0.006
Max |SMD| (all covariates)	0.143	0.025
N	1,653	1,653

Notes: Balance statistics are reported for the ANCOVA analytic sample (respondents with non-missing Wave-2 CES-D). Weighted absolute standardised mean differences (|SMD|) are computed using the final analysis weights, defined as the product of ATO overlap weights, baseline survey weights, and IPCW, with trimming at the 99th percentile. Lower weighted |SMD| values indicate improved covariate balance and overlap between treatment groups.

Table A3. Heterogeneity in the Insurance–Depression Association by Public Pension

Variable	(1) ANCOVA	(2) Change Score	(3) AOW
Panel A: BPL			
Treated × Public pension	−0.688	−0.199	−0.860
	(0.697)	(0.978)	(0.689)
Baseline CES-D (W1) included	Yes	No	Yes
Covariates included	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes
Weights (Survey/AOW)	Yes	Yes	Yes
N	790	790	790

Panel B: Full Sample			
Treated × Public pension	−0.184	−0.212	−0.191
	(0.524)	(0.682)	(0.509)
Baseline CES-D (W1) included	Yes	No	Yes
Covariates included	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes
Weights (Survey/AOW)	Yes	Yes	Yes
N	1,650	1,650	1,650

Notes: SEs are reported in parentheses. For the AOW estimator, SEs are based on 500 bootstrap replications. The sample consists of LASI-DAD panel respondents aged ≥60. Panel A (N=790) reports estimates for the BPL subsample comparing baseline government-insured and uninsured individuals, while Panel B (N=1,650) reports estimates for the full sample. Column (1) presents the ANCOVA specification, column (2) the change-score specification, and column (3) the AOW specification targeting the ATO. Baseline CES-D (Wave 1) is included in columns (1) and (3) but omitted in column (2). All specifications include the full set of covariates and state FEs, estimated using the primary weighting strategy combining the Wave 1 respondent survey weight, SIPCW, and OW where applicable. Coefficients represent the interaction between baseline insurance and pension status (ANCOVA/change-score) or the difference in ATO effects between pension subgroups (AOW). Panel A is restricted to BPL respondents. *p<0.10, **p<0.05, ***p<0.01.

Table A4. Permutation Inference for the Effect of Government Insurance on Depressive Symptoms

Sample	Estimator	Estimate (β)	Model SE	Asymptotic p-value	Permutation p-value	Valid Permutations
BPL	ANCOVA	0.926	0.342	0.007	0.007	2,000
	Change score	0.838	0.473	0.076	0.063	2,000
Full sample	ANCOVA	0.274	0.252	0.279	0.301	2,000
	Change score	−0.063	0.327	0.847	0.863	2,000

Notes: Permutation inference was conducted using 2,000 within-state permutations of government health insurance status while preserving the observed state-level treatment distribution. Reported coefficient estimates correspond to those obtained from the primary weighted regression models. Permutation *p*-values represent the proportion of permuted treatment effects with an absolute magnitude at least as large as the observed estimate. The close agreement between the asymptotic and permutation *p*-values indicates that the primary findings are robust to finite-sample distributional assumptions

Table A5. Leave-One-State-Out Sensitivity Analysis of the Association Between Government Health Insurance and Follow-up Depressive Symptoms

Specification	Mode	Full Sample Estimate	Mean Estimate	Minimum Estimate	Maximum Estimate	SD	Range	Most Influential State
BPL – ANCOVA	Weighted	0.926	0.926	0.852	1.040	0.069	0.192	32
Full Sample – ANCOVA	Weighted	0.274	0.273	0.113	0.432	0.084	0.319	32

Notes: Each iteration re-estimated the primary survey-weighted ANCOVA model after sequentially excluding one state from the analytical sample while retaining the original survey weights and model specification. The table reports the estimate obtained from the full analytical sample ("Main Estimate") together with the distribution of estimates across all leave-one-state analyses. The Most Influential State Omitted refers to the state whose exclusion produced the largest absolute deviation from the main estimate. The small variation in estimated coefficients across iterations indicates that the principal findings are not driven by any single state, supporting the geographic robustness of the results.

