Evaluating and pricing health insurance in lower-income countries: A field experiment in India

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Abstract

Universal health coverage is a widely shared goal across lower-income countries. We conducted a large-scale, 4-year trial that randomized premiums and subsidies for India's first national, public hospital insurance program, called RSBY. We find substantial demand ($\sim$ 60% uptake) even when consumers were charged a price equal to the premium the government paid for insurance. We also find substantial adverse selection into insurance at positive prices. Insurance enrollment increases insurance utilization, but not healthcare utilization, implying the primary benefit of insurance is financial. Many enrollees attempted to use insurance but failed, suggesting that learning is critical to the success of public insurance. We find very few significant impacts of insurance access or enrollment on health. Although there is substantial demand for insurance, we estimate that free insurance is unlikely to be welfare-improving given the high marginal cost of public funds in India.

JEL Codes: D1, I13

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1 Introduction

Sickness imposes substantial health and financial costs on individuals. Health insurance may mitigate these costs, so there may be substantial demand for such insurance. However, concerns about the absence or inefficiency of private insurance markets[2] have led many policymakers to advocate for publicly provided insurance. Moreover, equity concerns have inspired efforts to subsidize insurance premiums. These policy reforms are especially pressing in lower-income countries, where a high fraction of health care costs are paid out of pocket (World Health Organization, 2023).

Designing public policy to address these competing concerns about health financing requires information on several critical parameters: demand for insurance, utilization, impact on health, and the degree of market inefficiency stemming from issues such as adverse selection. It also requires analysis of the welfare effects of public insurance.

In this paper, we estimate these policy-critical parameters using a large-scale, nearly 4-year randomized controlled trial (RCT) where we varied premiums and subsidies for India's first national, public, hospital insurance program, Rastriya Swasthya Bima Yojana (RSBY). The RSBY insurance plan covers up to INR 30,000 ($1,712)[3] of treatment at in-network hospitals per annum per household.[4] We then combine these parameter estimates and the adverse selection model of Einav, Finkelstein and Cullen (2010) to determine whether free insurance improves welfare in a marginal value of public funds framework Hendren and Sprung-Keyser (2020).

Our study made the RSBY plan available to 10,879 above-poverty-level (APL) households (comprising 52,292 individuals) in 435 villages in Karnataka state who were not otherwise eligible for the plan.[5] Our study randomized these households to one of four arms: (A) zero premiums for RSBY insurance (full subsidy), (B) the full premium and a cash transfer equal to that premium, (C) full premiums for the plan (no subsidy), or (D) no access to RSBY insurance. Moreover, to estimate spillover effects across households, we randomized villages to different proportions of households assigned to each arm. We measured utilization of insurance and of healthcare as well as health outcomes for households at three points in time: at a baseline before enrollment, at a midline 18 months after enrollment, and at an endline 3.5 years after enrollment. We estimate both intent-to-treat (ITT) effects of randomization to each arm and complier-average-treatment effects

[2] One reason there are limited private health insurance markets, especially in rural areas, is the high fixed costs of developing rural networks and marketing (Gambhir et al., 2019). Market inefficiency also plays a role. Insurers report concerns about adverse selection (Gambhir et al., 2019), and about other insurers free-riding on work by initial entrants to create provider networks and demand (Sachdev, Shah and Ladwa, 2024). Insurance is a relatively new product in rural India. Finding willing and capable providers is costly; later entrants can use initial entrants' networks to find those providers at lower cost. The same logic applies to consumers. Initial entrants build consumer trust in insurance, a product that requires upfront payment for later, uncertain reimbursement. Later insurers can capitalize on familiarity and trust built by entrants.

[3] We employ the purchasing-power-parity exchange rate of INR 17.52/dollar (OECD, 2020).

[4] While our study focuses on RSBY, its has some applicability to the insurance program that succeeded it: Pradhan Mantri Jan Arogya Yojana (PM-JAY). PM-JAY offered extended free insurance to many of above poverty-line households like those in our sample.

[5] Outside our study, only below-poverty-line (BPL) individuals were eligible for RSBY insurance. The government purchased RSBY coverage from private insurance companies and provided it nearly for free to BPL households. RSBY plans were not offered to APL households in the private market and outside our study.

(CATE) of enrollment in insurance at midline and endline.[6]

One critical parameter we estimate is willingness to pay (WTP). WTP, as measured by the demand curve, captures subjective utility from insurance and impacts the investigator may not measure. Moreover, demand elasticity determines how much subsidies affect insurance consumption. We find substantial demand for insurance. Uptake was 72.24% when households were charged a full premium but were given a cash transfer equal to the insurance premium, while roughly 60% of our sample purchased insurance when charged the premium but were not given the cash transfer. When the price of insurance fell to zero, 78.71% of sample households purchased insurance.[7] These results show significant demand for insurance at positive prices, implying that people subjectively believe health insurance helps address some of the costs (financial, health and/or psychological) associated with (risk of) illness.

A second critical factor is adverse selection. This impacts whether private markets for community-rated insurance yield sub-optimal levels of consumption. It is also relevant for determining the value of free public insurance. We estimate a detectable and economically meaningful extent of adverse selection into insurance: average predicted health costs are economically and significantly higher among those who enroll at positive prices relative to those who enroll at zero price. Our adverse selection estimates are consistent with two other findings. First, households required to pay full price for insurance had higher levels of utilization than households charged a zero price for insurance. Second, households required to pay full price for insurance also reported lower rates of being unable to use their insurance card. These results are suggestive that price serves as a screen for households that have greater knowledge and/or propensity to utilize insurance.

A third critical parameter is how access to insurance effects utilization of both insurance and of health care. This sheds light on why consumers may value insurance, as well as on the cost of providing it. We find that insurance enrollment significantly and substantially increased utilization of insurance. Access to free insurance increased 6-month utilization of RSBY insurance by 6.73 pp over a control-group mean of 3.86% at 18 months, a 74% increase in insurance utilization. However, enrollment had insubstantial and statistically insignificant effects on use of hospital care. Hospital utilization rose only 10-15%, and even that estimate is imprecise. Combined, the insurance and hospital utilization effects suggest the predominant benefit of insurance is reducing financial risk.

Importantly, we find that 5% of enrolled households tried but were unable to use their insurance card (compared to a control-group failure rate of 1.5%).[8] We find that this difficulty reflects not

[6] The CATE is the local average treatment effect among compliers in an instrumental variable framework; see section 3.1.1.

[7] Combined, these numbers tell us about two demand curves. First, the difference between uptake in the zero-price arm and the sale-of-insurance arm tells us about the (uncompensated) Marshallian demand curve. Second, when Marshallian demand is combined with the difference between uptake in the zero-price arm and in the sale-plus-transfer arm, we obtain bounds on the (compensated) Hicksian demand curve. When income effects are positive, as is likely with health insurance, Marshallian demand is also a lower bound on Hicksian demand. Because the sale-plus-transfer arm compensated consumers even when they do not buy insurance, it provides an upper bound on Hicksian demand.

[8] Although households in the control group did not have access to RSBY at the start of the study, some obtained access over time and utilized RSBY. They may obtain RSBY either by falling into poverty and obtaining a BPL card, or by joining an RSBY-eligible occupation, and then signing up for RSBY during annual enrollment.

only supply-side constraints, but also demand-side obstacles such as households forgetting their card or trying to use RSBY at non-participating hospitals. This result suggests a need to educate enrollees on how insurance functions, and to improve the administration of insurance programs.

A fourth critical parameter is impact on health. Like utilization, this outcome sheds light on why consumers might value insurance. We find that insurance had minimal detectable effects on health. Health insurance showed statistically significant treatment effects on only 3 among 84 health-related outcomes across 2 waves of surveys. This remains true even if we do not apply multiple testing adjustments. This specific result is consistent with nearly all results from other RCTs of health insurance conducted in lower-income countries (Haushofer et al., 2020; King et al., 2009; Levine, Polimeni and Ramage, 2016; Thornton et al., 2010). Our standard errors imply that we cannot rule out clinically-significant health effects, on average equal to 11% (8.8%) of the standard deviation for each health outcome in ITT (CATE) analyses. However, many of our insignificant estimates suggest negative effects of insurance on health. Our findings are consistent with the conclusion either that insurance did not substantially increase health care consumption, or that the little it did had no significant impact on the health outcomes we measure.

Finally, we use our demand and adverse selection estimates to ask whether free insurance is a positive-value use of public funds. We employ the marginal value of public funds framework (Hendren and Sprung-Keyser, 2020). Applying this framework in our context highlights a central trade-off when setting insurance subsidies. Higher insurance premiums (lower subsidies) reduce uptake of insurance and thus its social benefits. However, higher premiums also reduce the fiscal externalities from subsidies—although this effect is less than one-for-one because adverse selection increases the average cost of insurance. Our estimates of insurance demand and cost curves imply that free insurance is not welfare-improving at plausible values of the marginal cost of public funds (MCPF) for a lower-income country (Auriol and Warlters, 2012). If the MCPF falls over time to the level observed in higher-income countries, free public insurance may become optimal. Another way to state our findings is that, in India, the government's cost of financing likely swamps the benefits of public insurance to enrollees.[9]

Our experiment contributes to a substantial literature on uptake and utilization of health insurance and other health programs, especially in lower-income countries. Focusing on uptake, this includes a literature on insurance price elasticity (Pendzialek, Simic and Stock, 2016), how user fees affect program uptake (e.g., Cohen, Dupas et al., 2010), and rate of health insurance uptake in India (Rathi, Mukherji and Sen, 2012; Banerjee, Duflo and Hornbeck, 2014; Berg et al., 2019). It

[9] In the appendix, we also consider what the optimal price for public insurance is. Our work on the optimal subsidy builds on Dobkin et al. (2018). We estimate optimal premiums of roughly 67% - 95% of average cost (INR 528-1052 or $30-60) holding fixed the rates of successful insurance use measured in our study, or 48% - 73% of average cost (INR 1900-2200, $108-126) if the unsuccessful utilization we observe translates into successful utilization over time.

Our primary calculations use estimates of demand measured after consumers had some information about their expected expenditures when they had insurance. We also calculate welfare using what Hendren (2021) calls *ex ante* demand, before consumers have any information on their expected costs. In the presence of adverse selection, *ex ante* demand is greater than *ex post* demand. We estimate that the optimal price of insurance falls to roughly INR 239-864 ($14-49) holding constant the rates of successful insurance use, or INR 281-1217 ($16-69) if unsuccessful use becomes successful use in time.

also adds to the literature on adverse selection into insurance in lower-income countries (Banerjee, Duflo and Hornbeck, 2014; Wagstaff et al., 2016; Asuming, Kim and Sim, 2024; Banerjee et al., 2021; Fischer, Frölich and Landmann, 2023). Turning to utilization of programs, we contribute to the literature on the low rate of healthcare utilization (Garg, Bebarta and Tripathi, 2020) and the effect of insurance on utilization (Haushofer et al., 2020; King et al., 2009; Levine, Polimeni and Ramage, 2016; Thornton et al., 2010; Das and Leino, 2011) in lower-income countries.

We also contribute to a large literature on the impacts of insurance on health. Much of that focuses on the US experience, but lower-income countries have different disease burdens and poorer quality health care (Das, Hammer and Leonard, 2008; Das et al., 2012; Mohanan et al., 2015). Most RCTs in lower-income countries find small effects of insurance on health (Haushofer et al., 2020; King et al., 2009; Levine, Polimeni and Ramage, 2016; Thornton et al., 2010), though one finds significant effects when insurance is combined with other health programs (Mahal et al., 2013), and some observational studies (e.g., Sood et al., 2014) have found reduced mortality from insurance.

Our paper employs the marginal value of public funds (MVPF) framework (Hendren, 2016; Finkelstein and Hendren, 2020; Hendren and Sprung-Keyser, 2020) and the price-theoretic model of adverse selection in Einav, Finkelstein and Cullen (2010) to evaluate the welfare effect of public insurance. We also apply Hendren (2021) to calculate the *ex ante* value of insurance before consumers have information on their expected costs.

Our paper has four main parts. Section 2 describes the health care financing in India and explains our experiment. Section 3 presents our empirical strategy. Section 4 presents our results on uptake, utilization, health, and adverse selection. Section 5 presents our welfare analysis.

2 Background and study design

2.1 Setting

India spends 3-4% of GDP on health care (World Health Organization, 2023). India's population obtains 75% of its care from private facilities (Government of India and Ministry of Health and Family Welfare, 2014-2015). Before 2008, only 75 million people had health insurance (Prinja et al., 2019). Uninsured patients pay out of pocket for care. If patients lack money to pay for care, a private hospital may deny it. Patients can obtain subsidized care at public facilities. However, these facilities have limited inventories of consumables such as anesthetics (Nair, 2018; Government of Uttar Pradesh, 2019), which patients must buy themselves. Over 60 million Indians are impoverished by healthcare expenditures each year (Shahrawat and Rao, 2012).

In 2008, the government adopted the RSBY public health insurance program. From 2008 to 2018, this program paid private insurance companies to provide an RSBY-defined health insurance plan to below-poverty-line (BPL) households and certain vulnerable occupations. (The poverty line in Karnataka in 2012 was annual income of INR 54,120 ($3,089) in rural and INR 65,340 ($3,729) in urban areas for a family of five (Prabhavathi and Naveena, 2014).) This program did not cover our sample. In 2015, the government paid an annual premium of INR 133 ($7.59) and INR 173

($9.87) per household in Gulbarga and Mysore, respectively, the two districts of Karnataka in our study.[10] Although the government paid the premiums, households had to pay INR 30 ($1.71) for an insurance card to enroll in the program.

The RSBY insurance plan covered inpatient treatments, select outpatient surgeries, and diagnostic tests. It covered care at in-network hospitals, which included both public and private hospitals.[11] RSBY did not cover primary care. The government was responsible for enrolling eligible households via occasional enrollment campaigns and at RSBY offices. Insurance coverage had no deductible or copay, but had an annual cap of INR 30,000 ($1,712) per household. The government dictated the prices for procedures; this cap was enough to cover, e.g., 4 Cesarean sections or 10 MRIs.[12] Up to 5 members per household were covered.

In 2019, RSBY was replaced by Pradhan Mantri Jan Arogya Yojana (PMJAY). PMJAY expanded RSBY to many above-poverty line (APL) households. It covered roughly the bottom 40% of the population (537 million persons) based on assets and vulnerability reported in the Socio-Economic and Caste Census (2011). Second, it raised the annual cap on covered expenditures from INR 30,000 to 500,000 ($1712 to 28,538) per household (Economic Times, 2021).

Our study was conducted before RSBY was replaced by PMJAY. Survey activities took place between March 2013 and June 2019. Study-related insurance access was provided from May 2015 to August 2018. Specifically, the study provided RSBY coverage to APL households, which were not eligible for RSBY, in collaboration with the national- and Karnataka state agencies running RSBY. We chose to experiment with expanding RSBY eligibility rather than providing more than hospital coverage to BPL populations because India did not have the information technology and contractual infrastructure to provide more than hospital insurance. We did not experiment with adding deductibles or co-pays to RSBY's insurance plan for the same reason. We decided to provide RSBY rather than private insurance because RSBY had a network of hospitals that private insurance did not; moreover, we expected that RSBY's structure and network would be the basis for any future expansion. (This largely turned out to be correct under PMJAY.)

2.2 Participants

The study was carried out in one state (Karnataka). We chose two geographically distinct districts within that state—a district in the far north (Gulbarga) and one in the south (Mysore) so that participants would be representative of central and southern India, respectively.

[10] The premium the government paid was low because the hospital utilization rate of below-poverty-line household is low and the government buys insurance from the insurance company bidding the lowest premium.

[11] Not all public hospitals were in-network because they were run by a different agency than ran RSBY. The value of RSBY at public hospitals is uncertain. On one hand, public hospitals were supposed to provide care for free. On the other hand, those hospitals are known to have shortage of consumables such as bandages, requiring patients to buy them (Government of Uttar Pradesh, 2019). RSBY revenue might have led public hospitals to purchase those consumables on behalf of insured patients.

[12] There is some concern that the prices the government set were low relative to medical procedure prices in local markets (Jain, 2021). We have posted the RSBY package rates for 2011 and 2016-2017 at https://github.com/anup-malani/IHIE/blob/main/RSBY.

Our sampling strategy first identified eligible villages and then eligible households within villages. In each district, villages were eligible if they were within 25 km (15.63 miles) of a hospital that was in-network for RSBY in 2013, to ensure that study participants had local access to covered hospitals. Within eligible villages, households were eligible for the study if they responded to our screening survey and had a member who held an above-poverty-line (APL) ration card.[13] Households were excluded from eligibility if, as of 2013, they (i) had a member who possessed a card indicating they were below-the-poverty-line (BPL); (ii) had RSBY coverage; or (iii) had a member that was enrolled in insurance that provided access to hospital care.[14]

Table 1 presents village-level statistics for sample villages. On average 18% of village populations were BPL, meaning a large fraction were APL and hence potentially eligible for this study. Villages were on average about 9 kilometers from a hospital.

Table 2 presents characteristics of respondent households by group at baseline. Because some variables in our dataset are right-skewed, we report medians and inter-quartile ranges (IQR) for non-binary variables; mean and standard deviation are reported for binary variables. The median annual household budget (inclusive of medical expenditures) in each treatment arm was roughly INR 105,000 ($6,000). Median medical expenditure was roughly INR 18,000 ($1,030). The share of medical to total spending is approximately 17%, quite similar to the figure of 17.4% found by Ahmad and Mohanty (2024) for a sample of older Indian adults.

2.3 Intervention and randomization

The study involves two-stage randomization, at the village and then at the household level. The four household-level premium and subsidy conditions are:

A. Access to RSBY for at 0 premium ("free-insurance" arm),
B. Opportunity to buy RSBY at the government's purchase price plus an unconditional cash transfer equal to that price ("sale-plus-transfer" arm),
C. Opportunity to buy RSBY at the government's price ("sale-of-insurance" arm), or
D. No access to RSBY (control arm).

The purchase price per household for groups B and C was INR 163 ($9.31) and INR 203 ($11.60) in Gulbarga and Mysore, respectively.[15] The transfer to group B had two purposes: to eliminate

[13] Households may apply for a "ration" card that entitles their household to food and other commodities at discounted prices at government sanctioned fair price or "ration" shops. Individuals who meet BPL get access to a greater quantity of subsidized food than those with APL cards.

[14] The sample was identified through a listing exercise and a consent process. The listing was carried out in two waves, in March–June 2013 and in November–December 2013. The actual randomized sample was smaller than the listing because not all listed households were available on the days we approached households for consent and because many households became ineligible by the time they were approached for consent. The main cause of ineligibility is that households obtained BPL cards. A total of 8,866 and 2,013 households were identified and enrolled from the two listing waves, respectively, for a total sample of 10,879 households.

[15] The purchase price was comprised of an annual premium and a fee for printing an insurance card. The premium was INR 133 ($7.59) and INR 173 ($9.87) in Gulbarga and Mysore, respectively. The smart-card fee was INR 30 ($1.71) in each district. The government's purchase price is not the same as the actuarially fair price. The government's price is determined by an auction run in each district. In that auction, public or private insurance

liquidity constraints when measuring demand, and to offset income effects and measure compensated demand for insurance. Because *ex ante* eligibility for RSBY was an exclusion criterion, group D had no access to RSBY via our study.[16] for more details.

At the village level, the study varied the share (i.e., allocation) of sample households in a village that were assigned to each of the four household groups above. Our purpose in varying the saturation of access to RSBY was to estimate spillover effects from one household's access to or enrollment in insurance on the decisions and outcomes of neighboring households.

Treatments were assigned in two stages (Hudgens and Halloran, 2008). First, villages were assigned one of five allocations (labeled I to V) with probabilities given in Appendix Table A.1. Second, households in a village were assigned to premiums and subsidy conditions in proportions given by the allocation for their village. In each stage, we stratified units before randomization because doing so balances covariates and reduces orthogonal variation (Imai, King and Clayton, 2009), thereby increasing statistical power. Details of the matching are provided in Appendix A.1.1.

Our focus in this paper is on the effects of the household allocations. We relegate discussion of spillover effects, which we also investigate in a separate paper (Imai, Jiang and Malani, 2021), to the appendix. Therefore, the most relevant statistic from Table A.1 is that, across all sample villages, 40% of households are assigned to the free insurance condition (group A), and 20% of households are assigned to each of the other household-level conditions. This implies that, on average across villages, 80% of sample households are given some form of access to insurance.

Balancing tests suggest covariates were balanced after randomization. Specifically, we estimated multinomial-logit models predicting household group assignment to the 4 treatment groups as a function of outcomes specified in our pre-analysis plan and measured at baseline, one outcome at a time.[17] Then, we conducted likelihood-ratio tests to determine if we can reject a null model equal to the multinomial model without any baseline outcome, i.e., reject that the baseline outcome has no explanatory power. If the block randomization was successful, then the p-values collected from these tests should stochastically dominate the uniform distribution.[18] A one-sided Kolmogorov–Smirnov test reveals covariates are balanced (p=1.000) across household-level arms (Appendix Figure A.1).

companies can bid per-beneficiary premiums for being the exclusive provider for the RSBY standard insurance plan to all RSBY-eligible enrollees. The company with the lowest premium is given the contract to provide insurance in the district, meaning the government's premium is the lowest bid in each district. It is possible that the winning bidder underestimates the cost of insurance, suffers the winners curse, or treats the RSBY product as a loss leader. We did not, however, test for whether the government price was actuarially fair because we did not have access to claims data from the government.

[16] Because a household could fall under the poverty line over time, it could obtain RSBY outside our study, through annual enrollment by the official RSBY program. Therefore, group D should be thought of as having no access to RSBY *at the beginning of the study.* See Sec. 2.4

[17] A pre-analysis plan (PAP) was posted prior to the endline survey at 3.5 years (AEARCTR-0001793) and data analysis was only conducted after that last survey. No analysis of midline data was conducted prior to the PAP in order to prevent any possibility of researcher discretion/gaming the PAP in light of midline results.

[18] We expect stochastic dominance relative to the uniform distribution due to stratification (intuitively, the groups will be more balanced than by chance alone).

2.4 Measurement and timing

Measurement. Our study measures several key outcomes. The first is demand, measured by enrollment in RSBY in our treatment arms. Enrollment is defined as a household enrolling in RSBY during the 1-2 days that we brought a mobile enrollment truck to their village or town during our 2015 enrollment drive.[19] Uptake of RSBY measures household benefits in two ways. One is that insurance only (directly) benefits those who take it up. The other is that demand may reveal dimensions of value that we do not directly measure, e.g., consumption smoothing.