Table A6. Falsification, Negative-Control, and Placebo Analyses

Panel A. Predetermined Negative-Control Outcomes

Negative-control outcome	Sample	(1) ANCOVA	(2) AOW
Father's education	BPL	0.001	0.002
		(0.059)	(0.058)
	Full	0.011	0.010
		(0.051)	(0.056)
Adult height (m)	BPL	−0.002	−0.002
		(0.005)	(0.005)
	Full	0.003	0.003
		(0.004)	(0.004)

Panel B. Baseline Placebo (Balance Diagnostic)

Sample	Model	Estimate	SE	95% CI	p-value
BPL	ANCOVA	0.113	0.412	−0.695, 0.921	0.784
	AOW	0.113	0.414	−0.699, 0.925	0.785
Full sample	ANCOVA	0.480	0.291	−0.091, 1.051	0.099
	AOW	0.480	0.299	−0.105, 1.066	0.108

Notes: Panel A reports predetermined negative-control outcomes (father's education and adult height), which cannot plausibly be affected by current government health insurance. Panel B presents a baseline placebo (balance diagnostic) using Wave 1 CES-D10. The absence of statistically significant associations across these analyses supports the specificity of the analytical strategy and suggests that the main findings are unlikely to be driven by residual confounding, implausible treatment effects, or baseline imbalance. ANCOVA models adjusted for baseline covariates. AOW estimates used 500 bootstrap replications. SEs are reported in parentheses for Panel A; Panel B reports SEs and 95% CIs.

Table A7. Sensitivity of main Estimates to Alternative Longitudinal Weighting and Household-Level Clustering

Sample	Estimator	Estimate (SE)
Panel A: Official LASI longitudinal weight		
BPL	ANCOVA	0.900**
		(0.367)
	Change-score	0.994**
		(0.498)
	AOW	0.902**
		(0.385)
Full sample	ANCOVA	0.296
		(0.270)
	Change-score	−0.011
		(0.350)
	AOW	0.292
		(0.278)
Panel B: Household-clustered standard errors		
BPL	ANCOVA	0.926***
		(0.346)
Full sample	ANCOVA	0.274
		(0.253)

Notes: Estimates represent the association between baseline government insurance and follow-up depressive symptoms relative to no insurance. The Official longitudinal participant weight specification replaces the primary analysis weight (Wave 1 respondent survey weight combined with SIPCW) with the survey-provided LASI-DAD longitudinal participant weight (r2hlwtresp). The Household-clustered SEs specification retains the primary weighting strategy while estimating household-clustered SEs. SEs are reported in parentheses; AOW estimates use bootstrap SEs based on 500 replications. ***p<0.01, **p<0.05, *p<0.10.

Table A8. Sensitivity of main Estimates to Alternative Adjustment for Baseline Chronic Disease Burden

Sample	Estimator	Binary chronic disease (Original)	Multimorbidity (0, 1, ≥2 chronic conditions)	Individual chronic disease indicators
BPL	ANCOVA	0.926***	0.926***	0.955***
		(0.342)	(0.342)	(0.342)
	Change score	0.838*	0.839*	0.874*
		(0.473)	(0.473)	(0.471)
Full sample	ANCOVA	0.274	0.277	0.260
		(0.252)	(0.252)	(0.252)
	Change score	−0.063	−0.061	−0.083
		(0.327)	(0.327)	(0.327)

Notes: Entries report the estimated coefficient of government health insurance from the same ANCOVA and change-score models reported in Table 3. SEs are reported in parentheses. The three columns differ only in the adjustment for baseline chronic morbidity: (i) a binary indicator for any chronic disease (primary specification), (ii) multimorbidity categories (0, 1, and ≥2 chronic conditions), and (iii) separate indicators for hypertension, diabetes, heart disease, cancer, and chronic lung disease. All other covariates, analytic samples, weighting strategy (Wave-1 respondent weight SIPCW× OW), and estimation procedures are identical to those used in Table 3.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A9. Insurance-Type Heterogeneity

Panel A. Government vs uninsured

	(1) Any inpatient spending (OR)	(2) Catastrophic inpatient ≥10 (OR)	(3) Catastrophic inpatient ≥25 (OR)	(4) Inpt OOPE ratio (cond.)
Insurance type indicator (treated)	1.296***	1.337***	1.352*	0.875
	(0.069)	(0.131)	(0.209)	(0.087)
Weights (ATO × survey wt)	Yes	Yes	Yes	Yes
N	64,098	64,158	64,158	3,616

Panel B. Private/other vs uninsured

	(1) Any inpatient spending (OR)	(2) Catastrophic inpatient ≥10 (OR)	(3) Catastrophic inpatient ≥25 (OR)	(4) Inpt OOPE ratio (cond.)

Insurance type indicator (treated)	1.342*	1.459	1.860	1.093
	(0.209)	(0.386)	(0.789)	(0.314)
Weights (ATO × survey wt)	Yes	Yes	Yes	Yes
N	51,792	51,865	51,865	2,817

Panel C. Mixed/multiple vs uninsured

	(1) Any inpatient spending (OR)	**(2) Catastrophic inpatient ≥10 (OR)**	**(3) Catastrophic inpatient ≥25 (OR)**	**(4) Inpt OOPE ratio**
Insurance type indicator (treated)	1.271	1.205	1.238	0.952
	(0.294)	(0.554)	(0.628)	(0.396)
Weights (ATO × survey wt)	Yes	Yes	Yes	Yes
N	51,403	51,476	51,476	2,803

Notes: Estimates are reported as ORs for binary outcomes and coefficients for the continuous outcome. SEs are in parentheses. Each panel reports a separate comparison of insurance type relative to the uninsured: Panel A (government insurance), Panel B (private/other insurance), and Panel C (mixed/multiple coverage). The treatment variable in each panel is an indicator for the respective insurance type. Column (1) reports any inpatient spending; column (2) catastrophic inpatient expenditure ≥10%; column (3) catastrophic inpatient expenditure ≥25%; and column (4) the inpatient OOPE ratio conditional on positive inpatient spending. All estimates are obtained using ATO specifications combined with baseline survey weights. The inpatient OOPE ratio is estimated on the subsample with positive inpatient OOPE. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