The second set of outcomes concerns insurance and health care utilization. This tracks both benefits to consumers and the cost of providing insurance. The latter includes hospital spending paid for by insurance, which depends on i) the rate at which households *utilize* insurance; ii) the average hospital spending of enrolled households. We will distinguish and measure both insurance utilization (use of RSBY to pay for hospital care) and different measures of medical and hospital spending (i.e., actual consumption of care). Insurance may affect the former without changing the latter. Moreover, in the Indian context, perhaps due to lack of knowledge about insurance, many households may attempt to use insurance to pay for care, but fail to obtain care or have the costs covered. We also track this failed use.

The third set of outcomes concerns the downstream effects of health insurance on health. We measure health via self-reported indicators and biomarkers. We also examine validated health scores that use self-reported health as inputs. We describe these metrics in the Appendix Section A.4 and indicate when they are measured in Table A.2. We estimate intent-to-treat effects and complier average treatment effects on each of these outcomes in Section 4. In addition, we examine the effect of price on uptake and costs for the purposes of welfare analysis in Section 5.

In addition to these three sets of outcomes, we measure a number of other household covariates at baseline, including household composition and finances. We employ these to predict household medical expenditure. This prediction is then used for estimating adverse selection of higher expected cost households into insurance coverage in Section 4.5.

Timing. Study households that enrolled in RSBY received initial coverage for one year beginning in mid 2015. Study households had the opportunity to re-enroll in RSBY. By the time of re-enrollment, RSBY had passed from the Ministry of Labour to the Ministry of Health. As a consequence, we could not get direct re-enrollment data from the government. As a result, at endline we directly collected information from households on RSBY card possession. Information about the levels of RSBY card possession measured at endline appear in Appendix Table A.9. Those that initially enrolled generally retained their cards; however, roughly 15% of households in the no-treatment arm were able to obtain RSBY cards, likely because they fell below the poverty line and were able to obtain RSBY through the standard RSBY program outside the study. RSBY

[19] In theory, households in arms 1, 2 and 3 also had the option to enroll by visiting the RSBY office in their district at any time, but we have no evidence that enrollment at the district office, which in general is very uncommon, occurred in our sample. Nor did the government conduct an RSBY enrollment drive for APL households outside the study after 2015. Study households were ineligible to enroll in RSBY via any channel unless they subsequently became eligible, e.g., by obtaining a BPL card.

was subsumed by PM-JAY in September 2018.

We measured outcome variables three times during the study. Approximately 18 months prior to the intervention, we conducted a baseline survey of several members in each sample household: the male head of household, a female knowledgeable about household finances, and a female with children below age 18. Those surveys asked about finances and self-reported health. In addition, we selected a random one-third of sample households and conducted a biomarker survey that gathered objective health measures on three members: the male most knowledgeable about household finances, a woman of childbearing age, and a child under the age of 18 (if present and available).

At 18 months after the intervention, we conducted a midline survey similar to baseline, including the biomarker survey. At 3.5 years after the intervention, we conducted an endline survey of one household member, the male head or a female knowledgeable about household finances. We did not conduct the biomarker survey at endline. As noted above, because the intervention (RSBY) ended 6 months before our endline, we asked the respondent to recall hospital utilization during the 6 months before a widely celebrated holiday, Dussehra on October 19, 2018, that occurred around when our intervention ended. Appendix A.2 provides additional details about our data collection.

2.5 Sample size and power

Our target sample size was 2,250 households for each of the four household-level groups. According to the National Sample Survey Organisation (2004), the hospitalization rate in 2004 was 10.5% and 11.8% in Mysore and Gulbarga, respectively. At this baseline rate, we estimated that 2,250 households per household-group would provide 80% power to detect a 25% change in hospitalization rate across household-level groups at the 5% significance level, allowing for 10% attrition. We doubled the sample size for the free-insurance group to increase power to detect effects regarding this most likely form for any future insurance expansion.

3 Estimation

We address three sets of research questions. First, what is the effect of access to insurance on insurance enrollment, and the effect of both access to insurance and of enrolling in insurance on insurance utilization; health care utilization; and health? We explain our estimators for the associated intent-to-treat (ITT) and complier average treatment effects (CATE), respectively, in Section 3.1. Second, is there adverse selection into insurance? To answer this question, we predict health spending at midline using baseline household covariates. We then modify our estimator of ITT effects to determine whether uptake is greater among households with higher predicted spending. We explain this approach in Section 3.2. The results appear in section 4. Third, we ask, does free public insurance improve welfare and what is the welfare-maximizing price of public insurance? To answer these questions, we estimate the relationship between insurance premiums, on the one hand, and insurance demand and hospital expenditures, on the other. This requires parametric assumptions on demand and cost functions. We explain our methods and findings

pertaining to this question in Section 5.

3.1 Effects on enrollment, utilization and heath

We estimate the intent-to-treat (ITT) effect of offering different premiums and subsidies for access to RSBY on enrollment, and both the ITT effects and complier average treatment effects (CATE) of enrollment in RSBY on utilization and health at 18 months and 3.5 years.

Intent-to-treat effect

ITT estimates are based on the following specification[20]:

$$y_{ijt} = \alpha + \sum_{h=1}^{3} \beta^h d_{ij}^h + \psi s_j + \sum_{h=1}^{3} \gamma^h (d_{ij}^h \cdot s_j) + \epsilon_{ijt} \tag{1}$$

where i, j and t index households, villages and time, respectively; y_{ijt} is an outcome; d_{ij}^h is an indicator for assignment to household condition $h \in \{1 = A, 2 = B, 3 = C, 4 = D\}$ where condition D is the baseline control condition; s_j is the share of the sample in village j that is "treated" (in household conditions A, B or C); and ϵ_{ijt} is an error term. We investigate spillover effects at the village level by examining effects on outcomes for a household in a given household condition at different values of s_j (i.e., shares of the village sample in groups A, B or C). In our setting, s_j ranges between 50–90%. The estimates of spillover effects are unbiased provided that assignment in villages $j' \neq j$ does not influence outcomes in another village j (partial interference) (Imai, Jiang and Malani, 2021).[21] The cluster robust HC2 standard error was used at the village level and account for the two-stage randomization design, an approach that can be shown to be conservative (Imai, Jiang and Malani, 2021).

The average effect of providing access to insurance via arm h to a given household (and to no other households) is labeled a "direct effect" and is estimated as the coefficient β^h on the indicators d_{ij}^h. The average effect on a given household in arm h of changing the share of other households given access to insurance via any arm (holding the treatment status of the given household constant) is labeled a "spillover" or "indirect effect" and is estimated as the sum of (a) the coefficient on the share s_j of the sample in the village in arms 1, 2, or 3 and (b) the coefficient on the interaction between the household-arm indicator and the share variable, $d_{ij}^h s_j$. This interaction allows the spillover effect to vary depending on the arm h to which a household is assigned.

The "total effect" of providing access to all sampled households in a village is defined as the sum of (a) direct effects and (b) indirect effects times the share of other sample households in a village that are offered insurance. We report total effects setting this share to 80%.[22]

[20] For binary outcomes, we use a linear probability model (LPM). For our ITT analysis we compared the LPM results with those from a logistic model and did not find economically significant differences between the two models.

[21] We tested this assumption for all outcomes by adding to the above specification the share of households given access in the village j' closest to the household i's village. For only 1 outcome (utilization of outpatient surgery) was the share in the nearest neighbor statistically significant.

[22] Another possible scenario is 100%, because a future insurance expansion might cover all other sample-eligible

3.1.1 Complier average treatment effect

We use an instrumental variables approach to estimate the complier average treatment effect (CATE) of RSBY enrollment. The CATE is the local average treatment effect among compliers in an instrumental variable framework (Imai, Jiang and Malani, 2021). We employ a two-stage least squares estimator in which the second stage regression is

$$y_{ijt} = \alpha + \phi r_{ij} + \theta z_j + \rho(r_{ij} \cdot z_j) + u_{ijt} \tag{2}$$

where r_{ij} is an indicator for RSBY enrollment and z_j is the share of the sample in village j that enrolled in RSBY. We instrument for $(r_{ij}, z_j, r_{ij}z_j)$ using variables $(d^h_{ij}, d^v_j, d^h_{ij}d^v_j)$, where d^v_j is an indicator for assignment to village-level arm v for $v \in (I, II, III, IV, V)$. Weighting, controls, and standard errors were handled in the same way as with the ITT estimator.

The CATE has a direct and indirect (i.e., spillover) component as well. The average effect on a given household of enrolling that household (and no other household) in insurance is labeled a "direct effect" and is denoted by ϕ. The average effect on a given household of changing the share of other households enrolled in insurance (holding the enrollment status of the given household constant) is labeled a "spillover" or "indirect effect". This effect is estimated using θ, the coefficient on the share enrolled, and ρ, the coefficient on the interaction of share and the indicator for household enrollment. As with the ITT estimate, the total CATE of enrolling all sample households in a village was estimated by summing (a) the direct effect and (b) the indirect effect of moving the percent of a village sample that was enrolled from 0% to 78.71%, the maximum uptake in any arm accounting for in-sample spillover effects. The cluster robust HC2 standard error is again used to cluster at the village level.

The exclusion restriction needed for the CATE analysis to identify the direct effects of *enrollment* in insurance is that the outcome of any given household is affected by the treatment assignments of households within the same village (including the given household) *only* through the actual enrollment decision of the latter households. This restriction is implied by Assumption 3 of Imai, Jiang and Malani (2021), which discusses the non-parametric identification of CATE estimates in two-stage experimental designs. Their discussion justifies use of the linear model above.

This assumption raises concerns about using the sale-plus-transfer arm B as an instrument. Perhaps the transfer affected outcomes, e.g., utilization or health, through a channel other than enrollment in insurance. We believe this risk is minimal. The amount of the subsidy is quite small, as the premium is small, relative to average household income. The subsidy may affect very short-term liquidity issues on the order of days, but not months or year-long liquidity issues, the latter of which are more likely to affect the outcomes we measure in our 18 month and 3.5 year surveys. Second, we estimated CATE effects omitting arm B as an instrument and obtained very similar results. Therefore, we report results that use arm B as one of our instruments.

households. However, we choose 80% because this is the average share of sampled households offered access to insurance in our experiment.

A second exclusion restriction, Assumption 5 in Imai, Jiang and Malani (2021), is required to identify spillover effects. That assumption states that, if a unit's treatment assignment does not influence its own take up (holding other units' treatment assignments constant), then its treatment assignment should not affect other units' outcomes. This restriction is satisfied, e.g., if never-takers do not affect others' outcomes. Importantly, this additional restriction allows for both spillover effects on take-up and on outcomes.

Both ITT and CATE analyses weight households equally. Because males and females were asked the same health questions at 18 months, we present estimates of a common effect across sexes.

Multiple testing. We present p-values for individual outcomes because all endline outcomes were pre-specified in our analysis plan. To test hypotheses pertaining to groups of related outcomes[23], we also report multiple-testing-adjusted critical values for those groups using a multiple-testing correction procedure (Rom, 1990) to control the family-wise error rate (FWER).

3.2 Adverse selection

One concern with charging positive prices for insurance is that willingness to pay (WTP) for insurance may be higher among those with higher *ex ante* expected costs; in other words, that higher prices may cause those with lower anticipated costs to dis-enroll and hence induce adverse selection (Chiappori and Salanié, 2013). In private markets with community-rated insurance, such selection can cause suboptimal levels of insurance consumption and even the collapse of insurance markets.[24] In public insurance programs, adverse selection can reduce fiscal relief governments obtain from charging premiums for public insurance, a topic we explore further in Section 5. Our study induces exogenous variation in the price at which households are offered access to insurance, allowing us to cleanly test for adverse selection.

Panel A of Figure 2 illustrates an insurance market in which adverse selection is present. Following Einav and Finkelstein (2011), the figure graphs demand for insurance (blue) and downward sloping average cost (red). The fact that that average cost is decreasing in the fraction of the population taking up insurance implies adverse selection: at higher prices only those with higher marginal cost will select into insurance.[25] Our empirical approach asks whether increasing price from p to p' increases average cost among those who enroll, i.e., if the average level of marginal cost (the green line) is greater above p' than above p.[26]

We implement this test by regressing uptake of RSBY insurance on indicators for groups that are

[23] We group outcomes separately by category, survey wave and ITT vs CATE (for instance, we group the three ITT effects we estimate (free insurance, sale of insurance plus transfer, sale of insurance) across three measures of healthcare utilization at the 3.5-year endline.

[24] With community-rated insurance, all members of an insurance pool pay the same premium, even if they have different expected costs to the pool. This premium is based on the average member's expected costs. Experience-rated insurance, by contrast, charges each beneficiary a premium based on their specific expected cost.

[25] Marginal cost need not be continuous or even monotonic, but should be lower among non-enrollees than enrollees at a given price if there is adverse selection. We depict average cost as continuous (which follows from continuous marginal cost) for simplicity.

[26] In our empirical setting, $p = 0$; however, graphically we depict two nonzero prices to make the graph more legible. The interpretation of the test is unchanged.

charged different insurance premiums, a measure of a household's expected cost, and the interaction of premium indicators and expected cost. We first explain how we estimate expected costs and then describe our estimating equation.

Measuring expected costs.

Our goal is to construct a measure of expected total household medical expenditure at midline and endline.[27] To do this, we forecast realized midline and endline medical spending in the control group (arm 4) as a function of our full set of baseline covariates using a LASSO regression. We fit the model on the control group to avoid predicting additional spending caused by insurance (i.e., moral hazard).[28] Using machine learning to select regressors avoids the need for researcher discretion in choosing what baseline characteristics are most predictive of subsequent usage/valuation of health insurance. To generate the prediction, we fit 10-fold cross-validated LASSO models on the control group. The resulting model is then used to generate predictions for the full sample. See Appendix A.5 for the LASSO procedure details.

Estimating equation. We test for differential selection using the following specification:

$$E_{ij} = \alpha + \sum_{h=2}^{3} \beta^h d_{ij}^h + \gamma C_i + \sum_{h=2}^{3} \phi^h (d_{ij}^h \cdot C_i) + \psi s_j + \epsilon_{ij} \tag{3}$$

where E_{ij} is the enrollment decision of household i in village j, d_{ij}^h is an indicator for assignment to treatment arm $h \in \{1, 2, 3\}$, C_i is the household's expected cost, and s_j is the share of the village sample assigned to arms $1, 2, 3$ as opposed to the control arm 4 in village j. In some specifications, we control for additional baseline covariates (baseline assets, education, Raven's matrix scores, and risk aversion) interacted with treatment status.

We measure variation in a household's costs (C_i) with our LASSO-based prediction of either midline or endline medical spending. We scale C_i to have unit standard deviation. The omitted category is the free-insurance group (arm 1). Therefore, γ identifies the correlation between predicted spending and enrollment in the free-insurance group and (ϕ_2, ϕ_3) identify the correlation between predicted spending and enrollment in the sale-plus-transfer (arm 2) and sale-of-insurance group (arm 3) respectively relative to γ in the free-insurance group.

We can connect these coefficients to the test for adverse selection illustrated in Figure 2. Our test, which asks whether increasing the price increases expected cost among those who enroll, is

[27] We focus on the broader measure of health care spending rather than hospital care for two reasons. First, RSBY covers inpatient care and some day surgeries, as described earlier, and it may be more difficult for households to forecast *ex ante* which conditions would require care of the type covered by RSBY versus forecasting their overall health spending needs. Second, our measure of hospital utilization is subject to measurement error at midline. Households were asked about hospital utilization but the definition of hospital was ambiguous; concurrent ethnographic work by our team revealed that many households referred even to clinics that did not provide inpatient care as hospitals. We provided a precise definition at endline. We focus on *ex ante* predicted healthcare spending, rather than *ex post* realized spending, for two reasons. One, enrollment is an *ex ante* decision; two, differences in realized spending would potentially conflate adverse selection and moral hazard or other *ex post* effects. In Section 5 we examine a realized cost measure that by design incorporates both *ex ante* and *ex post* responses to changes in prices.

[28] In theory there could be selection based on moral hazard (Einav et al., 2013). But as insurance is a novel product in India we suspect that enrollees use at best expected health care needs at current prices, rather than at prices under a novel contract, to determine their willingness to pay.

equal to a test of $(\phi_2 > 0, \phi_3 > 0)$. (These coefficients could also be negative, which would imply advantageous selection (Fang, Keane and Silverman, 2008).)

4 Results

Here we report the total effects of access to and enrollment in insurance for relevant outcomes. The total effect is the direct effect plus the spillover effect, evaluated when $\sim 80\%$ of sample households in a village obtain insurance, the average in our study.[29] We report direct and spillover effects specifically in Appendix B.

4.1 Insurance enrollment

Free-insurance arm. When insurance was offered for free, 78.03% of households enrolled. Figure 1 plots ITT estimates for RSBY enrollment (and Table A.3 provides details). One might wonder why all households offered free insurance did not take it up. However, incomplete take-up of a nominally free insurance is common. Even in the US, the Medicaid enrollment rate among eligible non-elderly adults was only 62% in 2008 (Sommers and Epstein, 2010). Enrollment rates tend to be higher among those with greater health care needs (Kenney et al., 2012). Partial uptake at zero price could be driven by shadow prices, which include the opportunity cost of the time required to enroll and the hassle costs of enrolling (Banerjee et al., 2021). Finally, enrollment may also be suppressed in India because health insurance is a newer and less well-known product there (Berg et al., 2019).[30]

Sale-of-insurance arm. When households were charged for insurance, the enrollment rate was 58.66%, 19.37 percentage points (pp) lower ($p < 0.001$) than in the free-insurance arm (78.03%). This reduction in enrollment implies that the price elasticity of demand for insurance is -0.33, well within the range of estimates in the literature (Pendzialek, Simic and Stock, 2016).[31,32]

[29] Using the notation of Equation 1, the total effect is $\beta^h + .802 \times (\psi + d_{ij}^h)$; the average share of sample households offered insurance is 80.2%.

[30] That said, we do not find heterogeneous enrollment rates by educational status, specifically an indicator for whether the health of household has more than a 10th grade education (unreported).

[31] (78.03% enrollment with free insurance – 58.66% enrollment with sale of insurance at an average price of INR 183)/58.66% = 0.33. We do not use the usual arc elasticity formula, which normalizes by the midpoint of enrollment and price, because our change in price is going from full price to zero price. Our formula implies this is a 100% reduction in price while the usual arc elasticity formula would imply this is a nonsensical 200% reduction in price.

[32] Although the enrollment rate in the sale-of-insurance group was lower than in the free-insurance group in our above-poverty-line (APL) sample, it was similar to the enrollment rate among below-poverty-line (BPL) households offered free insurance under the official RSBY scheme. The enrollment rate in the official RSBY program was 43.12% in Gulbarga, 59.97% in Mysore (RSBY, 2018). Enrollment among APL households in the free-insurance group is much higher than among BPL households offered free insurance. One possible explanation is that our sample has higher income, meaning higher compensated demand or fewer liquidity constraints. We find mixed evidence for this explanation. A regression of household-level uptake decisions on baseline household expenditures (as a proxy for income) interacted with treatment group indicators (and no main effect of household expenditures) in a sample that excludes the control group finds no significant coefficient on interactions with household expenditures (Table A.4). However, a regression of uptake that uses our wealth index does find a significant coefficient on wealth (Table A.5 from the section on adverse selection). An alternative explanation is that enrollment assistance is responsible for the higher in uptake in our study sample. While our study used the same promotional material that the official RSBY

Our estimate of enrollment in the sale-of-insurance arm sheds light on two questions in the literature. One concerns the level of demand, namely whether there is any positive demand for insurance with positive premiums. Banerjee, Duflo and Hornbeck (2014) suggested very low demand for health insurance in India.[33] Likewise, Banerjee et al. (2021) found low uptake ($< 10\%$) of unsubsidized public insurance in Indonesia. By contrast, our study estimates substantial take-up (58.66%) at unsubsidized prices. The other debate concerns the elasticity of demand, i.e., the effect of cost-sharing on uptake of health products and services. For example, Cohen, Dupas et al. (2010) estimate a 75% drop in uptake when they increase price of bed nets from 0 to 15% of the full cost. Our elasticity estimates are much smaller. The difference between our findings and the earlier literature may be attributable to differences in product, in income, and in enrollment assistance.

Sale-plus-transfer arm. In this arm, the enrollment rate was 71.47%, 12.81 pp higher ($p < 0.001$) than in the sale-of-insurance arm (58.66%).[34] If we use the sale-plus-transfer arm (rather than the sale-of-insurance arm) to calculate the price elasticity, the implied elasticity of (compensated) demand is -0.092, on the low end of the range of estimates of insurance demand elasticity in the literature Pendzialek, Simic and Stock (2016). This lower elasticity may be the product of rural households in an LMIC having a greater need for insurance because they lack other options for smoothing financial shocks due to health risk.

Our findings have implications for the efficacy of insurance pricing at raising enrollment (with welfare effects we discuss in more detail in Section 5). Because free insurance is akin to pure insurance plus an in-kind subsidy, we infer that in-kind subsidies raise enrollment by twice as much (from 58.66% to 78.03% v. to 71.47%) as unconditional cash transfers of the same amount ($p < 0.001$). However, ignoring concerns about distribution, pure insurance is a much more cost-effective means for the government to promote uptake than even free insurance. In our sample, we were able to achieve 58.66% enrollment while paying no additional premiums. To increase enrollment by a further 19.37 pp required paying premiums for both marginal and infra-marginal households—all told, 78.03% of households. This implies an effective premium roughly 4 times the actual premium per marginal (i.e., incremental free-insurance-complier) household.[35]

4.2 Insurance and hospital utilization

We measure utilization along two dimensions. First, we examine utilization of *insurance* (use of the RSBY insurance card to pay for care) separately from utilization of *hospital care* (overnight

scheme did, our study went a step further and visited each house in person to tell them where the enrollment station was on the designated day(s) of enrollment. Unfortunately, we cannot explore this hypothesis because we do not have any variation in marketing across households. However, Banerjee et al. (2021) found enrollment assistance increased public insurance uptake in Indonesia.

[33] In Banerjee, Duflo and Hornbeck (2014), microfinance borrowers were required to purchase insurance as a condition of obtaining a business loan, but could use the loan proceeds to pay for insurance; borrowers chose not to renew loans when this condition was imposed.

[34] The 13.08 pp increase in uptake with a transfer is consistent with the view that the sale-plus-transfer treatment relaxed liquidity constraints (Berkouwer and Dean, 2022; Casaburi and Willis, 2018).

[35] An additional issue with providing free insurance is distortions associated with raising revenue, while a concern with raising price is adverse selection; we return to these trade-offs below.

stay or same day surgery). These capture the effect of insurance at two margins: (i) insurance can change financing of care, holding level of care constant, and (ii) it can affect the level of care. Second, we distinguish successful and unsuccessful efforts to use insurance. Successful use affects insurer costs and beneficiary finances/care. Unsuccessful use reflects either administrative failures or beneficiaries' lack of knowledge about how to use insurance. We report ITT effects of insurance access and CATE of insurance enrollment. The CATE provides a scaled version of ITT, to facilitate comparisons across different interventions which may change enrollment by different amounts. Some measures of use at 3.5 years differ from those at 18 months due to differences between midline and endline surveys.