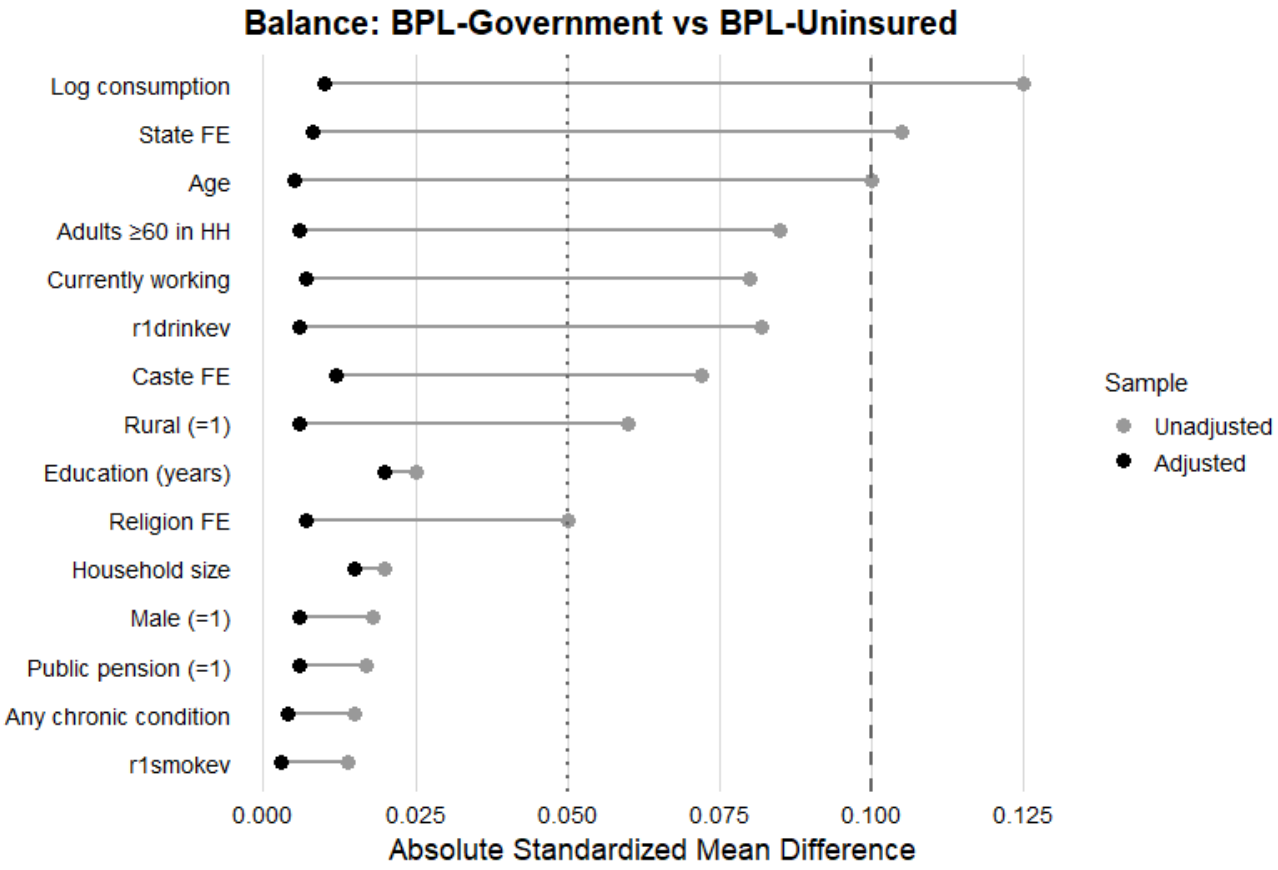


Figure A1. Covariate Balance: BPL-Government-Insured versus BPL-Uninsured Respondents

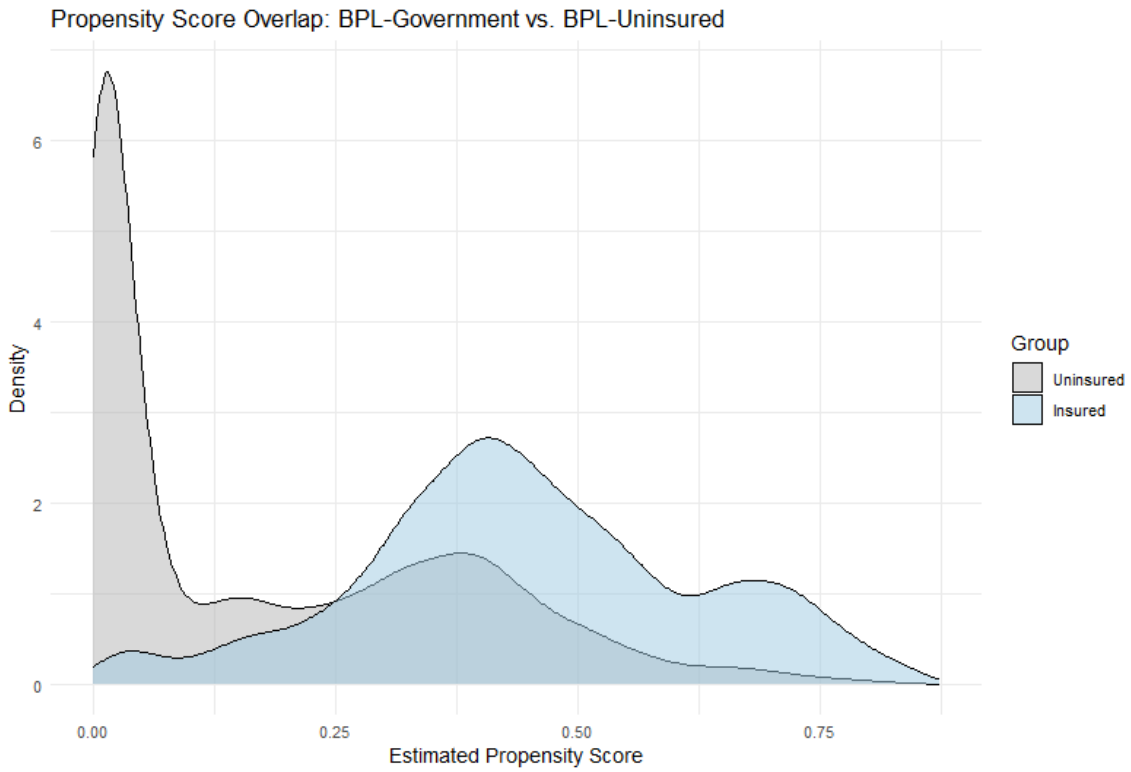


Figure A2. Propensity Score Overlap (BPL-Government vs BPL-Uninsured)

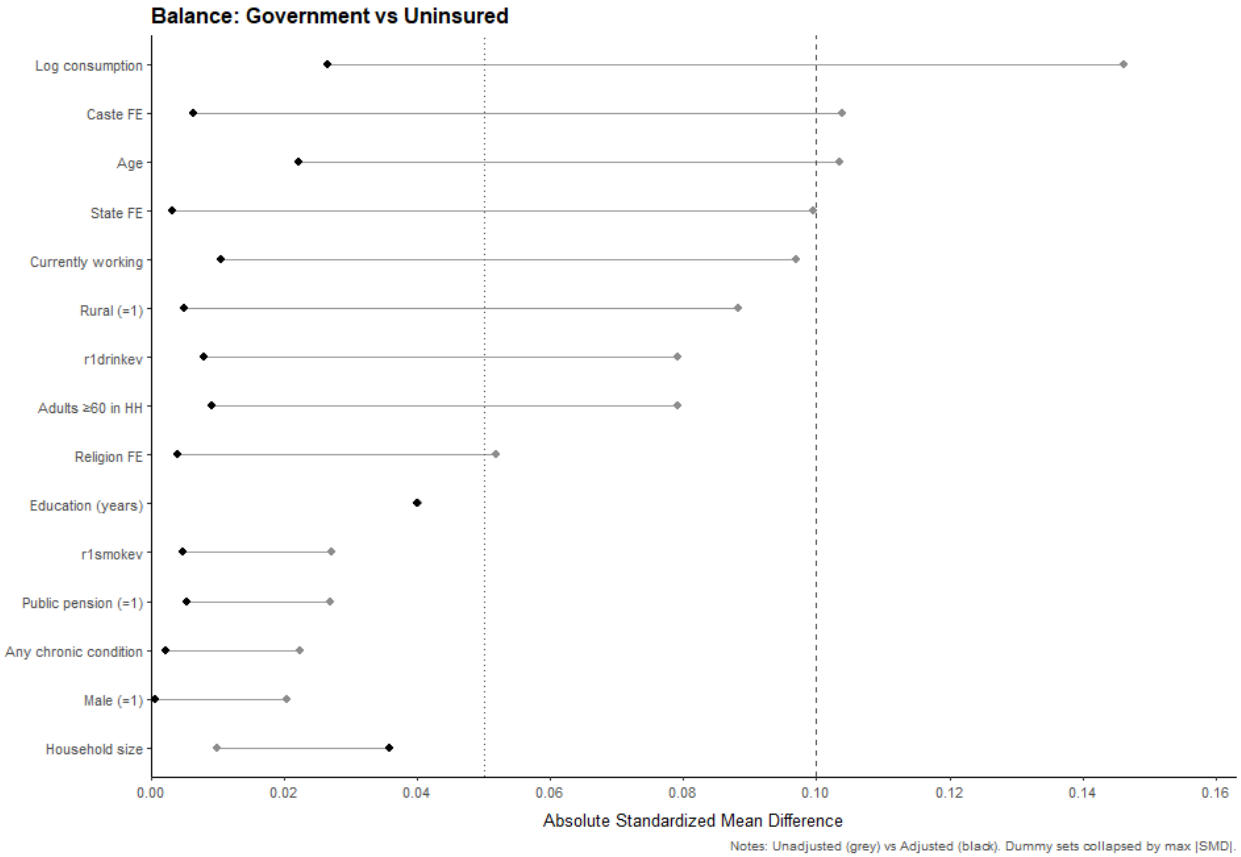


Figure A3. Covariate Balance: BPL-Government-Insured versus Uninsured Respondents