Insurance utilization. We find that access to insurance substantially increased successful utilization of insurance for payment (Table 3, with details in Table A.7) at 18 months and 3.5 years in all arms. Because we measure utilization over the last 6 months, the annualized rate is double our estimates if rates are constant over a year,[36] so the average annual insurance utilization rate at 18 months (3.5 years) is 20.26% (3.38%) in the free-insurance arms versus 7.72% (0.64%) in the control arm.[37] On average this effect amounts to a 62.44% (328%) increase in insurance utilization at 18 months (3.5 years).

Insurance enrollment also increased successful use of insurance for payment (total effect: Table 3, details: Table A.8). It raised annual insurance utilization at 18 months to 19.14% (from a base of 7.72%) and at 3.5 years (for the most serious event only) to 3.86% (from a base of 0.64%).[38]

All effects on successful and failed insurance utilization (ITT and CATE) at 18 months remain significant at 5% or better when using the FWER-adjusted 5% critical values. At 3.5 years, ITT and CATE effects on successful use over the past 6 months likewise remain significant at 5% or better. The CATE effects on successful and failed use at most serious health event also remain significant.

Hospital utilization. We estimate imprecise effects of insurance access and enrollment on utilization of hospital care at 18 months and 3.5 years, with some point estimates positive and some negative (total effects: Table 3, details: Appendix Tables A.7, A.8). We do not find evidence that insurance increased the intensity of use of hospitalization, as captured by length of stay, which we measured at the 3.5 year endline. Thus, we do not find significant effects on the extensive (admission) or intensive margin (length of stay) of hospital utilization. We discuss how the contrast between insurance and hospital utilization results sheds light on the value households obtain from

[36] The average 6-month insurance utilization rate at 18 months (3.5 years) is 10.13% (1.69%) in the free-insurance arms versus 3.86% (0.32%) in the control arm.

[37] Control group households can have positive utilization because it is possible for they obtain RSBY, e.g., by falling below the poverty line and obtaining a BPL card, or by switching into an RSBY-eligible occupation.

[38] It raised 6-month insurance utilization at 18 months to 9.57% (from a base of 3.86%) and at 3.5 years (for the most serious event only) to 1.93% (from a base of 0.32%).

As noted above in Section 2.4, households had the opportunity to re-enroll in RSBY approximately one year after their initial enrollment and we collected information at endline on RSBY card possession. CATE estimates in which we instrument endline card possession with treatment assignment appear in Appendix Table A.10; these estimates are qualitatively similar to our primary specification.

CATE estimates of total effects may be greater or less than analogous ITT estimates because total effects are a weighted sum of direct and indirect effects which may have opposite signs.

insurance in Section 4.4, after we discuss effects of insurance on health.

However, it is worth discussing whether the lack of significant hospital utilization results is due to inadequate power before we turn to health outcomes, because the latter are downstream of care utilization. We powered the study assuming hospital utilization was 10% based on the then-latest (2004) data from National Sample Survey Organisation (2004) for the two districts in our study. However, in our 2017 midline, actual utilization in the control group was 20.3%. This means that, while we were adequately powered *ex ante*, the *ex post* realization of variance was sufficiently high that we may not have been powered to detect utilization given our point estimates.

Failed utilization of insurance. Many households had difficulty using their insurance to pay for healthcare. At 18 months (3.5 years), access to free insurance increased the number of households who tried to use their insurance card but were unable to do so by 6.68 (1.84) pp annually, from a base of 2.68% (0.44%).[39] This excess failure rate is roughly 50% of the successful utilization effect. This result is congruent with Banerjee et al. (2021), who examine failure to *enroll* in insurance; we document failures in the *use* of insurance.

Lack of knowledge—about the purpose of insurance and how to use insurance—is a potential explanation for failed use. Because insurance is a relatively new product, both hospitals and beneficiaries may not know how to use it (Nandi et al., 2016; Rajasekhar et al., 2011; Berg et al., 2019). In our midline and endline surveys, we asked why households did not try to use their insurance card to pay for care and why they were unable to use the card even when they tried (Table A.15). The most frequent reasons given for not using the card were not knowing that the card could be used for insurance (15% at 18 months, 20% at 3.5 years), forgetting the card at home (13% at 18 months), and not knowing how or where to use the card (29% and 30% at 3.5 years). Besides these beneficiary-side problems, there were also supply-side problems. Of those who tried to use the card, 55% and 69% said that the hospital did not accept the card at 18 months and 3.5 years respectively, and 12% said that the insurance company did not accept the card (i.e., did not approve use) at 3.5 years.[40] This finding suggests that interventions on both the demand-side (e.g., education) and supply-side (e.g., IT and training) may be important for raising utilization of, and thus demand for, insurance in India and similarly situated countries.[41]

[39] On a 6 month basis, the analogous numbers are 3.34 pp and 1.34% for 18 months, and 0.92 pp and 0.22% for 3.5 years. The 18-month results on failed utilization all remain significant using the FWER-adjusted critical value.

[40] These should be interpreted with caution because we do not know if doctors correctly did not approve the card because a service was truly not covered, or incorrectly/strategically did so. Such strategic behavior has been documented in other contexts: Alexander (2020) shows that doctors in the US strategically turn away patients who are unlikely to generate large billable fees and Alexander and Schnell (2024) show that lower benefit generosity increases the rate at which providers turn away beneficiaries.

[41] We find no evidence that the lower absolute effect of insurance access or enrollment on insurance utilization at 3.5 years was due either to earlier negative experience with failed efforts to use insurance, or to reduced need for care due to earlier successful use of insurance. Specifically, we find no sizable or significant correlation between insurance use at 3.5 years and either (a) failed or (b) successful insurance use at 18 months (unreported). The absence of a significant effect of insurance access or enrollment on hospital use underscores this conclusion.

4.3 Health outcomes

Insurance had few significant effects on health at 18 months or 3.5 years. Having measured (a) 3 parameters (direct/indirect/total effects) for (b) 3 ITT effects (one per treatment arm) and one CATE effect for (c) 98 outcomes (91 specified and 7 index variables) over 2 surveys, only 50 of 1176 estimated coefficients (4.25%) were significant even without multiple-testing adjustments. Table 4 provides a summary and Tables A.16 and A.17 report estimates of ITT effects at 1.5 and 3.5 years, while Tables A.18 and A.19 report the corresponding CATE estimates.[42] We cannot reject the hypothesis that our estimated p-values are drawn from a uniform distribution ($p = 0.31$), the distribution we would expect if there are no effects of insurance on health outcomes. We also find no effects summary indices of health outcomes, also reported in Tables A.16 - A.19.

These insignificant health effect estimates should be interpreted with care. First, despite our large sample size, we may lack power to detect the effect of insurance on health, either because insurance has a small effect on the level of hospital care, or because hospital care has small effects on each health outcome (Das, Hammer and Leonard, 2008). Recall, our study was powered to detect a change in hospitalization rates, not health.

Second, our estimated confidence intervals cannot rule out medically significant effects for many outcomes. On average, the absolute value of an estimated ITT effect (CATE) for an outcome equals 11% (8.8%) the standard deviation of the outcome.[43] Appendix Tables A.16 - A.19 report standard errors for each outcome so that one can see what effects on health can be ruled out if one's prior hypothesis is that there are positive effects on health.

Third, we cannot rule out both positive effects for some outcomes and negative effects for others. Depending on what we classify as a negative (i.e., "bad") outcome, 23.6-47.2% of midline ITT estimates and 41.3-57.8% of endline ITT estimates imply negative (though typically insignificant) effects on health.[44] To illustrate the roughly balanced positive and negative range of nominal effects, Figures A.2 and A.3 (A.4 and A.5) show coefficient plots of ITT (CATE) estimates of the total effect (direct and spillover effect) of free insurance (insurance enrollment) on health outcomes at midline and endline.

Our findings are broadly consistent with prior RCTs of health insurance in low- and middle-income countries, none of which find significant effects on health. Our findings contrast with one other (observational) study in India that does find significant mortality effects from health insurance (Sood et al., 2014); however, that study examined a more generous insurance product that covered

[42] We report results where the impact of access or enrollment on a given outcome is restricted to be the same for women and men and each person is given equal weight. We obtain similar results – in terms of fraction of significant coefficients – if we estimate separate regression models for women and for men (not reported).

[43] This estimate is for particular health outcomes, not our index of outcomes.

[44] These numbers include direct, indirect, and total effects (as we define them for our ITT estimates) for particular outcomes (rather than our indices). If we classify being diagnosed with a condition as a negative statement about health (i.e., falling ill), but taking medicine as positive for health (i.e., getting treatment), then 47.2% and 57.8% of ITT estimates imply a reduction in health at midline and endline, respectively. If neither diagnosis nor being on medication for an ailment is treated as a negative outcome, these percentages are 23.6 and 41.3%, respectively. If being diagnosed is treated as neutral for health, but being given medicine as positive for health, then the numbers are 34 and 50%.

long-term or chronic hospital stays rather than short-term, acute-care stays.

4.4 Mechanisms through which insurance generates value

The greater utilization of insurance combined with insignificant effects on hospital utilization, documented in Section 4.2, suggests that insurance access primarily shifts the financing of care, rather than the level of care. The lack of significant effects on health is consistent with this story.

If insurance has mainly financial effects, we expect that it would reduce out-of-pocket (OOP) payments. A benchmark of how much OOP spending would change if RSBY had purely financial effects, i.e., changed the financing of infra-marginal spending with no additional changes in the level of care, is INR -1108 (-$63), calculated as (i) the control mean of medical OOP spending (INR 28,777), (ii) multiplied by the pooled treatment effect on RSBY insurance utilization, and (iii) multiplied by -1 since utilization reduces spending 1 for 1 under this benchmark). However, we do not find any reduction in OOP. Table A.25 reports ITT effects and Appendix Table A.11 reports the CATE. At 18 months, the total effects of assignment to free insurance, sale of insurance plus transfer, and sale of insurance were positive, and significantly greater than -1108 (though not significantly different from zero).[45] We are not the only paper not to find a reduction in OOP: Wagstaff et al. 2016, for example, also find that insurance does not mitigate OOP spending in Vietnam and Karan, Yip and Mahal (2017) find that RSBY is associated with higher OOP spending.

There are several ways to reconcile the utilization, health and OOP results. First, when insurance reduced their price for hospital care, respondents may have increased hospitalization and spending on OOP costs that were complements of hospitalization but not covered by insurance (such as on medicines prescribed at the hospital but obtained elsewhere). We believe this is the most probable answer. Note that, for OOP spending on complements to hospitalization to increase, hospitalization must have increased; while we do not find significant positive effects of insurance access or enrollment on hospital utilization, our hospitalization point estimates are positive and they have sufficiently wide confidence bars that we cannot rule out large positive effects.

A second way to reconcile our different results is that, while we focus attention on the extensive margin of healthcare utilization, insurance may increase utilization along the intensive margin (e.g., number of services per hospital visit). We do have one measure of the intensive margin, length of stay, though only at endline. However, we do not find that length of stay increased (Table 3).

Third, perhaps failed utilization caused some households to increase OOP spending (e.g., a household went to the hospital because they had insurance, but was unable to use the insurance and had to pay OOP). In principle, such increases could offset reductions in spending for other households. However, in Appendix Figure A.6, we plot the distribution of quantile treatment

[45] At the 3.5 year endline, the effects are negative but not significantly different than either 0 or -1108. To see if our results are a product of low power, we estimate a more parsimonious specification, regressing expenditure on premium and subsidy group, but omitting the share of sample members who are given access to insurance and any interaction between share and household-group. As Appendix Table A.12 shows, our results are materially unchanged. The OOP results remain insignificant when using the FWER-adjusted critical value.

effects and do not find evidence of large increases in OOP for some quantiles nor of decreases for others. Instead, throughout the distribution the estimated effect on OOP is (insignificantly) positive. Moreover, below the 80th percentile the effect is significantly greater than -1108.

A fourth possibility is that hospitals may charge insured patients an amount above and beyond what insurance pays. RSBY pays below-market rates for health care and hospitals may charge patients for all or part of the difference between market and RSBY reimbursement rates. Jain (2021) finds evidence of such "balance billing" in Rajasthan. As a joint test of these last two possibilities (failed use and balance billing), we examine whether treatment effects vary according to a proxy for the predicted likelihood to successfully use RSBY; however we do not find significant interactions (Table A.14).[46]

The discrepancy between the insurance utilization and OOP results raises a second question: why do households purchase insurance if neither improves health nor decreases OOP? Our analysis clearly shows demand for insurance. Health economists typically assume that value comes from financing care (i.e., reductions in OOP payments) or increases in healthcare (and health). But we do not find significant evidence for either effect. Our preferred explanation is that insurance has value even if it increases OOP spending. Lowering the price of hospital care frees up money for OOP spending on complementary medical care, such as at-home bandages and pain medication. If hospital utilization rose, then there is a substitution effect that increases consumption of complementary care. Even if hospital utilization did not increase, there is a positive income effect on non-hospital medical care, a normal good.

Another explanation is that we do not measure all aspects of value from insurance. Insurance may provide value via a variety of mechanisms, each of which may be difficult to statistically detect, particularly for a "no frills" insurance product such as RSBY. For example, having insurance may give beneficiaries some peace of mind even if they never fall ill. Indeed, other studies of health insurance (Haushofer et al., 2020; Finkelstein et al., 2012) have found effects on stress, though we measured but did not find significant effects on stress.

A third explanation is that our average treatment effects may mask heterogeneity in benefits from insurance, even on outcomes we do measure. To explore these, we use causal forests (Wager and Athey, 2018) in the manner outlined in Imai and Li (2025) to explore heterogeneity in enrollment and in treatment effects. While we detect statistically significant heterogeneity in enrollment that can be predicted by baseline covariates, no significant predictable heterogeneity is found in the group-average treatment effects of enrollment on downstream outcomes (Appendix Figure A.9).

A final possible explanation is that households were irrationally optimistic about the value of insurance. Our evidence on failed use is consistent with this explanation: perhaps individuals thought that insurance would be easier to use than it actually was.[47] However, it is not possible to

[46]Specifically, we use LASSO to predict the likelihood of successfully using RSBY in the treatment groups as a function of baseline covariates, generating predictions for treatment and control, and adding the resulting predicted use variable (levels and treatment interactions) to a regression predicting midline OOP spending.

[47]If consumers were, in fact, irrational when purchasing RSBY, that would also undermine the welfare analysis in the next section; that analysis is premised on the idea that the demand curve measures actual willingness to pay.

demonstrate that households were irrational. *Ex ante* the purchase may have been a good gamble, but *ex post* it was not, due to a common shock, e.g., insurance IT systems not working or RSBY hospital networks being inadequate.

4.5 Adverse selection

We find significant adverse selection into insurance at midline. Recall that our test for adverse selection is whether arms B and C, which impose a positive price on insurance, attract enrollees who have higher predicted cost, compared to arm A, which offers free insurance. This implies testing for $\phi_2 > 0$ and $\phi_3 > 0$ in regression Eq. (3). Table 6 presents our estimates.

Columns 1 and 2 use predicted midline spending.[48] Column 1 shows that, while a household with the mean level of predicted spending is 19 pp less likely to enroll under the sale-of-insurance treatment (arm C) than under the free-insurance treatment (arm A), a one standard deviation (SD) increase in predicted spending increases enrollment in arm C by 6 pp ($p < .01$), corresponding to 10.1% of the enrollment rate in arm C. Moreover, while an average expected-spending household in sale-plus-transfer treatment (arm B) is 6.6 pp less likely to enroll in RSBY, a one SD increase in predicted spending in that arm increases enrollment by 2.9 pp.

Our measure of predicted health spending may be correlated with other household characteristics that affect willingness/ability to pay for insurance. To investigate whether costs *per se* rise with price due to adverse selection, Column 2 includes controls for household baseline asset holdings, the education level of the household head, the head's score on a Raven's matrices test, and a measure of risk aversion. The magnitude and significance of the interactions between the positive-price insurance arms (B and C) and the predicted spending measure remain quite similar, suggesting that predicted health spending is not simply proxying for wealth, education, financial sophistication, or risk tolerance.[49]

Columns 3 and 4 show results obtained using predicted endline spending rather than midline. The magnitude of adverse selection is roughly half as large, consistent with the fact that it is likely more difficult for households to predict their spending 3.5 years in the future relative to 1.5 years.[50,51]

Price and utilization. Two additional results are consistent with adverse selection. The need to pay a higher price may select for those with greater motivation/ability to navigate the process

[48] We discuss the construction of this measure in Sec. 3.2; this is our preferred measure as households likely find it easier to predict expenses in the year following enrollment than expenses 3 years in the future.

[49] Adverse selection is the extent to which higher price increases the probability higher costs persons relative to the probability lower cost persons do, regardless of what the drivers of cost are (worse health, greater sophistication about using insurance, etc.). The results in Columns 2 and 4 demonstrate that selection on predicted cost is present after controlling for the direct effects of wealth, cognitive measures, education and risk aversion.

[50] See Appendix A.5 for details.

[51] We can also test for adverse selection another way. Specifically, we focus on a sample of households that enrolled in insurance and regress their predicted midline cost on separate indicators for assignment to the sale-of-insurance and sale-plus-transfer arms and a constant. The results appear in Table A.6. We again find evidence of adverse selection, namely higher predicted costs among the sample who enroll under the sale-of-insurance arm vs the free-insurance arm ($p = 0.034$).

of successfully utilizing insurance and, on the flip side, those who are less likely to experience failed utilization attempts. Table A.7 shows that the direct effect of access to paid insurance (arm 3) on successful utilization of insurance is 7.67%, almost 3 times as great as for free insurance (arm 1); a one-sided test of equality vs. the alternative of greater successful utilization in the paid arm is rejected with $p = 0.06$. [52] Second, the effect of assignment to free insurance on failed use is significantly larger than that of assignment to paid insurance (3.57% vs. 2.57%); a one-sided test yields a p-value of 0.05.[53]

Our evidence on adverse selection is distinct from but complements prior studies on adverse selection in health insurance markets in lower-income countries. In contrast to Banerjee, Duflo and Hornbeck (2014), we find evidence of adverse selection in Indian health insurance markets. Our evidence completes the picture from Fischer, Frölich and Landmann (2023), which find that there is within-household adverse selection in health insurance. Because higher risk household members are more likely to buy insurance, they suggest that household-level policies mitigate adverse selection. Our evidence shows that there is also a degree of adverse selection even in the sale of household-level policies in South Asia.

5 Welfare analysis

We employ the model of adverse selection in Einav, Finkelstein and Cullen (2010) and the marginal value of public funds (MVPF) framework (Hendren, 2016; Finkelstein and Hendren, 2020) to calculate whether offering free RSBY insurance improves welfare. In Appendix 5, we extend the model to calculate the optimal premium for public insurance.

Our welfare analysis compares free, public insurance to a counterfactual where neither the government nor private sector offer insurance. This is a reasonable counterfactual in India, where private insurance is largely unavailable outside of large cities (Gambhir et al., 2019). We examine the case where the counterfactual is private insurance in the appendix. When calculating welfare, we assume there are no externalities from consuming insurance, largely because we do not estimate externalities from hospital insurance.

5.1 Framework

We present a graphical sketch of our welfare analysis here; formal derivations are in the appendix. We begin with the canonical illustration of adverse selection with community-rated insurance from Einav and Finkelstein (2011) (Figure 2, Panel B). We arrange potential insurance consumers in

[52] A one-sided test is only appropriate for a test of e.g., adverse selection. If the question is whether there is any selection, adverse or advantageous, a two-sided test is appropriate and the relevant p-value is 0.12.

[53] Unlike our core test of adverse selection, these results on successful vs. failed utilization use an *ex post* measure and as such cannot separate selection effects — differential selection of those who are, at enrollment, more vs. less likely to successfully utilize — from treatment effects, wherein being offered a higher or lower price causes changes in, for instance, motivation to study and remember the rules via a mechanism such as sunk cost effects or price signaling value. Disentangling these is beyond the scope of our analysis; we do not have separate variation in offer prices vs. transaction prices as in Ashraf, Berry and Shapiro (2010).

order of willingness to pay for insurance and assume that the highest value consumers have the highest marginal cost of care, i.e., adverse selection. Consumers' Hicksian demand curve is blue. The marginal cost of care for incremental consumers is green. The socially optimal quantity of insurance q^* is given by the intersection of the demand and marginal cost curves. Total surplus at the optimal quantity is the area between the demand and marginal cost curves.

The usual application of this model is a private insurance market.[54] With community-rated (i.e., average cost) premiums and actuarially-fair private plans, consumers are charged the average cost of care (red). The equilibrium quantity q_p is given by the intersection of the demand and average cost curves. Because of adverse selection, the private-equilibrium quantity is suboptimal. The welfare loss from insurance is the area (in gray) to right of the community-rated quantity and left of the optimal quantity, below the demand curve and above the marginal cost curve.

Our context—free, public insurance—differs from the canonical model in two respects. First, the premium is 0, not set by community-rating. This means that, instead of suboptimal consumption, there may be excessive consumption. The equilibrium quantity with free insurance is the x-intercept of the demand curve, q_0. If marginal cost intersects the demand curve, q_0 will be greater than the socially-optimal quantity. Welfare loss now includes (at least) the area (in light red) from q^* to q_0, and between the marginal cost curve and maximum of the demand curve or 0.

Second, because public insurance is paid for by the government, we have to account for the marginal cost of public funds (MCPF). This is where we introduce the MVPF framework. The cost incurred by the state is the area (shaded with vertical lines) under the marginal cost line from the y-axis to q_0. This includes both costs for quantity q^* that is efficient but also costs for quantity $q_0 - q^*$ that is inefficient. All this cost has to be scaled by the MCPF r. That additional social cost reflects either a fixed government budget and the opportunity cost of foregoing other social programs, or the deadweight loss from raising funds with taxes.

To summarize, the welfare from free, public insurance is equal to the social benefits minus the social cost of this insurance. The social benefit is the area under the Hicksian demand curve from 0 to q_0. The social cost is the area under the marginal cost curve over the same range, multiplied by $1 + r$, reflecting the MCPF. More formally, if $G(p)$ is the quantity demand at price p, $D^H(q)$ is the Hicksian inverse demand at quantity q, and $c^{AC}(p)$ is average cost among consumers who buy insurance at p, then the welfare effect of free insurance is

$$MSB - MSC = \left[\int_{\infty}^{q(0)} D^H(q(p))dp\right] - \left[(1+r)c^{AC}(0)q(0)\right] \tag{4}$$

where the product of average cost and quantity captures the area under the marginal cost curve.