Table B1. Robustness of Government Insurance with Depression using SAGE

	Coefficient (Individual-level health payment)	**Coefficient (Household-level Insurance variable converted to individual level)**	**Elderly (≥60)**
Has Gov Insurance	-0.338	0.093*	2.242***
	(0.359)	(0.046)	(0.302)
Time	-0.164 ***	-0.171***	0.099
	(0.028)	(0.029)	(0.077)
Age	-0.009 ***	-0.008***	-0.237***
	(0.001)	(0.001)	(0.042)
Gender (Male=1)	0.094*	0.092*	-0.0003
	(0.045)	(0.045)	(0.004)

Education (Years)	0.018***	0.018***	-0.059
	(0.004)	(0.004)	(0.070)
Married	0.068	0.070	0.021***
	(0.052)	(0.052)	(0.006)
Poor Health	-0.472***	-0.474***	0.131
	(0.072)	(0.072)	(0.080)
Comorbidity Index	-0.091***	-0.093***	-0.497 ***
	(0.027)	(0.027)	(0.092)
Smoker	-0.121*	-0.119*	-0.084*
	(0.053)	(0.053)	(0.037)
Alcohol User	0.020	0.025	-0.038
	(0.078)	(0.078)	(0.074)
Has Gov Insurance x Time	-0.207	-0.001	0.067
	(0.383)	(0.082)	(0.120)
Constant	2.753***	2.748***	0.133
	(0.079)	(0.079)	(0.118)
N	9,642	9,629	4,344
R^2 / Adjusted R^2	0.080/0.079	0.078/0.077	-
Residual Std. Error	0.937	0.938	-
F Statistic	76.004***	74.119***	-

Note: Significance codes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Government insurance status is constructed using two approaches: (i) individual-level payment source variables, and (ii) household-level insurance information matched to individuals via household identifiers. The outcome variable, depression, is measured using standardised diagnostic criteria consistent with ICD-10/DSM frameworks and validated screening scales. All analyses are conducted on pooled samples, with age-heterogeneity assessed through stratified specifications for older adults (age ≥ 60). Estimates are weighted using individual-level survey weights.

Table B2. Lancet Sample and Variable Availability Diagnostics

Metric	**All adults**	**Age ≥60**
Sample size (N)	50,217	4,128
Unique cs_id count	50,217	4,128
Duplicate cs_id count	0	0

Age ≥60 count	4,128	4,128
Age ≥60 share (%)	8.3	100.0
Any insurance prevalence (%)	27.2	23.7
Non-missing OP psychiatric reason (b3)	41,766	3,495
Non-missing IP psychiatric reason (c3)	20,242	1,381
Non-missing OP OOPE (oope_total_op)	41,834	3,499
Non-missing IP OOPE (oope_total_ip)	20,242	1,381
Non-missing self-rated mental health (a4)	49,969	4,127
State coverage (unique states)	29	29
Survey weight variable available	No	No

Notes: The table reports sample integrity checks and outcome-specific item availability for the Lancet Citizens' Survey 2022–23 (single cross-section). The analytic sample includes 50,217 adults, of whom 4,128 are aged 60 and above (8.3%). Unique respondent identifiers (cs_id) are verified, with no duplicate observations. "Any insurance" is defined as having any form of insurance coverage and equals 27.2% in the full sample and 23.7% among older adults. Outcome availability varies by module: b3 (outpatient psychiatric reason) is observed for 41,766 respondents (3,495 aged 60+), c3 (inpatient psychiatric reason) for 20,242 (1,381), oope_total_op for 41,834 (3,499), oope_total_ip for 20,242 (1,381), and a4 (self-rated mental health) for 49,969 (4,127). The survey covers 29 states. Survey weights are not available in the released dataset.

Table B3. Psychiatric OP/IP Reason and Insurance (Logit Models)

Term	**(1) All adults: treatment-only**	**(2) All adults: adjusted + state FE**	**(3) Age ≥60: treatment-only**	**(4) Age ≥60: adjusted + state FE**
Psychiatric outpatient reason (b3==13): Any insurance	0.746* (0.130)	0.877 (0.165)	0.627 (0.212)	0.629 (0.254)
Psychiatric inpatient reason (c3==13): Any insurance	0.415** (0.172)	0.491*** (0.120)	0.811 (0.205)	1.105 (0.378)
Covariates included	No	Yes	No	Yes
State fixed effects	No	Yes	No	Yes
Clustered SE level	District	District	District	District
N (OP outcome)	41,766	40,434	3,495	3,356
N (IP outcome)	20,242	19,578	1,381	1,312

Notes: Outcomes are indicators for psychiatric reason code 13 (outpatient: b3 = 13; inpatient: c3 = 13), and the exposure is an indicator for any insurance coverage. Columns (1) and (3) report treatment-only logit

specifications, while columns (2) and (4) additionally include covariates (age, sex, education category, rural/urban residence, household size, log food expenditure, social category, and religion) and state FEs. Estimates are reported as odds ratios with district-clustered SEs. In the full sample, insurance is associated with lower odds of psychiatric reasons for care (outpatient OR = 0.746, $p < 0.10$; inpatient OR = 0.415, $p < 0.05$), with the inpatient association remaining negative and statistically significant after adjustment (OR = 0.491, $p < 0.01$). In the age 60 and above subsample, estimates are imprecise and not statistically distinguishable from one in adjusted models. All associations are descriptive.

Table B4. OOPE Associations and Insurance (OLS Models)

Term	(1) All adults: treatment-only	(2) All adults: adjusted + state FE	(3) Age ≥60: treatment-only	(4) Age ≥60: adjusted + state FE
Log (1+OP OOPE): Any insurance	-0.151	0.105	-0.165	0.020
	(0.148)	(0.103)	(0.206)	(0.141)
Log (1+IP OOPE): Any insurance	-0.548***	-0.245*	-1.114***	-0.734***
	(0.207)	(0.140)	(0.223)	(0.170)
Covariates included	No	Yes	No	Yes
State fixed effects	No	Yes	No	Yes
Clustered SE level	District	District	District	District
N (OP outcome)	41,834	40,494	3,499	3,360
N (IP outcome)	20,242	19,578	1,381	1,312

Notes: Outcomes are log (1 + oope_total_op) and log (1 + oope_total_ip). Columns (1) and (3) report treatment-only OLS specifications, while columns (2) and (4) additionally include SD2 covariates and state FEs. SEs are clustered at the district level. Insurance is not robustly associated with outpatient OOPE after adjustment, but is associated with lower inpatient OOPE in both samples (all adults: $\beta = -0.245$, $p < 0.10$; age ≥ 60: $\beta = -0.734$, $p < 0.01$). Estimates represent cross-sectional associations.

Table B5. Association Between Health Insurance and Self-Reported Mental Health

Term	(1) All adults: treatment-only	(2) All adults: adjusted + state FE	(3) Age ≥60: treatment-only	(4) Age ≥60: adjusted + state FE
Poor mental health (a4 in {1,2}): Any insurance	2.185***	2.305***	1.261	1.352
	(0.409)	(0.355)	(0.249)	(0.254)
Good/very good mental health (a4 in {4,5}): Any insurance	0.685***	0.593***	1.075	1.071
	(0.095)	(0.081)	(0.163)	(0.146)

Covariates included	No	Yes	No	Yes
State fixed effects	No	Yes	No	Yes
Clustered SE level	District	District	District	District
N (Poor MH)	49,969	48,094	4,127	3,955
N (Good MH)	49,969	48,094	4,127	3,955

Notes: Outcomes are indicators for poor self-rated mental health ($a4 \in \{1, 2\}$) and good/very good mental health ($a4 \in \{4, 5\}$). Columns (1) and (3) report treatment-only logit specifications, while columns (2) and (4) additionally include SD2 covariates and state fixed effects. Estimates are reported as ORs with district-clustered SEs. In the full sample, insurance is associated with higher odds of poor mental health (OR = 2.185–2.305, $p < 0.01$) and lower odds of good/very good mental health (OR = 0.685–0.593, $p < 0.01$). Among respondents aged 60 and above, estimates are imprecise and not statistically distinguishable from one. These associations are descriptive and not directly comparable to the longitudinal CES-D estimates.