An interesting question is what premium the government should optimally charge. We address

[54] Einav and Finkelstein (2023) make an analogous figure using data from an RCT in Pakistan that randomized the price of insurance, to demonstrate adverse selection (Fischer, Frölich and Landmann, 2023). An important difference between that paper and this one is that the former uses the figure to calculate the welfare loss from adverse selection, while we leverage the graph to employ the MVPF framework to determine the welfare loss from free insurance and the optimal price of public insurance.

this in the appendix. In the private insurance context, firms should charge $p^* = p(q^*)$, but instead charge $p(q_p) > p^*$ because of average cost pricing and adverse selection. However, the optimal price for the government is greater than p^* because social cost for public insurance is not just the area under the marginal cost curve, but that area scaled by the marginal cost of public funds $(1 + r)$. So the optimal price of public insurance will be greater than marginal cost.

Calculations. We apply the analysis above to our context by, first, estimating individual demand and average cost curves. We estimate linear specifications because we only observe behavior at two prices (zero in group A and full premium in groups B and C):

$$q_i(p_i) = q(0) - \gamma p_i + \epsilon_i \tag{5}$$

$$c_i^{AC}(p_i) = c^{AC}(0) + \kappa p_i + \upsilon_i \tag{6}$$

where i indexes households, $q_i(p_i) \in \{0, 1\}$ is household i's enrollment decision, p_i is the premium in household's treatment group, c_i^{AC} is an enrolled household's average cost to the insurance pool, $\gamma > 0$ measures the slope of demand, and $\kappa > 0$ if there is adverse selection.

We simultaneously estimate both equations using linear regression. Our primary sample includes (A) the free-insurance group (charged a price of zero) and (B) the sale-plus-transfer group (charged the full premium). This sample produces an upper bound on Hicksian (i.e., compensated) demand, which is the relevant curve for estimating the willingness to pay. The unconditional cash transfer, which is equal to the premium, is a sort of compensation. However, because even households that do not purchase insurance receive the compensation, we may overestimate Hicksian (compensated) demand. Nevertheless, this sample yields our preferred estimates for demand as liquidity constraints are likely important in LMIC contexts (Berkouwer and Dean, 2022; Casaburi and Willis, 2018).[55]

Household average cost is measured using hospital expenditure at midline (18 months).[56] We

[55] As a robustness check, in the appendix we estimate demand and welfare with a second sample that includes the (A) free-insurance and (C) sale-of-insurance groups. This sample produces estimates of Marshallian demand. That is a lower bound on demand because income effects are surely positive.

A common assumption in demand estimation in health economics is that there are no income effects. In that case, Marshallian demand is equal to Hicksian demand. This assumption is mainly for convenience, however, because there is also a sizable literature finding that income increases healthcare expenditure, though micro and macro estimates differ on magnitude (Acemoglu, Finkelstein and Notowidigdo, 2013).

While using group B overestimates Hicksian demand, group C underestimates it. We believe that the latter error is more serious. Some of the lower uptake in C is driven by liquidity constraints, which we think would be relaxed in an expansion of RSBY: enrollment drives would be predictable and the PMJAY program that replaced RSBY allowed year-round enrollment at hospitals when required. Moreover, the magnitude of the premium in our study ($\sim$ 200 INR, \$11.42) is small relative to annual income, so likely has a small income effect.

[56] Our measure of midline cost is the product of (a) a household's hospital expenditure at endline and (b) whether the household used RSBY insurance to pay for care in the last 6 months before midline, times two. We based midline costs on a measure of endline hospital expenditures (rather than on midline medical expenditure) because many households, when asked about hospital care at midline, mistakenly reported non-acute clinic care as hospital care. (This occurred because the term "hospital" can, in rural India, mean a clinic with same-day treatment, and we did not tell respondents at midline to report only hospital care that involved an overnight stay. We corrected our survey at endline by defining hospital care as care at a facility with overnight stays.) Our measure of midline hospital costs assumes midline and endline hospital costs are roughly the same given the long time-span between them (reducing concerns of negative serial correlation). We convert endline hospital expenditures to midline costs from use by multiplying endline hospital expenditures by *midline* use of RSBY to pay for hospital care. We multiply the product by two to get annual costs because endline use, a binary variable, covers use over 6 months.

consider costs at endline (3.5 years) in the appendix. The sample for the cost regression only includes households in treatment arms (groups A and C, not the control group) that actually enrolled in insurance. We exclude the sale-plus-transfer group because, outside this experiment, uncompensated (Marshallian) demand determines enrollment. We exclude the control group because they cannot enroll under our experiment.

In both regressions, the free insurance group A is coded as paying a price of 0 and the sale-plus-transfer and sale-of-insurance groups B and C are coded as paying a price of 203 in Mysore and 173 in Gulbarga. This is the government premium in each district plus the INR 30 paid for the insurance card. We cluster standard errors at the village level (as in our ITT model).

We plug our estimates of Eqs. (10) and (11)—reported in Table A.30 and plotted in panel A of Figure 3—into Eq. (4) to calculate the welfare effect of free public insurance.

Using a MCPF of $r = 1.25$ to account for the high opportunity cost of government spending or inefficiency of tax systems in lower-income countries like India[57] we calculate that free insurance reduces welfare by INR 63 ($3.60) per household at midline (Table A.30, row 1), though our estimate is imprecise.[58]

Our findings are driven by the level of utilization, the costs that the government must finance, and by the marginal cost of public funds. If we include in our measure of utilization not just successful utilization, but also failed attempts at utilization (to capture the idea that households may utilize successfully more often over time), then free insurance reduces welfare by 534 INR ($30) per household even at endline (Table A.30, column 4).

To determine how robust our calculations are to the MCPF, panel B of Figure 3 plots the welfare from free insurance (magenta line) as the MCPF increases. Welfare falls as r rises because the costs of financing utilization increases. An important policy implication is that even if public insurance is not valuable today, it may become valuable as the tax system becomes more efficient.

To further determine how robust our findings are, we calculate the value of free insurance using sale-of-insurance arm (C) rather than arm B to estimate *ex post* demand and other measures of hospitalization costs (see Appendix table A.27). Our results are qualitatively similar: free insurance lowers welfare at our realistic MCPF.

We provide MVPF calculations using using other measures of cost, including midline medical expenditures, in the appendix (Table A.27). While cost curves differ, the MVPF calculations yield similar results.

These average cost measures are not the same ones we use for estimating adverse selection in Section 4.5. There the goal was to use predicted expenditure based on information available prior to enrollment and to avoid including *ex post* moral hazard in our prediction; here want to use actual expenditure to measure actual cost, including moral hazard, because that contributes to the insurance company's (or government's) cost.

[57] Our estimate is at the lower end of the range used for MCPF for such countries. Historical data on the MCPF from India suggest an $r = 1.5$, but those estimates are from the mid-1980s (Ahmad and Stern, 1987). A more recent survey of the MCPF from Africa suggests a median estimate of $r = 1$ (Auriol and Warlters, 2012). (Basri et al., 2021), studying the optimal tax rate in Indonesia, focus on the cases where $r = 1.5$ and 2. These estimates are higher than convention for US-focused studies, which use $r = 0.3$ (Finkelstein and Hendren, 2020).

[58] Standard errors on welfare calculations are obtained using the delta method.

6 Conclusion

This paper reports on a large-scale RCT that estimates a range of policy-relevant parameters concerning health insurance in India. We estimate substantial demand for insurance, but also adverse selection into insurance. We estimate that insurance enrollment increases insurance utilization, but that many beneficiaries are unable to use insurance to pay for care. Finally, although there is substantial demand for insurance, we do not find systematic positive effects of insurance on health. Combining these findings with realistic estimates of the cost of public funds in India, we calculate that free public insurance may not be welfare improving.[59]

Our study has, however, a number of limitations. First, it examines a limited product (hospital insurance without primary care or drug coverage) for a limited population (above-poverty line rather than below-poverty line households). Second, while our study is able to estimate Marshallian demand for insurance, it is based on just two prices and our study can only set identify, not point identify, Hicksian demand. Third, our measures of *ex post* medical expenditure, including out-of-pocket (OOP) expenditure, are limited or noisy. While we are able to demonstrate adverse selection based on *ex ante* predicted expenditure, we are unable to estimate precisely effects on post-enrollment expenditure. (However, all the *ex post* measures of cost also show that free insurance is not welfare improving at reasonable values of the marginal cost of public funds for India.) Fourth, although our RCT has a large sample size, it is still not powered to detect or rule out plausible health effects. Moreover, we only measure effects on health out to roughly 3.5 years. There may be longer-term health effects of insurance we were not powered or unable to estimate.

We find that many enrollees attempted to use RSBY but were unable to do so. This has implications for both insurance policy design and the external validity of this study. Some explanations for inability to use RSVY insurance were demand side, e.g., forgetting the insurance card at home or not knowing which treatments or hospitals were covered. Others were supply side, e.g., the RSBY card did not work at a hospital, perhaps because the IT system failed. Health insurance programs in LMICs like India can address these problems by providing eligible population education about how to use an insurance card and what benefits and facilities are covered. It is also critical that public insurance make mundane but critical investments in insurance infrastructure, including payment systems, communications, and eligibility and claims databases. Speaking with both RSBY administrators and private insurers, we also learned that it is important, if the government is going to outsource insurance to private companies, to ensure these companies have the incentive to pay for covered claims. Lowest-price auctions and reliance on insurance companies for education campaigns may not ensure that beneficiaries receive all the services that the government intends. If a public insurance plan were to address these implementation issues, it may have greater benefits and costs than those estimated in this paper.

Our study also raises several questions that warrant further investigation. First, does experience with insurance increase utilization over time? Second, are supply constraints a limit on the

[59] An corollary we explore in the Appendix is that the optimal premium for public insurance is not zero.

utilization effects of insurance? Third, how much would co-insurance (deductibles or co-pays) affect utilization of insurance? Relatedly, how does raising the maximum coverage, which PMJAY (the program that replaced RSBY does) affect utilization? Fourth, is lack of power, low-productivity of healthcare, or substitution of insurance for OOP payments responsible for the common finding that health insurance does not significantly and systematically improve health? Finally, because policy-making is sensitive to the marginal cost of public funds, what is the government's cost of capital in India, and in lower-income countries?

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Figures

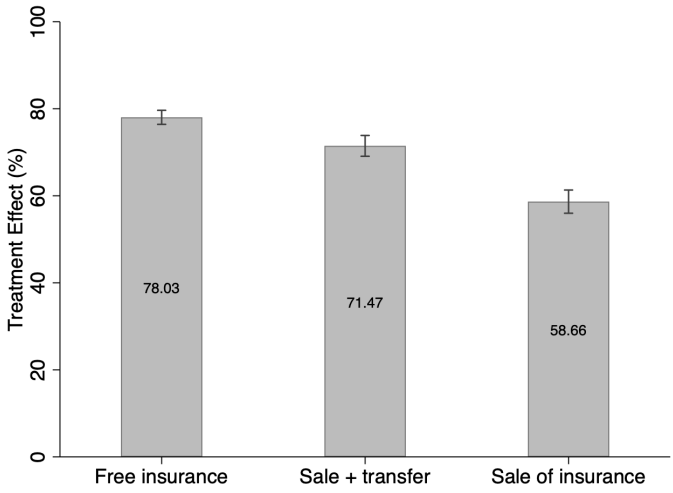
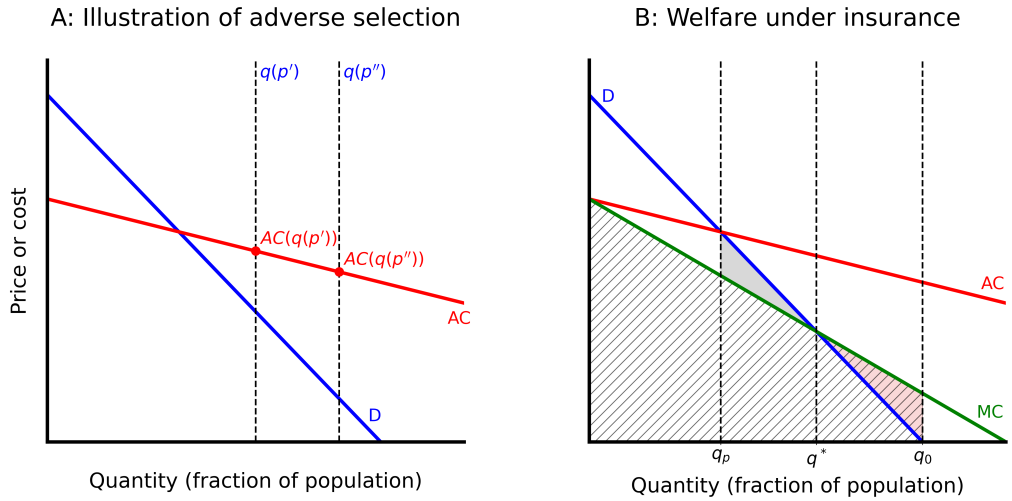


Figure 1: Enrollment by insurance access arm

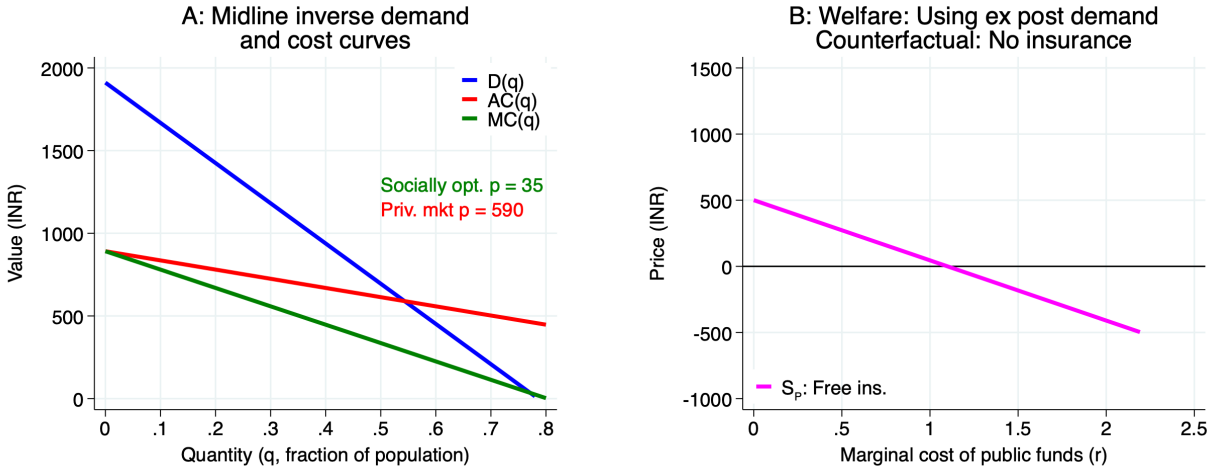
Notes. Bar chart illustrates RSBY enrollment under different premium and subsidy levels indicated (the horizontal axis). Results are from an OLS regression of enrollment on indicators for access arm (A to C), share of village treated, and the interaction of access indicators and share treated. The omitted group is D, no treatment; enrollment was 0 in this group. Standard errors are clustered at the village-level. Bars illustrate and are labeled with the total effect of access on enrollment at 80% saturation. Whiskers show 95% confidence intervals.

Figure 2: Illustration of adverse selection and welfare



Notes. Panel A illustrates how we identify the existence of adverse selection. The population is arranged on the x-axis in declining order of willingness to pay for insurance. The blue line is inverse Hicksian demand (D) for insurance; the red line is average cost (AC) in an insurance pool with all individuals to the left of q. Adverse selection exists if average cost of enrollees in a plan sold at a higher price p' (AC at p') is higher than average cost of enrollees in a plan sold at a lower price p'' (AC at p''), i.e., the average cost curve is decreasing. Panel B illustrates welfare at private market (q_p), socially-optimal (q^*) and free insurance quantities (q_0). This figure replicates the figure in panel A, but adds a green marginal cost (MC) curve. The solid gray area gives welfare loss with private community-rated, actuarially-fair insurance. The shaded light red area gives the part of the welfare loss under zero-priced insurance due to excessive consumption. The hatched area under the MC cost curve gives public expenditure on medical care with free insurance. Social cost of free public insurance (against a counterfactual of no insurance) is this expenditure scaled up by the cost of capital $(1 + r)$.

Figure 3: Inverse demand, cost and welfare calculations at midline.



Notes. Note. Figure shows midline values and welfare. Panel A shows estimated (ex post) demand and cost curves. Demand (blue) is estimated using data on arms A and B; it is an upper bound on Hicksian demand. Average cost (red) is estimated using midline hospital costs, which is endline hospital expenditure x midline successful use. Marginal cost curve (green) is derived from average cost curve. Panel B provides estimates of welfare from free public insurance at different levels of marginal cost of public funds (r). We use ex post estimates of demand and a no-insurance counterfactual. Formulas for MVPF with free insurance (magenta) are given in main text.

Tables

Table 1: Characteristics of sample villages

	Mean	SD	10th pct	90th pct
Population (2011 Census)	2,754	2,040	887	5,420
Poverty rate	0.18	0.11	0.06	0.33
Annual hhld. income, INR 1000s	127.56	66.15	60.58	212.28
Mean hhld. size	5.09	0.95	4.00	6.32
Distance to any hospital	9.04	4.75	2.80	15.24
Distance to a public hospital	14.03	9.33	5.39	32.15
Distance to a private hospital	18.24	14.94	3.32	42.68

Notes. Table presents characteristics of 435 sample villages. Abbreviations: SD, standard deviation; pct, percentile; hhld, household; INR, Indian rupee.

Table 2: Household characteristics in different access-to-insurance conditions.

	Free insurance	Sale + transfer	Sale of insurance	No access to insurance
	Median (IQR)	Median (IQR)	Median (IQR)	Median (IQR)
Demographic				
Number of hhld. members	5 (4-6)	5 (4-6)	5 (4-6)	5 (4-6)
Number of children in hhld.	1 (0-2)	1 (0-2)	1 (0-2)	1 (0-2)
Age of head of hhld., yrs	50 (42-60)	51 (40-60)	50 (41-61)	50 (41-60)
Education of male head of hhld., years	6.52 (4.96)	6.69 (4.93)	6.65 (4.94)	6.55 (4.98)
Distance to nearest town, km	9.7 (6.6-13)	9.7 (6.8-13)	9.3 (6.6-13)	9.1 (6.5-13)
Financial				
Number of rooms in house	3 (2-4)	3 (2-4)	3 (2-4)	3 (2-4)
Number of concrete rooms	0 (0-2)	0 (0-2)	0 (0-2)	0 (0-2)
Annual hhld. expenditure, INR 1000s	105 (72-154)	106 (71-161)	106 (73-156)	105 (71-155)
Annual food expenditure, INR 1000s	37 (25-52)	37 (24-52)	37 (25-52)	37 (24-52)
Utilization				
Visited provider, past 1 yr.	0.98 (0.13)	0.98 (0.12)	0.98 (0.12)	0.98 (0.14)
Annual medical expenditure, INR 1000s	18 (7.4-39)	19 (7.8-42)	19 (7.6-39)	18 (7.2-40)
Health				
Major illness in household	0.16 (0.37)	0.16 (0.37)	0.16 (0.37)	0.17 (0.37)
Good health	0.63 (0.48)	0.61 (0.49)	0.63 (0.48)	0.63 (0.48)
Told has hypertension	0.11 (0.32)	0.12 (0.32)	0.11 (0.32)	0.12 (0.33)
Told has diabetes	0.05 (0.22)	0.05 (0.23)	0.05 (0.22)	0.06 (0.24)
Told has heart disease	0.05 (0.22)	0.04 (0.20)	0.04 (0.20)	0.04 (0.20)
Delivered in facility past 1 yr.	0.18 (0.38)	0.17 (0.37)	0.16 (0.36)	0.19 (0.39)

Notes. Table presents median and interquartile range (IQR) for certain characteristics of sample households by the premium/subsidy arm to which they are assigned. All data is from the baseline survey with a few exceptions. Number of household members, education of male head of household, number of rooms, and major illness in household is from listing survey. Distance to nearest town is from GPS coordinates.

Table 3: Total effects of premium and subsidy combinations (ITT) and of enrollment (CATE) on insurance and hospital utilization

			ITT			
		Control	Free insurance	Sale + transfer	Sale of insurance	CATE Enrollment
	N	Mean (SD)	Coef (SE) p	Coef (SE) p	Coef (SE) p	Coef (SE) p
Utilization at 18 months						
Successful use (past 6 mos.)	9960	3.856	6.276	6.766	7.465	5.713
		(19.259)	(2.065)	(2.059)	(2.028)	(2.352)
			0.003	0.001	0.000	0.015
Failed use (past 6 mos.)	9960	1.337	3.336	3.154	2.597	3.416
		(11.487)	(1.173)	(1.203)	(1.109)	(1.199)
			0.005	0.009	0.020	0.004
Hospitalized on last visit (past 1 yr.)	9053	20.309	2.656	4.444	2.630	5.374
		(40.241)	(8.177)	(8.526)	(8.351)	(8.351)
			0.745	0.602	0.753	0.520
Utilization at 3.5 years						
Successful use (past 6 mos.)	9458	0.322	1.373	1.612	1.271	1.607
		(5.669)	(0.547)	(0.574)	(0.582)	(0.547)
			0.013	0.005	0.030	0.003
Successful use (most serious event)	9450	0.107	0.551	0.495	0.544	0.954
		(3.276)	(0.414)	(0.417)	(0.418)	(0.365)
			0.184	0.236	0.194	0.009
Failed used (most serious event)	9451	0.215	0.918	0.224	0.631	1.429
		(4.631)	(0.527)	(0.493)	(0.532)	(0.510)
			0.082	0.650	0.237	0.005
Overnight stay for treatment	9488	22.579	-3.501	-3.772	-4.129	-1.978
		(41.821)	(4.466)	(4.454)	(4.548)	(4.018)
			0.434	0.397	0.364	0.623
Length of hospital stay	9483	1.266	-0.261	-0.007	-0.236	0.031
		(4.805)	(0.518)	(0.531)	(0.522)	(0.445)
			0.615	0.990	0.651	0.944
Outpatient (day) surgery	9474	6.517	1.457	0.935	1.652	3.483
		(24.689)	(2.612)	(2.644)	(2.602)	(2.479)
			0.577	0.724	0.526	0.160

Notes. Table presents total effect of insurance access (ITT) and enrollment (CATE) on insurance and healthcare utilization. The outcome variables are transformed so coefficients show percentage point changes from the control group. Each observation is a household and has equal weight. Standard errors were clustered at the village level. Coefficients were transformed to show percentage point changes from the control group. ITT and CATE cells gives coefficient, standard error and p-balue. (1) Mean and standard deviation in the control group refers to the group without access to insurance. (2) For ITT: The total effect is the direct effect for an arm plus 0.8024*(spillover effect), where 0.8024 is the average fraction of sample households given insurance access. (3) For CATE: The total effect is the direct effect or enrollment plus 0.7183*(spillover effect), where 0.7183 is the fraction of sample households enrolled in arms A, B, and C. The FWER adjusted 5% critical values for the ITT effects are: 0.017 (0.017) for successful (unsuccsessful) insurance use at 18 mos; 0.017 for healthcare use at 18 mos; 0.009 (0.017) for successful (unsuccsessful) insurance use at 3.5 yrs; 0.006 for healthcare use at 3.5 yrs. The FWER adjusted 5% critical values for the CATE effects are: 0.050 (0.050) for successful (unsuccsessful) insurance use at 18 mos; 0.050 for healthcare use at 18 mos; 0.025 (0.050) for successful (unsuccsessful) insurance use at 3.5 yrs; 0.017 for healthcare use at 3.5 yrs.

Table 4: Number of significant IIT and CATE estimates for health and health-related outcomes, per category of outcomes, at 18 months and 3.5 years

	18 months (midline)				3.5 years (endline)				
	ITT			CATE	ITT			CATE	
	(A) Free insurance	(B) Sale of insurance + transfer	(C) Sale of insurance	Enrollment	(A) Free insurance	(B) Sale of insurance + transfer	(C) Sale of insurance	Enrollment	Total
Self-reported measures of health									
Total outcomes	5	5	5	5	5	5	5	5	10
Total estimators	15	15	15	15	15	15	15	15	120
Sig. direct effects	0	0	1	1	0	1	0	1	4
Sig. spillover effects	1	1	0	0	1	1	0	0	3
Sig. total effects	0	0	1	1	0	0	1	1	2
Sig. effects (all)	0	0	1	2	1	2	1	2	9
Chronic disease									
Total outcomes	16	16	16	16	18	18	18	18	34
Total estimators	48	48	48	48	54	54	54	54	408
Sig. direct effects	1	2	2	1	0	2	4	0	12
Sig. spillover effects	2	0	1	0	2	0	1	0	6
Sig. total effects	0	0	0	0	0	0	0	0	0
Sig. effects (all)	2	3	3	1	2	2	5	0	18
Health-related quality of life, ADLs, and physical health symptoms									
Total outcomes	2	2	2	2	15	15	15	15	17
Total estimators	6	6	6	6	45	45	45	45	204
Sig. direct effects	0	0	0	0	0	0	1	0	1
Sig. spillover effects	1	0	5	0	1	0	5	0	6
Sig. total effects	1	1	1	2	1	1	1	2	5
Sig. effects (all)	0	0	0	0	2	1	7	2	12
Mental and behavioral health									
Total outcomes	0	0	0	0	4	4	4	4	4
Total estimators	0	0	0	0	12	12	12	12	48
Sig. direct effects	0	0	0	0	0	0	0	0	0
Sig. spillover effects	0	0	1	0	0	0	1	0	1
Sig. total effects	0	0	0	0	0	0	0	0	0
Sig. effects (all)	0	0	0	0	0	0	1	0	1
Fertility									
Total outcomes	9	9	9	9	11	11	11	11	20
Total estimators	27	27	27	27	33	33	33	33	240
Sig. direct effects	0	0	0	0	0	0	0	0	0
Sig. spillover effects	0	2	0	0	0	2	0	0	2
Sig. total effects	0	0	0	0	0	0	0	0	0
Sig. effects (all)	0	0	0	0	0	2	0	0	2
Mortality									
Total outcomes	0	0	0	0	5	5	5	5	5
Total estimators	0	0	0	0	15	15	15	15	60
Sig. direct effects	0	0	0	0	0	0	0	0	0
Sig. spillover effects	0	0	0	0	0	0	0	0	0
Sig. total effects	1	0	0	0	1	0	0	0	1
Sig. effects (all)	0	0	0	0	1	0	0	0	1
Biomarkers									
Total outcomes	8	8	8	8	0	0	0	0	8
Total estimators	24	24	24	24	0	0	0	0	96
Sig. direct effects	1	1	0	2	0	0	0	0	4
Sig. spillover effects	0	0	0	0	0	0	0	0	1
Sig. total effects	0	0	0	0	0	0	0	0	2
Sig. effects (all)	2	2	1	2	0	0	0	0	7

Notes. Table provides a summary of a large number of intent-to-treat (ITT) and complier average treatment effect (CATE) regressions on health outcomes. Each outcome is associated with a separate regression. The table summarizes the number of outcomes, the number of estimators, and the number of significant effects for each outcome, by treatment type and survey date. Each panel summarizes regression involving a different set of outcomes, grouped by the panel heading. The first (second) 4 columns summarize results from 2 regressions for each outcome (i.e., ITT and CATE regressions) measured at 18 months (3.5 years). Each of the first 8 column in a panel reports on a different treatment. The last column lists the total of each row, except for the first row of each panel. That first row gives the total number of outcomes; outcomes are the same across treatments; so, the number of outcomes is just the number of outcomes for arm A at midline and arm A at endline. The last row of each panel gives the total number of significant effects for that panel, by column; i.e., it adds up significant direct, indirect or spillover, and total effects. The following explains each regression underlying the tabulation in this table. Treatment variables in ITT analysis are household assignments: free insurance (A), sale of insurance + cash transfer (B), sale of insurance (C). Treatment variables in CATE analyses are enrollment in insurance; enrollment is instrumented with assignment to groups A, B or C. All models estimated with OLS. Each observation was a household and had equal weight. Each treatment arm was fully interacted with the share of the village allocated to A, B, or C (combined) to estimate spillover effects in ITT analysis. Each treatment arm was fully interacted with the share of the village enrolled to estimate spillover effects in CATE analysis; the instrument for the share enrolled is the fraction allocated to groups A, B, or C. Standard errors were clustered at the village level. No multiple-testing adjustments were applied in calculating significance results in this table.

Table 5: Total effects of premium and subsidy combinations (ITT) and of enrollment (CATE) on out of pocket medical spending

			ITT			
		Control	Free insurance	Sale + transfer	Sale of insurance	CATE Enrollment
	N	Mean (SD)	Coef (SE) p	Coef (SE) p	Coef (SE) p	Coef (SE) p
			Spending at 18 months			
Annual medical spending (INR, thous.)	10030	28.777	5.557	3.715	5.518	1.592
		(31.206)	(4.215)	(4.232)	(4.154)	(4.577)
			0.188	0.380	0.185	0.728
Log annual medical spending	10030	9.594	-0.156	-0.223	-0.110	-0.374
		(1.912)	(0.356)	(0.369)	(0.362)	(0.348)
			0.661	0.547	0.762	0.282
Annual medical non-hospital spending (INR, thous.)	10030	23.981	2.804	1.751	2.692	0.636
		(24.866)	(3.839)	(3.833)	(3.778)	(4.150)
			0.465	0.648	0.476	0.878
Log annual medical non-hospital spending	10030	9.374	-0.268	-0.347	-0.248	-0.438
		(2.036)	(0.365)	(0.380)	(0.373)	(0.362)
			0.463	0.362	0.508	0.227
			Spending at 3.5 years			
OOP medical spending (most serious event, INR, thous.)	9396	21.470	-5.207	-2.865	-7.194	-5.242
		(144.220)	(15.837)	(15.857)	(15.966)	(12.880)
			0.742	0.857	0.653	0.684
Log OOP medical spending (most serious event)	4821	2.343	-0.318	-0.309	-0.332	-0.324
		(1.615)	(0.266)	(0.266)	(0.275)	(0.238)
			0.233	0.245	0.228	0.174

Notes. Table presents total effect of insurance access (ITT) and enrollment (CATE) on medical spending. Mean and standard deviation in the control group are percentages from group D (no access to insurance). The outcome variables are transformed so coefficients show percentage point changes from group D. Each observation is a household and has equal weight. Standard errors were clustered at the village level. ITT and CATE cells gives coefficient, standard error and p-balue. (1) For ITT: The total effect is the direct effect for an arm plus 0.8024*(spillover effect), where 0.8024 is the average fraction of sample households given insurance access. (2) For CATE: The total effect is the direct effect or enrollment plus 0.7183*(spillover effect), where 0.7183 is the fraction of sample households enrolled in arms A, B, and C. The FWER adjusted 5% critical values for ITT (CATE) are: 0.004 (0.013) for spending at 18 mos; 0.009 (0.025) for spending at 3.5 yrs.

Table 6: Enrollment by predicted spending

	(1)	(2)	(3)	(4)
Sale + transfer (B)	-0.066	-0.14	-0.066	-0.15
	(0.013)	(0.052)	(0.013)	(0.052)
	[0.000]	[0.005]	[0.000]	[0.005]
Sale of insurance (C)	-0.19	-0.19	-0.19	-0.19
	(0.014)	(0.057)	(0.014)	(0.057)
	[0.000]	[0.001]	[0.000]	[0.001]
Cost	0.0017	-0.0058	0.012	0.0033
	(0.0078)	(0.0080)	(0.0077)	(0.0083)
	[0.825]	[0.466]	[0.124]	[0.690]
B ×	0.029	0.026	0.023	0.016
Cost	(0.011)	(0.011)	(0.012)	(0.013)
	[0.010]	[0.022]	[0.056]	[0.192]
C ×	0.060	0.047	0.034	0.028
Cost	(0.016)	(0.017)	(0.013)	(0.014)
	[0.000]	[0.006]	[0.011]	[0.051]
Dep var mean	0.718	0.718	0.718	0.718
Dep var SD	0.450	0.450	0.450	0.450
Obs	8727	8727	8727	8727
Demog. controls	N	Y	N	Y
Cost variable	EL1 medical exp, predicted	EL1 medical exp, predicted	EL2 medical exp, predicted	EL2 medical exp, predicted

Notes. Outcome is enrollment in RSBY during the enrollment drive. SEs clustered at village level. Omitted (base) category is arm A (free insurance). All specifications control for village-level treatment saturation. Cost measure in columns 1-2 (3-4) are predicted midline (endline) medical expenditure as defined in Sec. 3.2. Spending variables are standardized to have unit standard deviation. Controls for levels and interactions with education, raven score, and risk aversion are included but not reported in columns 2 and 4. Education is a categorical variable recording the educational attainment of household head (1 = Never attended class 1, 2 = Class 1-5, 3 = Class 6-8, 4 = Class 9-10, 5 = Class 11-12, 6 = Graduate and above). Risk aversion is a dummy variable that equals 1 if respondent had a certainty equivalence smaller than 180 in a gamble game. Missing indicators of assets, raven scores, risk aversion and education are included.

Online Appendix

"Evaluating the impact and design of health insurance
in low-income countries: A field experiment in India"

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A Methods

A.1 Power calculations

Sample size calculations for household-level arms did not consider within village-correlation in outcomes. Moreover, we did not conduct power calculations for the size of our village-level arms.

A.1.1 Implementation of two-stage random assignment

Our two-stage randomization procedure was implemented separately in each district (Gulbarga, Mysore). In each stage, we matched units before randomization because matching reduces orthogonal variation (Imai, King and Clayton, 2009) and thereby increases statistical power.

The first stage was implemented in two steps. First, blocks of 20 matched villages (within each district) were created. Specifically, villages were stratified into quintiles based on the number of eligible households per village. Within each quintile, blocks were constructed using village-level sample averages, Mahalanobis matching on continuous and integer variables (head of household's level of education, age of head of household, number of children and number of rooms in the house), and caliper matching on binary variables (had major illness in last year and head of household was unemployed). These variables were constructed from the listing exercise to determine eligible households in each village of our sample prior to our baseline survey. Second, within each block, villages were randomly assigned to the 5 village-level conditions.

The second stage of our randomization also had two steps. First, households were sorted into blocks of 10 matched households. These blocks were constructed using household-level data gathered during our listing exercise and Mahalanobis caliper matching on the same variables used for constructing village blocks. Second, within each block, households were randomly assigned to 4 household conditions based on the village condition to which we assigned their village in stage one.

A.1.2 Roll-out of intervention

This experiment employed the same enrollment method (mobile enrollment vans that visit villages on a specific day) the government used for RSBY enrollment of below poverty-line households (BPL), a population excluded from our study. However, there were two differences in the marketing of RSBY to the above poverty-line households in our sample relative to the government's marketing to BPL households. First, households were informed of their treatment group assignment and, if appropriate, given a cash transfer roughly 14 days prior to arrival of the enrollment van. Second, study personnel visited households in groups 1-3 the day of enrollment to guide interested households to the enrollment van. By contrast, the government conducted its enrollment drive by circulating flyers (chits) to eligible households a few days before the van arrived. The government did not guide eligible households to the enrollment van.[1] We collected the purchase price from sample households in groups 2 and 3 (sale of insurance with and without an

[1]The study's greater advance notice allowed households in the pure insurance condition more time to get funds together to pay the premium, if desired.

unconditional cash transfer) that enrolled in RSBY at the van. For all sample households in group 1 (free insurance), we paid for the full purchase price from grant funds.

The Karnataka government automatically renewed RSBY coverage annually for non-study and enrolled study households in 2016 and 2017 without any action—even payment—by enrollees or the study. RSBY technically ended on August 31, 2018, because it was replaced by Pradhan Mantri Jal Arogya Yojana (PMJAY). As of completion of data gathering, Karnataka had agreed to implement PMJAY but had not yet rolled it out. The state effectively transitioned from RSBY to PMJAY in late 2019.[2]

A.2 Data collection

In March to June 2013 and again in November–December 2013, we conducted listing exercises wherein we surveyed 1 adult in 25,000 households in candidate villages to identify eligible households and gather data to construct blocks of similar villages and households prior to randomization.

In August 2013 to January 2014, a baseline survey was administered to the female and male most knowledgeable about household finances and a female of childbearing age in each sample household we could reach. The biomarker survey conducted as part of the baseline was administered to the male most knowledgeable, a woman of childbearing age, and a child under the age of 18 if available in roughly, a randomly-selected one-third of sample households. This subsample was selected in two steps. First, we stratified households by the two districts in our study. Second, we selected one third of villages in each district and conducted the biomarker survey on each sample household in the selected villages. A discrepancy between one-third of households and the number on which the biomarker survey was attempted reflected both the fact that we selected one-third of villages not households and villages have different sample sizes. The actual number of households ultimately surveyed – for both the main and biomarker survey – was less than the number attempted because of non-response. Households were paid INR 250 ($14.27) as a participation incentive for completing major sections of the survey. We performed back checks on 10% of households, a rate known to surveyors ex ante.

In January to May 2017, a midline survey was administered in the same manner as the baseline survey, including the biomarker survey on the same randomly-selected sample households. Households were paid the same participation incentives and back checks were performed in the same manner.

In March to June 2019, we conducted an endline survey of all sample households to measure outcomes after approximately 3.5 years. We asked the female most knowledgeable about household finances from baseline a subset of questions about personal health status and household health care utilization and finances. No biomarker survey was conducted at endline. We paid households INR 50 ($2.85) as a participation incentive since only 1 individual was surveyed and for a shorter period. We performed back checks on 10% of households, a rate known to surveyors ex ante.

Figure A.7 presents the study timeline, both in terms of the intervention and the multiple surveys conducted.

Figure A.8 presents a chart that shows the flow of subjects through each arm of the two-stage design. It also shows attrition at each data collection point.

A.3 Economic calculations

We convert Indian Rupees (INR) to 2019 US Dollars ($) using a purchasing power parity adjusted exchange rate of INR 17.52/dollar (OECD, 2020).

We calculated the demand elasticity for hospital insurance with the following formula:

$$\frac{\text{(Enrollment in Group 1 - Enrollment in Group 2)/Enrollment in 2}}{\text{(Price for insurance in 2 - Price in 1)/Premium in 2}}$$

The price for group 2 is INR 183 ($10.45), including the cost of the insurance card. We do not use the usual arc

[2]Because RSBY ended 6 months before our endline survey, we asked the respondent to recall hospital utilization 6 months before a notable holiday, Dussehra, that occurred just after the intervention ended.

elasticity formula, which normalizes by the midpoint of enrollment and price, because our change in price is going from full price to zero price. Our formula implies this is a 100% reduction in price while the usual arc elasticity formula would imply this is a nonsensical 200% reduction in price.

A.4 Health data

We examine multiple categories of health outcomes. Each category included multiple individual indicators: self-reported health (2 categories at midline, 3 at endline), objective health indicators (7 midline), chronic disease (15 midline, 17 endline), quality of life (1 midline, 14 endline), mental health (3 endline), childbirth (8 midline, 10 endline), and mortality (4 endline). A final secondary health outcome was an index of health, following Kling, Liebman and Katz (2007), equal to the average of z-scores for individual health outcomes.

Biomarkers. Biomarkers reported in Table A1 were constructed using anthropometric measurements from adult respondents at the midline survey. These included recording an individual's weight, height, waist, hip, and mid-upper arm circumferences, skinfolds, and blood pressure. Mid-upper arm circumference and an aggregate measurement of skinfolds (biceps, triceps, and sub-scapular) were included directly in the model. Using these measurements, we created additional outcomes of interest. Overweight or obese was categorized as a body mass index (BMI) greater than or equal to 25, while underweight was categorized as a BMI less than 18.5 for both adult males and females. Abdominally obese was categorized using an individual's waist-to-hip ratio (WHR); adult males with a WHR greater than 0.9 and adult females with a WHR greater than 0.85 were classified as abdominally obese. Finally, we categorized individuals as having Hypertension, grade 1 or Hypertension, grade 2 based on their systolic and diastolic blood pressure measurements. An individual was considered to have Hypertension, grade 1 if systolic blood pressure was greater than or equal to 130 and less than 140 OR a diastolic blood pressure greater than or equal to 80 and less than 90. Hypertension, grade 2 was defined as systolic blood pressure greater than 140 OR diastolic blood pressure greater than 90.

A.5 LASSO details

Predicted midline medical spending is constructed as follows. Medical spending at midline is winsorized at 0.5% and 99.5%. A model is then estimated which predicts midline medical spending as a function of the full set of available baseline covariates which relate to health and health spending[3], as well as indicators for missing data on each baseline variable. The model is estimated with linear regression. Predictions are fitted via 10-folds cross-validated LASSO on the control group of 2152 (or smaller due to missing outcomes). We then predicted the outcomes in treatment group with the trained model. The penalty parameter is selected under the minimum rule. Figure A.10 shows the resulting distribution of predicted values for midline medical spending. The correlation between predicted midline medical spending and actual, winsorized midline medical spending is 0.119, significantly greater ($p < 0.001$) than the 0.057 correlation between actual, winsorized baseline medical spending and actual, winsorized midline medical spending.

Predicted endline medical spending is calculated and employed in the same manner as predicted midline medical spending, with one change. Consistent with the difficulty of forecasting medical spending 3.5 years in the future, LASSO models select only the intercept when we predict endline spending with baseline variables. We therefore construct predicted endline spending using the covariates which are selected by LASSO to predict midline spending. Despite this change, the correlation between predicted endline medical spending and actual, winsorized endline medical spending is 0.071, greater than the 0.054 correlation between actual, winsorized baseline medical spending and actual winsorized midline medical spending, but not significantly so ($p = 0.368$).

[3]The baseline questionnaire is available at https://drive.google.com/file/d/1RAORj0wbnDU1R-QU1j6zAI5UL3FCFkTV/view?usp=sharing.

A.6 Selection by baseline variables

An alternate approach to testing for adverse selection would be to use baseline health and spending directly as proxies for subsequent health/health costs. Here we describe the this approach and the results, displayed in Table A.5 .

Inasmuch as RSBY insurance covers visits to empanelled facilities, the likelihood of visiting a health care facility is a natural predictor to use when forecasting differential incentives to enroll. Columns 1 to 4 use the baseline realization or predicted midline probability of visiting a medical facility for the male and female respondent.[4] Using baseline values (cols 1 and 2) yields very small and insignificant estimates of the degree of selection (i.e., δ_3); moreover, the sign of the (negligible) coefficient estimate flips sign between specifications using the male vs female respondent. One way to benchmark the magnitude of selection (if any) is to compare the degree of selection implied by the point estimate relative to mean enrollment: using the (insignificant) point estimate for the effect of male facility visits, a one standard deviation (SD) reduction (i.e., lower risk) is associated with a 1.4% increase in the enrollment rate; the number for female health is even smaller in magnitude and opposite in sign (-0.8%). Using the predicted midline values (cols 3 and 4) yields even smaller (and likewise insignificant) estimates of the degree of selection, with a one SD reduction in predicted probability for males leading to a 0.9% reduction in predicted enrollment; and a 0.0% effect associated with changing predicted probability for females. In summary, we find no evidence of selection using either baseline facility visits or predicted midline facility visits. For comparison, the relative average enrollment rates in arm B vs arm C (paid+cash vs. paid) demonstrate that providing a INR 220 unconditional cash transfer causes an increase in enrollment of 22% (71.6pp vs 58.8pp), an order of magnitude larger than any of the (insignificant) selection effects.

Columns 5 to 8 focus on the overall health of the male and female survey respondents. Using baseline health of either (cols 5 and 6), there is no statistically significant selection; δ_3 is not significantly different from zero. In addition to being statistically indistinguishable from zero, the point estimates imply very small degrees of selection relative to mean enrollment: using the (insignificant) point estimate for the effect of male health, a one standard deviation improvement in baseline health is associated with only a 2.1% reduction in the enrollment rate; the number for female health is similar (2.0%).

We next turn to predicted midline health (cols 7 and 8). Using male health (col 7) shows no detectable selection. In the case of female health (col 8), we do observe marginally statistically significant selection; the sign of $delta_3$ is positive, implying *advantageous* selection. However, the point estimate is small, implying that a one standard deviation improvement in predicted midline female health is associated with only a 3.6% increase in the enrollment rate. This is less than one fifth of the 22% effect of the unconditional cash transfer. In addition, as we discuss below, once we control for additional baseline characteristics and/or correct for multiple testing, the estimate is no longer significantly different from zero at conventional levels.

Next we examine total household medical expenditure (columns 9 and 10). As with visiting a medical facility, this is a potentially important variable which households might forecast and use to determine their willingness to pay to enroll in insurance; it is also arguably the key variable from the perspective of the government forecasting its costs. When we examine baseline medical spending, we find a very small and statistically insignificant δ_3 coefficient of -0.005, which would imply that a 1 SD decrease in baseline medical spending is associated with only a 0.8% decrease in enrollment under cost-sharing. Turning to *predicted* midline health spending, the estimated δ_3 is -0.04, significantly different from zero at the 1% level. Consistent with adverse selection, those with lower predicted spending are differentially less likely to enroll under cost sharing.

B Results: Direct and Indirect Effects

In the main text and tables in the main article focus on total effects – direct plus spillover effect assuming 80% treatment saturation in our sample across villages. In tables to this appendix we report a breakdown of total effects into direct and spillover effects. In this section we summarize our spillover effects estimates.

[4] We flip the sign so that a higher number corresponds to better health. We do the same for expenditure, below.

Enrollment. Spillover effects in enrollment are not statistically significant (Table A.4, col 2). Prior to enrollment, households were given roughly 2 weeks notice about the treatment arm to which they were assigned. Although it is possible that households communicated, such that there could be spillovers, in practice it appears that there were not learning or other spillovers on the enrollment margin.[5] Although we do not find significant spillovers in enrollment, we do find spillovers in utilization, which we discuss below.

Insurance utilization. Spillover effects play a quantitatively important role in insurance utilization. Table A.7 reports direct, spillover, and total effects for treatment arms $i = 1, 2, 3$.[6] We find that the total effects of insurance access on our measures of utilization are significant, although ITT estimates of the direct effects of insurance access are not separately significant at conventional levels.[7] The CATE effects largely follow a similar pattern. In terms of magnitudes, the spillover effects are of comparable magnitudes as the direct effects: indirect effects, even though they are imprecisely estimated, are quantitatively important for generating the significant total effects for insurance utilization.[8,9]

This spillover result is unlikely to be due to supply constraints because we find that RSBY access and enrollment increase insurance utilization substantially, but hospitalization only a relatively slight amount. These spillover effects are consistent with people learning about insurance via word-of-mouth from neighbors, as reported in prior studies of insurance in Karnataka and Andhra Pradesh (Chatterjee et al., 2018; Debnath and Jain, 2020).[10]

C Welfare

In this section we formalize and extend the welfare analysis in the main text. First, we derive the formula for the welfare effect of free public insurance using the model of adverse selection from Einav and Finkelstein (2011) and the MVPF framework (Hendren, 2016; Finkelstein and Hendren, 2020). Second, we extend our calculations to different measures of demand (specifically, *ex ante* demand per Hendren (2021)) and different counterfactuals (private insurance rather than no insurance). Third, we calculate the optimal price of public insurance.

[5] This contrasts with the findings of Cai, De Janvry and Sadoulet (2015), who find local spillover effects in the decision to enroll in weather insurance in China. In that context, adoption spillovers were driven by diffusion of information from intensive information sessions. Our study did not provide equally intensive information, and baseline knowledge about RSBY is low (Berg et al., 2019).

[6] These effects correspond to β^h (direct), $\gamma^h + .9 \times \phi$ (spillover), and $\beta^h + .9 \times \phi + .9 \times \gamma^h$ (total) from estimating equation (1) with measures of utilization as outcomes. The terms for the village-level treatment intensity, ϕ, and its interaction with the household-level treatment indicators γ^h, are scaled by 0.9, the maximum in-sample share assigned to receive access to insurance.

[7] The ITT effect at 18 months for arm 3, and at 3.5 years for arm 2, are significant at the 10% level.

[8] Recall that our exclusion restriction is that one household's access to insurance cannot affect enrollment or outcomes of other households, but the former's enrollment decision can. This permits, for example, compliers' enrollment and outcomes to affect the enrollment and outcomes of other households.

[9] Total effects of insurance are estimated more precisely than the component parts — direct and spillover effects — for two reasons. Conceptually, the total effect leverages all of the variation in the data, from both village- and individual-level randomization. Econometrically, the covariance terms between β_h, γ_h and ϕ are negative, making the sum more precisely estimated than the components.

[10] To explore learning, we examined how direct and indirect utilization varies by wealth of households — wealth may be a proxy for experience with financial products. (We define a high (low) wealth household as a household with an above (below) median value of on a wealth index created by taking the average of the following: z-score of the value of farm animals, z-score of the amount of silver, z-score of the amount of gold, the average of z-scores of different durable goods (stoves, fridges, etc.), z-score of land, z-score of the number of rooms in the household, and z-score of savings.) We find that, at 18 months, high-wealth households experience a direct effect, but no indirect effect, on insurance use; low-wealth households experience the opposite (ITT: not reported, CATE: Table A.13). This evidence is consistent with uninformed, low-wealth households learning from others but informed, high-wealth households being relatively unaffected by the behavior of neighbors.

C.1 Does offering (free) public insurance improve welfare?

Our analysis in the main text compares welfare with free, publicly-financed, insurance against a counterfactual where neither the government nor the private sector offer insurance. If the counterfactual were private insurance, the MVPF spent on free public insurance might be positive due either to social demand exceeding private demand (i.e., positive externalities from, e.g., controlling infectious diseases) or to adverse selection leading to sub-optimal take-up of private insurance. In this analysis, we assume that there are no externalities from consuming insurance. This is in part because we do not estimate all possible externalities from hospital insurance. However, we will explore a counterfactual with private insurance and adverse selection in an extension in Section C.4.

We first calculate the marginal social benefit (MSB) of offering a public insurance product at price p (versus not offering insurance).[11] Then we calculate the marginal social cost (MSC) of offering insurance at price p (versus not). This is equal to the cost of covered healthcare minus revenue from premiums. We then estimate whether MSB is greater than MSC at a zero premium using our estimates of demand and insurance cost; we evaluate welfare at $p = 0$ because that is the price the government charged when it expanded RSBY (the program we evaluate) to include above-poverty-line households via PM-JAY (the successor to RSBY).

We do this exercise, first, using information that consumers have at time of enrollment. Then, in an extension in Section C.5, we repeat it assuming consumers do not have any information on their expected costs. The former case generates what Hendren (2021) calls *ex post* demand, the latter *ex ante* demand. In this section, we focus on *ex post* demand, which is the demand curve the literature typically works with.

Marginal social benefit of public insurance. Our measure of the marginal social benefit of providing public insurance at price p (versus not providing public insurance) is aggregate willingness to pay for insurance with that price, equivalent to the area under the aggregate Hicksian demand curve for insurance above p:

$$MSB(p) \approx \int_0^{G(p)} [D^H(q) - p]dq = \int_0^{G(p)} D^H(q)dq - pG(p). \tag{7}$$

where $D^H(q)$ is the inverse demand curve for the government service and $G(p)$ is quantity demanded.[12] Without loss of generality, normalize quantity by population so that the units of G are fraction of the population. The marginal social benefit from free insurance is $MSB(0)$.

Marginal social cost of public insurance. We assume that the government pays for insurance through a combination of charged premium p (i.e., a user fee) and financing at a marginal cost of public funds of r. The marginal social cost of funds spent on providing the government service is then the sum of the government's net expenditure on all consumers who purchase the government service at price p:

$$MSC(p) = (1 + r)[c^{AC}(p)G(p) - pG(p)] \tag{8}$$

where $c^{AC}(p)$ is the average cost across all beneficiaries that enroll in insurance at price p. The first element in square brackets is the average cost of providing insurance amongst those who take it up at price p; the second element is the government's revenue from user fees. The net of these is scaled up by $1 + r$ to account for the government's cost of financing.

MVPF of offering public insurance with (i) *ex post* demand and (ii) no private insurance. The decision to provide RSBY insurance at p is welfare-improving if the marginal social benefit is greater than the marginal social cost: MSB(p) - MSC(p) ≥ 0. In the case where $p = 0$, which is policy-relevant and one we evaluate with data,

[11] Marginal social impact in the MVPF framework is not our estimate of health impacts of insurance. Due to issues of power, we may not have power to estimate these with adequate precision. Moreover, there may be health benefits we did not attempt to measure, or could not measure well (e.g., stress). Insurance may have non-health benefits, e.g., smoothing non-medical consumption. Finally, in a subjective utility framework, a product may offer subjective benefits that do not match objective benefits, but which still count towards utility and welfare.

[12] A detailed derivation of MSB(p) (Eq 7) and MSC(p) in Eq. (8) is presented in Appendix Section C.6.1.

MVPF is positive if

$$S_P(0) = \int_0^{G(0)} D^H(q)dq - (1+r)c^{AC}(0)G(0) \geq 0 \tag{9}$$

This condition is not exactly the same as the condition that social surplus should be positive at $G(0)$ because the costs are inflated by $1+r$ due to government borrowing on behalf of consumers. This is the so-called fiscal externality in the MVPF framework.

We illustrate the MVPF trade-off in Figure A.11. Panel A illustrates the calculation using demand and cost curves from midline.[13] The MSB is the area under the aggregate inverse demand curve between quantity demanded at zero price ($q = 0.79$) and zero quantity. The MSC is (i) the area under the marginal cost curve in the same range of quantity times (ii) $(1 + r)$, which captures the cost of public funds. The difference between the marginal cost curve in this figure and in our calculation ($c^{MC}(p)$) is that the figure shows the marginal cost curve as a function of quantity demand rather than price, i.e., it shows $c^{MC}(D(G(p))$. The MVPF can also be illustrated with the average cost curve. The MSB is the same. But the MSC is now (i) the average cost at the zero offer price ($\approx$ 500 INR, \$29) times the quantity demanded at that price ($q = 0.79$), times (ii) $(1+r)$. The MSC, and thus the result of the MVPF calculation, is the same whether one uses the marginal or average cost curve.

Application with estimates of linear demand and average cost curves. We apply the analysis above to our context by, first, estimating individual *ex post* demand curves and average cost curves. We impose a linear specification for both curves, partly because we only observe behavior at two prices (zero premium in group A and full premium in groups B and C) and partly to keep things simple:

$$g_i(p_i) = g(0) - \gamma p_i + \epsilon_i \tag{10}$$

$$c_i^{AC}(p_i) = c^{AC}(0) + \kappa p_i + \upsilon_i \tag{11}$$

where i indexes households, $g_i(p_i) \in \{0, 1\}$ is household i's demand, p_i is the premium in the insurance-access treatment group to which the households is assigned, c_i^{AC} measures an enrolled household's cost to the insurance pool, $\gamma > 0$ measures the slope of demand, and $\kappa > 0$ if there is adverse selection.[14]

We simultaneously estimate both equations using linear regression. Household demand is a binary variable that indicates enrollment. Price is determined by treatment group. We estimate the demand equation on two samples. Our preferred sample includes (A) the free-insurance group (charged a price of zero) and (B) the sale-plus-transfer group (charged the full premium). This sample produces an upper bound on Hicksian (i.e., compensated) demand, which is the relevant curve for estimating the willingness to pay. The unconditional cash transfer, which is equal to the premium, is a sort of compensation. However, because even households that do not purchase insurance receive the compensation, we may overestimate Hicksian (compensated) demand. Nevertheless, this sample yields our preferred estimates for demand as liquidity constraints are likely important in LMIC contexts (Berkouwer and Dean, 2022; Casaburi and Willis, 2018).

As a robustness check, in the appendix we estimate demand and welfare with a second sample that includes the (A) free-insurance and (C) sale-of-insurance groups. This sample produces estimates of Marshallian demand. That is a lower bound on demand because income effects are surely positive.[15]

[13] Einav and Finkelstein (2023) make an analogous figure using data from an RCT in Pakistan that randomized the price of insurance, to demonstrate adverse selection (Fischer, Frölich and Landmann, 2023). An important difference between Einav and Finkelstein (2023) and this paper is that the former uses the figure to calculate the welfare loss from adverse selection, while we leverage the graph to employ the MVPF framework to determine the optimal price of public insurance.

[14] Our average cost equation does not link average cost to quantity but to price. However, we can use it just the same in our MVPF calculation. We cannot identify a cost-quantity equation because quantity is not exogenous. Instead, we estimate the reduced form equation (8) and then use the demand equation (10) to translate price to quantity when calculating MVPF, using the delta method to calculate standard errors.

[15] A common assumption in demand estimation in health economics is that there are no income effects. In that case, Marshallian demand is equal to Hicksian demand. We suppose this assumption is mainly for convenience

Household average cost to the insurance pool is measured in two ways. One is hospital expenditure at midline (18 months), the other is hospital expenditure at endline (3.5 years).[16] Neither is the measure we use for estimating adverse selection in Section 4.5. There the goal was to use predicted expenditure based on information available prior to enrollment and to avoid including *ex post* moral hazard in our prediction; here want to use actual expenditure to measure actual cost, including moral hazard, because that contributes to the insurance company's (or government's) cost. The sample for the cost regression only includes households in treatment arms (groups A and C, not the control group) that actually enrolled in insurance. We exclude the sale-plus-transfer group because, outside this experiment, uncompensated (Marshallian) demand determines enrollment. We exclude the control group because they cannot enroll under our experiment.

In both regressions, the free insurance group A is coded as paying a price of 0 and the sale-plus-transfer and sale-of-insurance groups B and C are coded as paying a price of 203 in Mysore and 173 in Gulbarga. This is the government premium in each district plus the INR 30 paid for the insurance card. We cluster standard errors at the village level (as in our ITT model). However, we do not include village allocations in our specification. Because allocation is also randomized, its omission does not cause bias. One should interpret the results as the total effect of price including a full direct effect and 80% of an indirect effect, because on average 80% of other sample households receive some access to insurance across arms.

We can plug our estimates of Eqs. (10) and (11)—which are reported in Table A.30 and plotted in the A panels of Figures A.11 and A.12—into Eq. (9) to obtain the condition required for free insurance to be a welfare-improving use of public funds from the perspective of *ex post* demand:

$$S_P(0) = \frac{g(0)}{2\gamma} - (1+r)c^{AC}(0) \geq 0 \tag{12}$$

Using a MCPF of $r = 1.25$ to account for the inefficiency of lower-income country tax systems (such as India[17]) and the free-insurance arm (A) and sale-plus-transfer arm (B) to estimate demand,[18] we calculate that free public insurance reduces welfare by INR 63 ($3.60) per household at midline (though our estimate is imprecise[19]) and

because there is also a sizable literature finding that income increases healthcare expenditure, though micro and macro estimates differ on magnitude (Acemoglu, Finkelstein and Notowidigdo, 2013).

[16]Our measure of midline cost is two times the product of (a) a household's hospital expenditure at midline and (b) whether the household used RSBY insurance to pay for care in the last 6 months before midline. We use endline hospital expenditures rather than midline medical expenditure because we did not define hospital expenditure at midline and many households labeled non-acute clinic care as hospital care. We corrected the survey at endline by defining hospital care as care at a facility with overnight stays. Our measure of midline hospital costs assumes midline and endline hospital costs are roughly the same given the long time-span between them. We convert endline hospital expenditures to midline costs from use by multiplying endline hospital expenditures by midline use of RSBY to pay for hospital care. We multiply by two to get annual costs because endline use, a binary variable, covers use over 6 months rather than 12 months.

Our measure of endline cost is two times the product of (a) a household's hospital expenditure at endline and (b) whether the household used RSBY insurance to pay for care in the last 6 months before endline.

We provide MVPF calculations using using other measures of cost, including midline medical expenditures, in the appendix (Table A.27). While cost curves differ, the MVPF calculations yield similar results.

[17]Our estimate is at the lower end of the range used for MCPF for such countries. Historical data on the MCPF from India suggest an $r = 1.5$, but those estimates are from the mid-1980s (Ahmad and Stern, 1987). A more recent survey of the MCPF from Africa suggests a median estimate of $r = 1$ (Auriol and Warlters, 2012). (Basri et al., 2021), studying the optimal tax rate in Indonesia, focus on the cases where $r = 1.5$ and 2. These estimates are higher than convention for US-focused studies, which use $r = 0.3$ (Finkelstein and Hendren, 2020).

[18]We use arm B rather than sale-of-insurance arm C because it is a more realistic estimate of demand. As Table A.27 shows, demand is greater and has flatter slope when using arm B enrollment. While group B overestimates Hicksian demand, group C underestimates it. We believe that the latter error is more serious. Some of the lower uptake in C is driven by liquidity constraints, which we think would be relaxed in an expansion of RSBY: enrollment drives would be predictable and the PMJAY program that replaced RSBY allowed year-round enrollment at hospitals when required. Moreover, the magnitude of the premium in our study ($\sim$ 200 INR, $11.42) is small relative to annual income, so likely has a small income effect.

[19]Standard errors on welfare calculations are obtained using the delta method.

increases welfare by INR 516 ($29) per household at endline (Table A.30, row 1).

Our findings are driven by the level of utilization, the costs that the government must finance, and by the marginal cost of public funds. If we include in our measure of utilization not just successful utilization, but also failed attempts at utilization (to capture the idea that households may utilize successfully more often over time), then free insurance reduces welfare by 534 INR ($30) per household even at endline (Table A.30, column 4). Moreover, B panel of Figures A.11 and A.12 plot the welfare from free insurance (magenta line) as the MCPF increases. Welfare falls as r rises because the costs of financing utilization increases. An important policy implication is that even if public insurance is not valuable today, it may become valuable as the tax system becomes more efficient.

To further determine how robust our findings are, we calculate the value of free insurance using sale-of-insurance arm (C) rather than arm B to estimate *ex post* demand and other measures of hospitalization costs (see Appendix table A.27). Our results are qualitatively similar: free insurance lowers welfare at our realistic marginal costs of public funds (MCPF). Versions of B panels in Figures A.11 and A.12 for those alternative demand and cost curves (not reported) show that free insurance loses value as MCPF rises. However, in some cases, when MCPF is sufficiently low (usually around levels observed in higher-income countries), free insurance can improve welfare, much as what we see in panel B of Figure A.11.

C.1.1 MVPF of public insurance with *ex post* demand and private insurance

An alternative counterfactual against which to judge public insurance is private insurance, specifically a private insurance plan identical to the public plan and offered at a community-rated price with zero load.[20] Here we calculate the MVPF under free public insurance against this counterfactual in two steps. First, we calculate the surplus S_P from public insurance, and then subtract the surplus from private insurance S_M. Since we have already discussed how we calculate S_P, here we focus on how we calculate S_M.

Marginal social benefit of private insurance. The MSB of private insurance is the aggregate willingness to pay for such insurance sold in a market at a private insurance equilibrium price, assuming that such insurance is sold at all. To determine whether private insurance is sold and at what price, we use the model of Einav and Finkelstein (2011). Under community rating, price is determined by the average cost curve rather than the marginal cost curve. If the average cost curve is always above the demand curve or crosses the demand curve from above, there will be no private policy offered in the market. Either it will be cost-prohibitive from the start or will collapse due to adverse selection, respectively. If average cost intersects demand form below, as in Panel A of Figure A.11, the private market price p_m will be the price at the intersection of average cost and demand. In the latter case, the marginal social benefit of private insurance is the social surplus from insurance, i.e., the area (i) under the demand curve to the left of $G(p_M)$ and (ii) above the average cost at $G(p_M)$. Because price is equal to average cost, this is identical to the area under the demand curve and above the price p_M.

Marginal social cost of private insurance. Assuming it is offered in a market, the MSC of private insurance is zero. To see why, note that the cost of insurance is given by equation (8) except where one uses the capital cost r appropriate for a private insurance firm. However, the private firm chooses a (community-rated) price equal to average cost: i.e., $p_m = c^{AC}(p_m)$. Therefore, $MSC(p_m) = 0$. Note, there is a private cost to private insurance, but we have included this in the MSB calculation discussed in the previous paragraph.

MVPF of offering public insurance where there is private insurance. The marginal social surplus with private, market insurance is MSB(p_M) - MSC(p_M), or

$$S_M(p_M) = \max\left\{0, \int_0^{G(p_M)} D^H(q)dq - c^{AC}(p_M)G(p_M)\right\} \tag{13}$$

[20]The private insurance policy may not be the same as the public insurance. Because the possibilities are innumerable and difficult to model, to make our problem tractable we assume the private policy is identical to the public policy. We assume zero load because we implicitly assume that in public insurance, the cost of which is equated to out-of-pocket consumer expenditures reduced. We assume community rating (price equal to average cost) because Indian insurers have poor information on individual health risk, especially in rural areas.

There are two cases to consider. First, if there is no private insurance offered, the social surplus from private insurance is zero, i.e., $S_M = 0$. Second, if average cost intersects demand from below, then $S_M > 0$.

The MVPF for public insurance when there is private insurance is welfare under public insurance minus welfare under private insurance, or $S_P(0) - S_M(p_M)$. Consider the same two cases we discussed in the last paragraph. First, if there is no private insurance offered, then the incremental value of public insurance taking into account private insurance is the same as when there is no private insurance, i.e., $S_P(0) - S_M(p_M) = S_P(0)$. Second, if private insurance is offered in the market, then the value of public insurance when there is private insurance is greater than public insurance when there is no private insurance: $S_P(0) - S_M(p_M) < S_P(0)$, which flows directly from the fact that $S_M(p_M) \geq 0$.

Application using estimates of linear demand and average cost curves. To calculate the value of public insurance where there is private insurance, we first have to solve for the private market price of insurance. Setting average cost in Eq. (11) equal to price in Eq. (10), we get a market clearing price of $p_M = c(0)/(1-\kappa)$. This is positive if $\kappa < 1$ and there is private sale of insurance if $g(0) > c(0)$. With this price we can plug our estimates of demand from Eq. (10) and average cost from Eq. (11) into Eq. (22) to obtain the surplus from private insurance with linear demand and cost:

$$S_M(p_M) = \frac{1}{2\gamma}[g(p_M)]^2 = \frac{1}{2\gamma}\left[g(0) - \frac{\gamma}{1-\kappa}c(0)\right]^2 \tag{14}$$

Then the condition required for free insurance to be a welfare-improving use of public funds from the perspective of *ex post* demand is that $S_P(0)$ from Eq. (12) minus $S_M(p_M)$ from Eq. (23) is greater than zero.

Using a MCPF of $r = 1.25$ and the free-insurance arm (A) and sale-plus-transfer arm (B) to estimate demand, we calculate that free public insurance reduces welfare by INR 1219 ($70) per household at midline and INR 397 ($23) at endline (second panel of Table A.30). Our findings are graphically illustrated in the C Panels of Figures A.11 and A.12, respectively. The surplus from private insurance is INR 1151 and 912 ($66 and 52) per household at midline and endline, respectively, so (zero-load, community-rated) private insurance is offered in equilibrium without public insurance. But free public insurance crowds out positive-price private insurance and the social surplus from public insurance is INR -69 and 515 (-$3.93 and $29) at midline and endline, respectively, less than the surplus with private insurance.

C.1.2 MVPF of public insurance with *ex ante* demand and no private insurance

Let us return to the counterfactual where there is no private insurance offered in the absence of public insurance. The condition in (9) for whether free insurance is a positive MVPF policy uses an *ex post* demand to value insurance, i.e., values insurance after individuals have some private information about their expected costs, though before the insurance contract is signed and all covered costs are revealed. The willingness to pay for insurance may be on average higher if measured behind a veil of ignorance, before consumers have any private information on their expected costs (Hirshleifer, 1971; Hendren, 2021), and if there is adverse selection. After some information is revealed, those with low expected cost may decide not to buy insurance, raising the average cost and thus premiums for the remaining population. Before information is revealed, consumers know there is a risk that information will reveal they have high expected costs, causing them to face a higher premium. If they are risk averse, consumers will be willing to pay some amount to avoid the risk of a higher premium. This amount is proportional to the difference in the marginal utility of those who buy insurance after the cost realization and those who do not, because the former pay higher prices (and have lower consumption) and the latter get the opposite.

Hendren (2021) provides an adjustment to *ex post* inverse demand—demand after some information is revealed—that transforms it into *ex ante* (EA) inverse demand before information is revealed. This adjustment shifts demand from $D^H(G)$ to

$$D^{H,EA}(G) = D^H(G) + M(G) \quad \text{where} \quad M(G) = G(1-G)\left|\frac{\partial D^H}{\partial G}\right|\beta(G) \tag{15}$$

where the additive markup $M(G)$ is intended to capture the additional amount households are willing to pay to avoid variation in insurance prices after their expected costs become apparent, and $\beta(G)$ is the percentage difference in marginal utilities of income for the insured relative to the uninsured.[21] If there is adverse selection, then information revelation increases the premiums for those who enroll. This implies that enrollees have lower consumption and higher marginal utility of consumption than non-enrollees, so that $\beta(G)$ is positive. Moreover, under some assumptions,[22] a first-order Taylor approximation of $\beta(G(p))$ is $\sigma[D^H(G(p)) - \int_{G(0)}^{G(p)} D^H(s)ds]$, the difference between willingness to pay of the marginal enrollee at price p and the average willingness to pay of non-enrollees at that price, scaled by σ, the coefficient of absolute risk aversion.

The condition for the MVPF spent on free public insurance to be positive when we use *ex ante* demand for insurance and assume no insurance in the absence of public insurance is given by Eq. (9), except that one replaces $D^H(q)$ with $D^{H,EA}$ in Eq. (9) to capture *ex ante* demand.

Application using estimates of linear demand and average cost curves. To calculate the *ex ante* value of free insurance, we take three steps. First, we solve the linear demand in Eq. (10) for price. Second, we estimate the markup $M(G)$ using the first-order Taylor approximation for $\beta(G)$ suggested by Hendren (2021). We add this to the price estimated in the first step to obtain the function $D^{H,EA}(G)$.[23] We illustrate this *ex ante* demand with the dashed blue line in the A Panels of Figures A.11 and A.11. Third, we take a first-order Taylor approximation of the markup. This reveals that, if we define

$$\frac{1}{\gamma^{EA}} = \frac{1}{\gamma}\left(1 + \frac{\sigma}{\gamma}G(0)[1 - G(0)]\right) > \frac{1}{\gamma} > 0 \tag{16}$$

we can replace γ with γ^{EA} in Eq. (12) to approximate the value of free insurance.[24] In our calculations, we assume a coefficient of risk aversion of $\sigma = 5 \times 10^{-3}$, in the range of estimates in India and other lower-income countries (Binswanger, 1981; Just and Lybbert, 2012).

The resulting welfare calculations for the case where $r = 1.25$ are presented in the third panel of Table A.30. *Ex ante* demand is sufficiently greater than *ex post* demand that free insurance is now always positive for welfare. The D panels of Figures A.11 and A.12 show that using *ex ante* demand to value free insurance raises the welfare value of free insurance at all levels of r. However, using midline estimates of cost, free insurance remains a welfare-reducing policy for MCPF above $r = 1.5$.

C.2 What is the optimal public insurance premium?

In this section, we modify our MVPF analysis to ask: what is the optimal price of RSBY insurance, conditional on offering it. We first derive optimal price using *ex post* demand, and then with *ex ante* demand.

Marginal social benefit. The marginal social benefit of *increasing* the price of the government service is the sum of private benefits across individuals who buy the service:

$$MSB(p) = -\sum_i \mathbb{I}(g_i^* = 1) = -G(p). \tag{17}$$

where we are again working with *ex post* (Marshallian) demand. This is proportional to aggregate quantity demanded at price p due to Roy's identity. Intuitively, raising price by INR 1 does not change demand much, but does reduce consumer surplus by 1 INR for each unit purchased. Note that this MSB is different than the MSB of offering a free service, which was the area under the demand curve. The reason for the difference is the counterfactual. Before it was no service at all, while here it is differently (lower) priced service.

[21] See Propositions 1 and 2 in Hendren (2021).

[22] The two assumptions are that the utility from non-medical consumption and health are separable and that there are no differences in average income of the insured and uninsured. Propositions 3 and 4 in Hendren (2021) derive the approximation.

[23] See Appendix C.6.2 for details.

[24] A derivation is presented in Appendix Section C.6.2.

Marginal social cost. The social cost of providing the government service at price p is equal to $SC(p) = (1+r)[c^{AC}(p) - p]G(p)$. This is identical to the marginal social cost in the last section because the comparison in the last section was providing insurance or not. Here we assume insurance is provided, but compare value at a higher or lower price. So the marginal social cost is the derivative of social cost in this paragraph with respect to price:

$$MSC(p) = (1+r)\frac{\partial c^{AC}(p)}{\partial p}G(p) - (1+r)G(p) + (1+r)[c^{AC}(p) - p]\frac{\partial G(p)}{\partial p} \tag{18}$$

The first term is new and reflects the change in average cost as price increase. Importantly, this is positive if the service is insurance and there is adverse selection. The second term is the reduction in expenditure as revenues rise. The third term reflects the reduction in sales with higher price. This is negative if average costs exceed price. (If price were zero to start, then the first term would be positive, but the latter two negative.)

Optimal price. The first-order, necessary condition for p^*, the optimal price for the government service, is that the marginal social benefit equals the marginal social cost of that service: $MSB(p^*) - MSC(p^*) = 0$, i.e.,

$$-\frac{\partial c^{AC}(p^*)}{\partial p^*}G(p^*) + \frac{r}{1+r}G(p^*) - [c^{AC}(p^*) - p^*]\frac{\partial G(p^*)}{\partial p^*} = 0 \tag{19}$$

(A full derivation is presented in Appendix Section C.6.3.) The incremental cost to consumers ($G(p^*)$) of raising the price of government service is just a transfer to the government, reducing its expenses, so those terms cancel in the second line. What remains is the government's saving on borrowing costs ($rG(p^*)$). Dividing by $(1+r)$ gives the trade-off in rupees before financing costs. An important constraint on the optimal price is that it must be greater than 0. If it falls below 0, price is below marginal cost, which is non-negative, and incremental consumption produces a social loss.[25]

Optimal price using the *ex ante* demand value of insurance. The condition above for the optimal price for the government service uses an *ex post* valuation of insurance, i.e., after individuals have some private information about their expected costs. The willingness to pay for insurance is higher if measured behind a veil of ignorance. This will affect both the marginal social benefits and costs of raising the price of insurance. To implement this change we need to invert the Marshallian analogue to the demand function in Eq. (24). To do so define $D^{EA}(p) = D^M(G) + G(1-G)[\partial D^M(G)/\partial p]\beta(G)$ and $G^{EA}(p)$ as the inverse of this function. The optimal price is given by a version of Eq. (19) that replaces $G(p^*)$ and $\partial G/\partial p^*$ with $G^{EA}(p^*)$ and $\partial G^{(EA)}(p^*)/\partial p^*$.

Application with linear demand and cost. Using the linear demand (10) and average cost (11) curves we estimated with our experiment, we can solve analytically for the price that balances marginal social costs and benefit using the *ex post* demand value of insurance:

$$p^* = \frac{\left[\kappa - \frac{r}{1+r}\right]g(0) - c^{AC}(0)\gamma}{\left[\kappa - \frac{r}{1+r}\right]\gamma + [\kappa - 1]\gamma} \tag{20}$$

This is a maximum if the second order condition is satisfied:

$$\kappa < 1 - \frac{1}{2}\left(\frac{1}{1+r}\right) \tag{21}$$

i.e., adverse selection is not too severe.

With $r = 1.25$, we estimate that the optimal price is INR 1052 ($60) using cost estimates from midline, or INR 528 ($30) using the lower cost at endline (Table A.30, row 2). Adverse selection is sufficiently low that the optimal price rises with costs (columns 3 and 4).[26] The B panels of Figures A.11 and A.12 show that optimal price rises

[25] An incidental question the reader may have is whether the insurance companies that provided insurance under RSBY made or lost money under the premiums that the government paid them in Gulbarga and Mysore. The answer is that insurance companies lost money at midline because average cost was always above the roughly INR 200 ($11.42) premiums. However, at endline, the companies barely broke even when the government subsidized insurance prices to make it free to consumers.

[26] We obtain qualitatively similar optimal prices when we use the sale-of-insurance arm (C) to and/or other measures

with the MCPF at midline and endline, respectively. As financing costs rise, the government wants to reduce public expenditures. Since we have fixed the RSBY contract, the government cannot reduce its healthcare spending via cost-sharing. But it can raise more revenue by charging consumers a higher premium.

Our main takeaway from our MVPF calculations using the *ex post* value of insurance is that, although estimated levels of adverse selection limit the value of raising premiums, high financing costs swamp the benefits of subsidized public insurance in India.

To calculate the optimal price using the *ex ante* demand value of insurance, before consumers have any information on their own expected cost, we take three steps. First, we invert our estimate of the linear function $D^{H,EA}$ from our value-of-free-insurance calculations, so we have quantity as a function of price $G^{EA}(p)$. Second, we replace $G(p^*)$ with $G^EA(p^*)$ in the first-order condition (20) and solve for p^*. The resulting welfare calculations for the case where $r = 1.25$ are presented in the third panel of Table A.30.

Although free public insurance is a positive MVPF policy, the optimal price for public insurance is still positive, though generally below where the optimal price using *ex post* demand. The D panels of Figures A.11 and A.12 show that using the *ex ante* demand function increases the range of r (MCPF) over which free insurance is optimal at midline and endline, respectively. However, for higher r, the optimal price actually increases. The reason is that *ex ante* demand is greater, but has lower slope—which exerts mixed effects on the marginal social cost of raising premiums in Eq. (18). Moreover, the marginal social cost function weights the effects of demand and the slope of demand with the MCPF.

C.3 Formal derivation of welfare with ex po

C.4 Special case: *ex post* demand and private insurance

An alternative counterfactual against which to judge (free) public insurance is private insurance, specifically a private insurance plan identical to the public plan and offered at a community-rated price with zero load.[27] Here we calculate the MVPF under free public insurance against this counterfactual in two steps. First, we calculate the surplus S_P from public insurance, and then subtract the surplus from private insurance S_M. Since we have already discussed how we calculate S_P, here we focus on how we calculate S_M.

Marginal social benefit of private insurance. The MSB of private insurance is the aggregate willingness to pay for such insurance sold in a market at a private insurance equilibrium price, assuming that such insurance is sold at all. To determine whether private insurance is sold and at what price, we use the model of Einav and Finkelstein (2011). Under community rating, price is determined by the average cost curve rather than the marginal cost curve. If the average cost curve is always above the demand curve or crosses the demand curve from above, there will be no private policy offered in the market. Either it will be cost-prohibitive from the start or will collapse due to adverse selection, respectively. If average cost intersects demand form below, as in Panel A of Figure A.11, the private market price p_m will be the price at the intersection of average cost and demand. In the latter case, the marginal social benefit of private insurance is the social surplus from insurance, i.e., the area (i) under the demand curve to the left of $G(p_M)$ and (ii) above the average cost at $G(p_M)$. Because price is equal to average cost, this is identical to the area under the demand curve and above the price p_M.

Marginal social cost of private insurance. Assuming it is offered in a market, the MSC of private insurance is zero. To see why, note that the cost of insurance is given by equation (8) except where one uses the capital cost r appropriate for a private insurance firm. However, the private firm chooses a (community-rated) price equal to average cost: i.e., $p_m = c^{AC}(p_m)$. Therefore, $MSC(p_m) = 0$. Note, there is a private cost to private insurance, but we have included this in the MSB calculation discussed in the previous paragraph.

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of *ex post* costs to estimate demand and average costs. See Table A.27.

[27] The private insurance policy may not be the same as the public insurance. Because the possibilities are innumerable and difficult to model, to make our problem tractable we assume the private policy is identical to the public policy. We assume zero load because we implicitly assume that in public insurance, the cost of which is equated to out-of-pocket consumer expenditures reduced. We assume community rating (price equal to average cost) because Indian insurers have poor information on individual health risk, especially in rural areas.

MVPF of offering public insurance where there is private insurance. The marginal social surplus with private, market insurance is MSB(p_M) - MSC(p_M), or

$$S_M(p_M) = \max\left\{0, \int_0^{G(p_M)} D^H(q)dq - c^{AC}(p_M)G(p_M)\right\} \tag{22}$$

There are two cases to consider. First, if there is no private insurance offered, the social surplus from private insurance is zero, i.e., $S_M = 0$. Second, if average cost intersects demand from below, then $S_M > 0$.

The MVPF for public insurance when there is private insurance is welfare under public insurance minus welfare under private insurance, or $S_P(0) - S_M(p_M)$. Consider the same two cases we discussed in the last paragraph. First, if there is no private insurance offered, then the incremental value of public insurance taking into account private insurance is the same as when there is no private insurance, i.e., $S_P(0) - S_M(p_M) = S_P(0)$. Second, if private insurance is offered in the market, then the value of public insurance when there is private insurance is greater than public insurance when there is no private insurance: $S_P(0) - S_M(p_M) < S_P(0)$, which flows directly from the fact that $S_M(p_M) \geq 0$.

Application using estimates of linear demand and average cost curves. To calculate the value of public insurance where there is private insurance, we first have to solve for the private market price of insurance. Setting average cost in Eq. (11) equal to price in Eq. (10), we get a market clearing price of $p_M = c(0)/(1-\kappa)$. This is positive if $\kappa < 1$ and there is private sale of insurance if $g(0) > c(0)$. With this price we can plug our estimates of demand from Eq. (10) and average cost from Eq. (11) into Eq. (22) to obtain the surplus from private insurance with linear demand and cost:

$$S_M(p_M) = \frac{1}{2\gamma}[g(p_M)]^2 = \frac{1}{2\gamma}\left[g(0) - \frac{\gamma}{1-\kappa}c(0)\right]^2 \tag{23}$$

Then the condition required for free insurance to be a welfare-improving use of public funds from the perspective of *ex post* demand is that $S_P(0)$ from Eq. (12) minus $S_M(p_M)$ from Eq. (23) is greater than zero.

Using a MCPF of $r = 1.25$ and the free-insurance arm (A) and sale-plus-transfer arm (B) to estimate demand, we calculate that free public insurance reduces welfare by INR 1219 ($70) per household at midline and INR 397 ($23) at endline (second panel of Table A.30). Our findings are graphically illustrated in the C Panels of Figures A.11 and A.12, respectively. The surplus from private insurance is INR 1151 and 912 ($66 and 52) per household at midline and endline, respectively, so (zero-load, community-rated) private insurance is offered in equilibrium without public insurance. But free public insurance crowds out positive-price private insurance and the social surplus from public insurance is INR -69 and 515 (-$3.93 and $29) at midline and endline, respectively, less than the surplus with private insurance.

C.5 Special case: *ex ante* demand and no private insurance

C.5.1 MVPF of (free) public insurance

Let us return to the counterfactual where there is no private insurance offered in the absence of public insurance. The condition in (9) for whether free insurance is a positive MVPF policy uses an *ex post* demand to value insurance, i.e., values insurance after individuals have some private information about their expected costs, though before the insurance contract is signed and all covered costs are revealed. The willingness to pay for insurance may be on average higher if measured behind a veil of ignorance, before consumers have any private information on their expected costs (Hirshleifer, 1971; Hendren, 2021), and if there is adverse selection. After some information is revealed, those with low expected cost may decide not to buy insurance, raising the average cost and thus premiums for the remaining population. Before information is revealed, consumers know there is a risk that information will reveal they have high expected costs, causing them to face a higher premium. If they are risk averse, consumers will be willing to pay some amount to avoid the risk of a higher premium. This amount is proportional to the difference in the marginal utility of those who buy insurance after the cost realization and those who do not, because the former pay higher

prices (and have lower consumption) and the latter get the opposite.

Hendren (2021) provides an adjustment to *ex post* inverse demand—demand after some information is revealed—that transforms it into *ex ante* (EA) inverse demand before information is revealed. This adjustment shifts demand from $D^H(G)$ to

$$D^{H,EA}(G) = D^H(G) + M(G) \quad \text{where} \quad M(G) = G(1-G)\left|\frac{\partial D^H}{\partial G}\right|\beta(G) \tag{24}$$

where the additive markup $M(G)$ is intended to capture the additional amount households are willing to pay to avoid variation in insurance prices after their expected costs become apparent, and $\beta(G)$ is the percentage difference in marginal utilities of income for the insured relative to the uninsured.[28] If there is adverse selection, then information revelation increases the premiums for those who enroll. This implies that enrollees have lower consumption and higher marginal utility of consumption than non-enrollees, so that $\beta(G)$ is positive. Moreover, under some assumptions,[29] a first-order Taylor approximation of $\beta(G(p))$ is $\sigma[D^H(G(p)) - \int_{G(0)}^{G(p)} D^H(s)ds]$, the difference between willingness to pay of the marginal enrollee at price p and the average willingness to pay of non-enrollees at that price, scaled by σ, the coefficient of absolute risk aversion.

The condition for the MVPF spent on free public insurance to be positive when we use *ex ante* demand for insurance and assume no insurance in the absence of public insurance is given by Eq. (9), except that one replaces $D^H(q)$ with $D^{H,EA}$ in Eq. (9) to capture *ex ante* demand.

Application using estimates of linear demand and average cost curves. To calculate the *ex ante* value of free insurance, we take three steps. First, we solve the linear demand in Eq. (10) for price. Second, we estimate the markup $M(G)$ using the first-order Taylor approximation for $\beta(G)$ suggested by Hendren (2021). We add this to the price estimated in the first step to obtain the function $D^{H,EA}(G)$.[30] We illustrate this *ex ante* demand with the dashed blue line in the A Panels of Figures A.11 and A.11. Third, we take a first-order Taylor approximation of the markup. This reveals that, if we define

$$\frac{1}{\gamma^{EA}} = \frac{1}{\gamma}\left(1 + \frac{\sigma}{\gamma}G(0)[1-G(0)]\right) > \frac{1}{\gamma} > 0 \tag{25}$$

we can replace γ with γ^{EA} in Eq. (12) to approximate the value of free insurance.[31] In our calculations, we assume a coefficient of risk aversion of $\sigma = 5 \times 10^{-3}$, in the range of estimates in India and other lower-income countries (Binswanger, 1981; Just and Lybbert, 2012).

The resulting welfare calculations for the case where $r = 1.25$ are presented in the third panel of Table A.30. *Ex ante* demand is sufficiently greater than *ex post* demand that free insurance is now always positive for welfare. The D panels of Figures A.11 and A.12 show that using *ex ante* demand to value free insurance raises the welfare value of free insurance at all levels of r. However, using midline estimates of cost, free insurance remains a welfare-reducing policy for MCPF above $r = 1.5$.

C.5.2 Optimal price

The condition in the main text for the optimal price for the government service uses an *ex post* valuation of insurance, i.e., after individuals have some private information about their expected costs. The willingness to pay for insurance is higher if measured behind a veil of ignorance. This will affect both the marginal social benefits and costs of raising the price of insurance. To implement this change we need to invert the Marshallian analogue to the demand function in Eq. (24). To do so define $D^{EA}(p) = D^M(G) + G(1-G)[\partial D^M(G)/\partial p]\beta(G)$ and $G^{EA}(p)$ as the inverse of this

[28] See Propositions 1 and 2 in Hendren (2021).

[29] The two assumptions are that the utility from non-medical consumption and health are separable and that there are no differences in average income of the insured and uninsured. Propositions 3 and 4 in Hendren (2021) derive the approximation.

[30] See Appendix C.6.2 for details.

[31] A derivation is presented in Appendix Section C.6.2.

function. The optimal price is given by a version of Eq. (19) that replaces $G(p^*)$ and $\partial G/\partial p^*$ with $G^{EA}(p^*)$ and $\partial G^{(EA)}(p^*)/\partial p^*$.

Using the linear demand (10) and average cost (11) curves we estimated with our experiment, we can calculate the optimal price using the *ex ante* demand value of insurance, before consumers have any information on their own expected cost. To do so, we take two steps. First, we invert our estimate of the linear function $D^{H,EA}$ from our value-of-free-insurance calculations, so we have quantity as a function of price $G^{EA}(p)$. Second, we replace $G(p^*)$ with $G^EA(p^*)$ in the first-order condition (20) and solve for p^*. The resulting welfare calculations for the case where $r = 1.25$ are presented in the third panel of Table A.30.

Although free public insurance is a positive MVPF policy, the optimal price for public insurance is still positive, though generally below where the optimal price using *ex post* demand. The D panels of Figures A.11 and A.12 show that using the *ex ante* demand function increases the range of r (MCPF) over which free insurance is optimal at midline and endline, respectively. However, for higher r, the optimal price actually increases. The reason is that *ex ante* demand is greater, but has lower slope—which exerts mixed effects on the marginal social cost of raising premiums in Eq. (18). Moreover, the marginal social cost function weights the effects of demand and the slope of demand with the MCPF.

C.6 Derivations

In this section, we derive the welfare formulas we report in the main text and the two sections above.

C.6.1 Does free insurance improve welfare?

Marginal social benefit. Assume that a given consumer i obtains utility $u(g_i, x_i)$ from consuming a government service and other goods x_i, where we make the usual assumptions required for u to be well-behaved. In our case, the government service, i.e., RSBY insurance, is discrete or indivisible and the consumer can only consume one unit of it at a price or user fee of p, i.e., $g_i(p) \in \{0, 1\}$. (Except for the case where we calculate the "*ex ante* value of insurance", however, these equations generalize to any government services, not just insurance.) The consumer has income y_i. We normalize the price of other goods to be 1, but we assume that the consumer must pay a consumption tax of rate τ on those goods.[32] Although the government could finance the government service partly with a user fee and partly with taxes (implying that taxes depend on the price of the government service), we assume that the tax rate is fixed. We justify this later.

The consumer's indirect utility is

$$V(y_i, \tau, p) = \max\{ \max_{x_i} u(1, x_i) + \lambda_i[y_i - p - (1+\tau)x_i, \\ \max_{x_i} u(0, x_i) + \lambda_i[y_i - (1+\tau)x_i\} \tag{26}$$

Let $g_i^*(y_i, \tau, p)$ and $x_i^*(y_i, \tau, p)$ be the consumer's optimal choice of government service and other goods, and let $\lambda_i^*(y_i, \tau, p)$ be the associated Lagrange multiplier. The marginal private benefit of providing insurance (versus not) at price p to consumer i is equal to her willingness to pay for insurance ($WTP_i(y_i, \tau, p)$).[33] In our situation, where

[32] In India, individuals must pay a goods and service tax that averages 18%. This generated 53% of government revenue in 2022 (Thakur and Nagarajan, 2023)

[33] In the MVPF framework, MSB is equated to WTP for insurance, which we measure using revealed preference for insurance. An alternative, objective measure, might employ the impacts of RSBY access on different dimensions of health and non-medical consumption times WTP for each dimension. We would again face the question of how to measure WTP for each dimension. Moreover, we would have ensure that we do not fail to measure any relevant dimension that might be valued. We have no direct measure of WTP for health and non-medical consumption. Although we have a large number of health measures, there are surely many we miss. But we do measure demand for insurance, so use that our measure of WTP for the insurance.

the offer price is zero, this is approximately

$$WTP_i(y_i, \tau, 0) \approx \frac{u(1, x^*(y_i, \tau, 0)) - u(0, x^*(y_i, \tau, 0))}{\lambda^*(y_i, \tau, 0)} \tag{27}$$

where we could replace the approximation with an equality if utility were separable in the government service and other goods.

Assuming equal welfare weights, the marginal social benefit at price p is the sum of individual WTP for government service at that price across the population.[34] Let $G(p)$ be aggregate quantity demanded for the government service at price p. If insurance is a small portion of budget or there are no income effects, marginal social benefit at price p is approximately the area under the inverse aggregate Hicksian demand curve $D^H(G)$ and above p.[35] For notational convenience, we will treat aggregate demand curves as continuous, so

$$MSB(p) = \sum_i WTP_i(y_i, \tau, p) \approx \int_0^{G(p)} [D^H(q) - p]dq = \int_0^{G(p)} D^H(q)dq - pG(p). \tag{28}$$

The marginal social benefit from free insurance is this expression evaluated at $p = 0$.

Marginal social cost. The government's net expenditure on consumer i is

$$t_i(y_i, \tau, p) = [c_i^{MC}(p)g_i^*(y_i, \tau, p) - pg_i^*(y_i, \tau, p) - \tau x_i^*(y_i, \tau, p) \tag{29}$$

where $c_i^{MC}(p)$ is the government's marginal cost of providing service g_i^* to consumer i—in our context, the government's expenditure on healthcare for consumer i given her coverage. Marginal cost depends on price because of adverse selection: $\partial c_i^{MC}/\partial p > 0$. We assume income effects are sufficiently small or the user fee is sufficiently small that we can ignore that marginal cost also depends on the tax rate. The government obtains revenue from the price for the government service (the second term in the equation above) and from sales tax (the last term).

The government can finance the provision of its service by a combination of (a) charging for it directly (user fees), (b) taxing other goods, and (c) borrowing the money from other programs or creditors. In this section, we will assume the government relies on user fees and borrowing, and that the government's cost of funds is $R = 1 + r > 1$. (In the next section, we consider a combination of user fees and borrowing.) This assumption is reasonable because the Indian government is unlikely to change the tax rate based on the provision of public health insurance, if for no other reason than that government expenditures on such insurance are a tiny fraction of its budget.[36]

The marginal social cost of funds spent on providing the government service is the sum of the government's net expenditure on all consumers who purchase the government service at price p:

$$\begin{aligned} MSC(p) &= (1+r)\sum_i [c_i^{MC}(p) - p]g_i^*(y_i, \tau, p) \\ &\approx (1+r)\left[\int_{\overline{p}}^{p} [c^{MC}(z)G(z)]dz - \int_{\overline{p}}^{p} [zG(z)]dz\right] \qquad (30) \\ &= (1+r)\left[\int_0^{G(p)} [c^{MC}(D(w))w]dw - pG(p)\right] \qquad (31) \\ &= (1+r)[c^{AC}(p)G(p) - pG(p)] \qquad (32) \end{aligned}$$

where $D(q)$ is the inverse demand curve for the government service. We treat these marginal cost curves as continuous so that we can approximate them with continuous functions $c^{MC}(p)$ in Eq. (30). We swap axes of integration

[34] Since we are dealing with a non-marginal change in government service from 0 to 1, this is better described as an incremental social benefit.

[35] Alternatively, if insurance is a small portion of budget or there are no income effects, marginal social benefit at price p is approximately the area under the inverse aggregate Marshallian demand curve $D^M(G)$ and above p.

[36] PMJAY, the successor to RSBY, constitutes less than 10% of the budget of the Ministry of Health & Family Welfare in India. And government spending on health is roughly 3.5% of India's total government budget and less than 1% of India's GDP (National Council of Applied Economic Research, 2023).

and integrate over quantity in Eq. (31). In the final step we use the fact that the area under the marginal cost curve from $G = 0$ to $G(p)$ to in the price-quantity plane is equal to average cost at $G(p)$ times $G(p)$: $c^{AC}(p) = \int_{\overline{p}}^{p}[c^{MC}(q)G(q)]dq/G(p)$.

C.6.2 Valuation with *ex ante* demand and linear demand and cost functions

Even though we estimate a linear demand function, inverting that function to obtain *ex ante* willingness to pay (WTP) for insurance in Eq. (24) yields a non-linear function. We can numerically integrate it, but obtaining standard errors on our estimate is non-trivial. To simplify estimation, we use a first-order approximation of the non-linear *ex ante* WTP for insurance.

Ex ante demand has two parts, *ex post* inverse demand $D(p)$ plus a markup $M(p)$. Here we suppress the H superscript because we will vary how we estimate demand, estimating both a Marshallian demand (with group C) or an upper bound on Hicksian demand (with arm B). We need to linearize both $D(p)$ and $(M(p)$. We will indicate linearized functions with a upper-bar: $D^{\overline{EA}}(G) = \bar{D}(G) + \bar{M}(G)$.

Our estimates of demand are, by assumption, already linear. We start with estimates for the linear *ex post* demand in Eq. (10). The implied inverse *ex post* demand is $\bar{D}(G) = [G(0)/\gamma] - [1/\gamma]G$, where we suppress the i subscript that indexes households and we replace lowercase g with capital G because we will be speaking of demand in terms of fractions of all households rather than for an individual household.

Next we linearize the markup $M(G) = G(1-G) \cdot |\partial D/\partial p| \cdot \beta(G)$. We follow Hendren (2021) and start with approximating $\beta(G)$ with $\tilde{\beta}(G) = \sigma[D^H(G(p)) - \int_{G(0)}^{G(p)} D^H(s)ds]$. This changes the (still non-linear) markup to

$$M(G) = G(1-G) \cdot \left|\frac{\partial D}{\partial G}\right| \cdot \tilde{\beta}(G) \tag{33}$$

If we plug linear demand into $\tilde{\beta}(G)$ we get $\tilde{\beta}(G) \approx \sigma[\bar{D}(G) - (1/2)(G(0) - G)\bar{D}(G)] = \sigma[1 - (1/2)(G(0) - G)]\bar{D}(G)$, where σ is the coefficient of absolute risk aversion.

We take a first-order approximation around $G(0)$ and obtain $\bar{M}(G)|_{G(0)} \approx M(G(0)) + M'(G(0))[G - G(0)]$. We can zero out the first term $M(G(0))$ right away because $\bar{D}(G(0)) = 0$ implies $\tilde{\beta}(G) = 0$. This leaves us with

$$\bar{M}(G)|_{G(0)} \approx M'(G(0))[G - G(0)] \tag{34}$$

The derivative of the markup evaluated at $G(0)$ is

$$M'(G(0)) = \left[(1 - 2G(0)) \cdot \frac{1}{\gamma} \cdot \tilde{\beta}(G(0))\right] + \left[G(0)[1 - G(0)] \cdot \frac{1}{\gamma} \cdot \tilde{\beta}'(G(0))\right] \tag{35}$$

Let's compute each part. The first term is 0 because $\tilde{\beta}(G(0)) = 0$. The second term depends on $\tilde{\beta}'(G)$, which is

$$\tilde{\beta}'(G) = \sigma\left(\frac{1}{2}\bar{D}(G) - \left[1 - \frac{1}{2}(G(0) - G)\right]\frac{1}{\gamma}\right) \tag{36}$$

Evaluated at $G(0)$, which implies this becomes $\tilde{\beta}'(G) = -\sigma/\gamma$ because $\bar{D}(G(0)) = 0$. This implies $M'(G(0)) = -G(0)[1 - G(0)]\sigma/\gamma^2$. Plugging this into our approximation of the markup yield

$$\bar{M}(G)|_{G(0)} \approx -\frac{\sigma}{\gamma^2}G(0)[1 - G(0)](G - G(0)) > 0 \tag{37}$$

This is positive because $G < G(0)$—quantity is larger at zero price. It converges to 0 as G approaches $G(0)$, maximal demand.

Returning to linearized *ex ante* inverse demand, we plug in linear *ex post* inverse demand and linearized markup

to obtain

$$\begin{aligned}\bar{D}^{EA}(G) &= \left[\frac{1}{\gamma}\right](G(0)-G) - \left[\frac{\sigma}{\gamma^2}G(0)[1-G(0)]\right](G-G(0)) \\ &= \frac{1}{\gamma}\left(1+\frac{\sigma}{\gamma}G(0)[1-G(0)]\right)(G(0)-G) \\ &= \frac{1}{\gamma^{EA}}(G(0)-G) \end{aligned} \tag{38}$$

where

$$\frac{1}{\gamma^{EA}} = \frac{1}{\gamma}\left(1+\frac{\sigma}{\gamma}G(0)[1-G(0)]\right) > \frac{1}{\gamma} > 0 \tag{39}$$

This means that *ex ante* inverse demand as a steeper slope than *ex post* inverse demand. Moreover, because inverse demand is 0 when $G = g(0)$, inverse demand is a rotation around a hinge at $G(0)$ on the x-axis.

C.6.3 What is the optimal insurance premium?

In this section, we modify our MVPF analysis to ask: what is the optimal price of RSBY insurance, conditional on offering it.

Marginal social benefit. An individual consumer's indirect utility conditional on purchasing the government service is

$$V(y_i, \tau, p) = u(1, x_i^*) + \lambda_i^*[y_i - p - (1+\tau)x_i^*] \tag{40}$$

where we suppress the reliance of optimal x_i and the multiplier on income, tax rate and government service price. The willingness to pay for an increase in price is marginal utility from increasing price divided by the marginal utility of income: $(\partial V_i/\partial p)/\lambda_i^* = -1$. This is simply Roy's identity. It is negative because a higher price lowers utility conditional on buying the government service. A lower price would have the opposite signed effect.

The marginal social benefit of increasing the price of the government service is the sum of private benefits across individuals who buy the service:

$$MSB(p) = -\sum_i \mathbb{I}(g_i^* = 1) = -G(p). \tag{41}$$

This is proportional to aggregate quantity demanded at price p.

Marginal social cost. The social cost of providing the government service at price p is equal to $SC(p) = (1+r)[c^{AC}(p) - p]G(p)$. This is identical to the marginal social cost in the last section because the comparison in the last section was providing insurance or not. Here we assume insurance is provided, but compare value at a higher or lower price. So the marginal social cost is the derivative of social cost in this paragraph with respect to price:

$$MSC(p) = (1+r)\frac{\partial c^{AC}(p)}{\partial p}G(p) - (1+r)G(p) + (1+r)[c^{AC}(p) - p]\frac{\partial G(p)}{\partial p} \tag{42}$$

The first term is new and reflects the change in average cost as price increase. Importantly, this is positive if there the service is insurance and there is adverse selection. The second term is the reduction in expenditure as revenues rise. The third term reflects the reduction in sales with higher price. This is negative if average costs exceed price. (If price were zero to start, then the first term would be positive, but the latter two negative.)

Optimal price. The first-order, necessary condition for p^* to be the optimal price for the government service

is that the marginal social benefit equals the marginal social cost of that service: $MSB(p^*) - MSC(p^*) = 0$, i.e.,

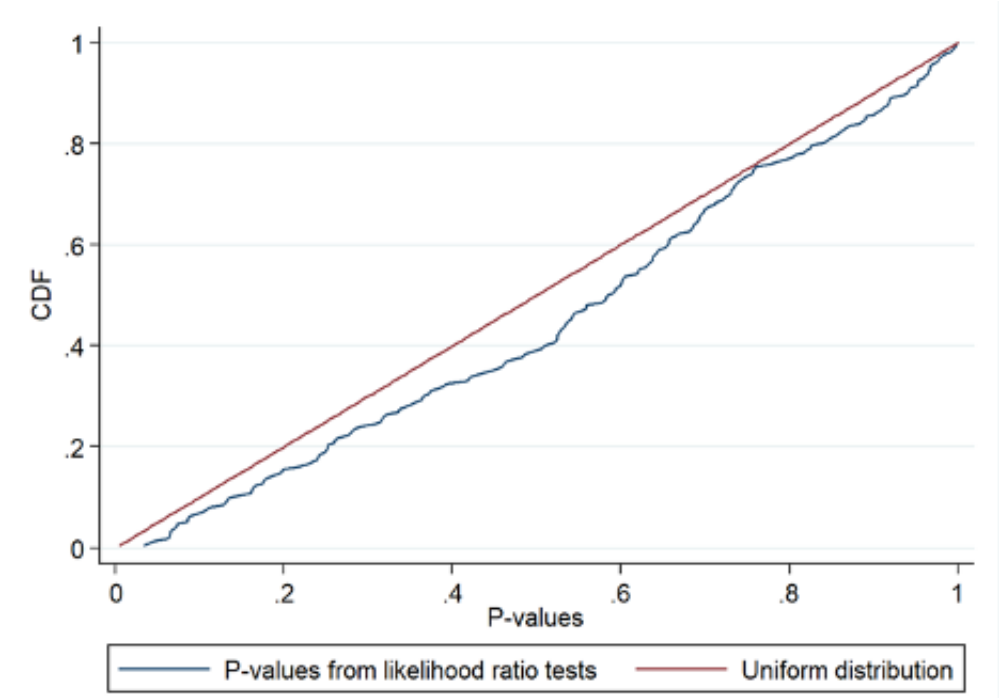
$$-G(p^*) - \left[(1+r)\frac{\partial c^{AC}(p^*)}{\partial p^*}G(p^*) - (1+r)G(p^*) + (1+r)[c^{AC}(p^*) - p^*]\frac{\partial G}{\partial p^*}\right] = 0 \tag{43}$$

$$-\frac{\partial c^{AC}(p^*)}{\partial p^*}G(p^*) + \frac{r}{1+r}G(p^*) - [c^{AC}(p^*) - p^*]\frac{\partial G}{\partial p^*} = 0 \tag{44}$$

The incremental cost to consumers ($G(p^*)$) of raising the price of government service is just a transfer to the government, reducing its expenses, so those terms cancel in the second line. What remains is the government's saving on borrowing costs ($rG(p^*)$). Dividing by $(1+r)$ gives the trade-off in rupees before financing costs. An important constraint on the optimal price is that it must be greater than 0. If it falls below 0, price is below marginal cost, which is non-negative, and incremental consumption produces a social loss.

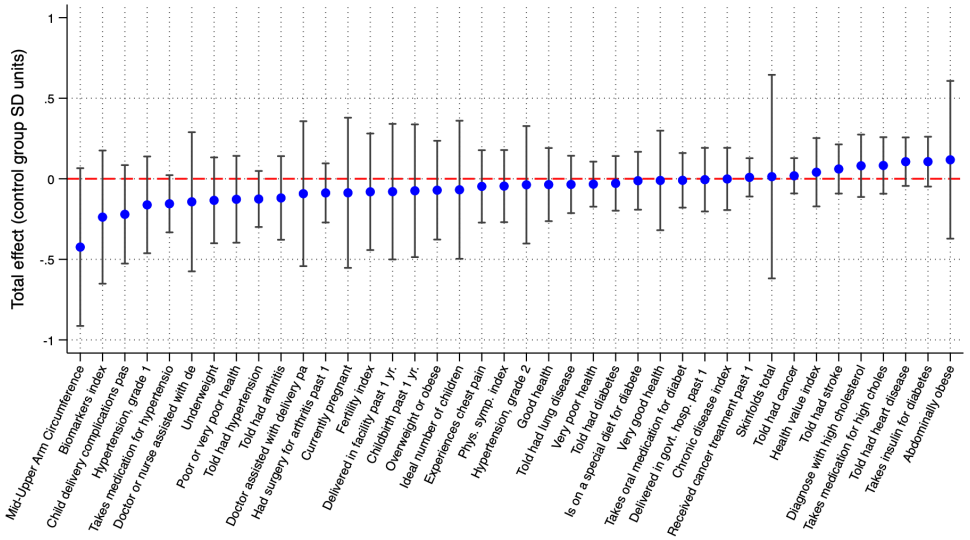
D Figures

Figure A.1: Balancing test result.



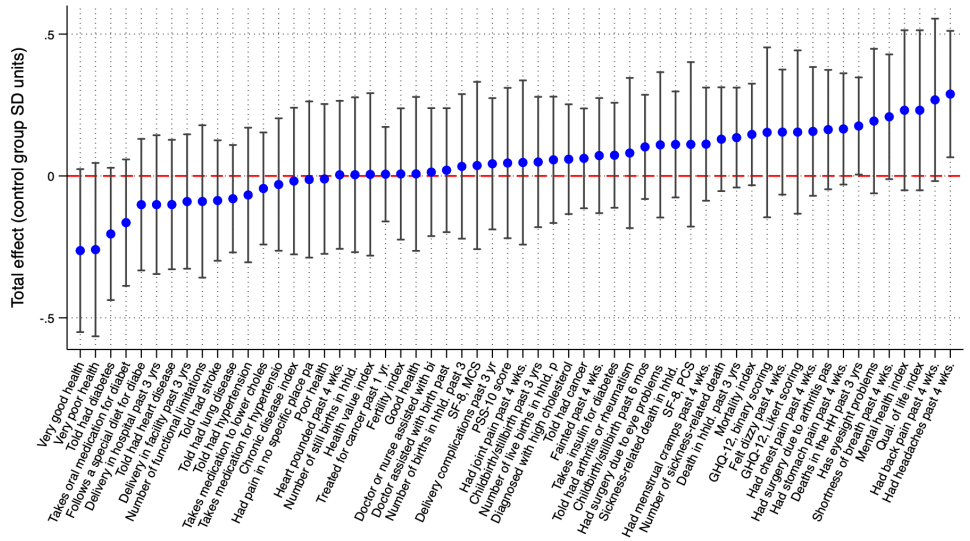
Notes. Figure presents the cumulative distribution of p-values (a) from likelihood ratio tests checking balance in outcomes across arms and (b) from a uniform distribution (capturing perfect randomization).

Figure A.2: Estimates of total effects of free insurance (IIT, group A) on health outcomes from midline (18 months).



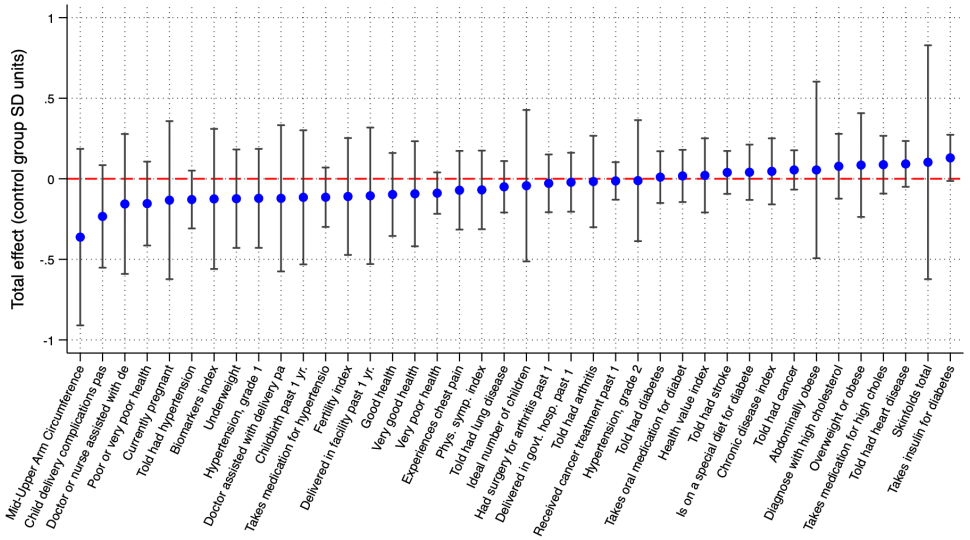
Notes. Figure presents a coefficient plot of estimates of total effects of free insurance based on ITT coefficients for health outcomes from group A at midline (18 months after treatment). Blue dots are coefficient estimates. Whiskers are 95% confidence intervals. Confidence intervals are based on standard errors that do not correct for multiple testing.

Figure A.3: Estimates of total effects of free insurance (ITT, group A) on health outcomes from endline (3.5 years).



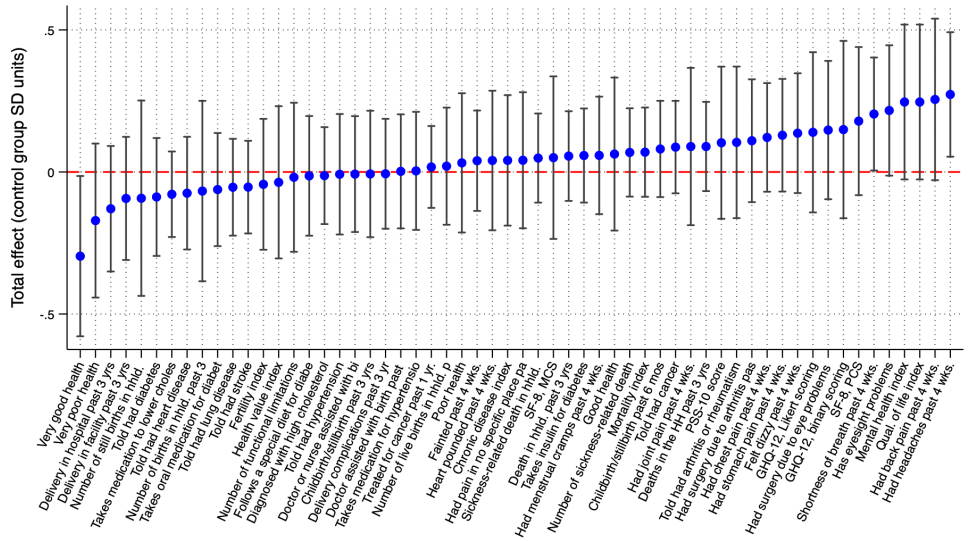
Notes. Figure presents a coefficient plot of estimates of total effects of free insurance based on ITT coefficients for health outcomes from group A at endline (3.5 years after treatment). Blue dots are coefficient estimates. Whiskers are 95% confidence intervals. Confidence intervals are based on standard errors that do not correct for multiple testing.

Figure A.4: Estimates of total effects of insurance (CATE) on health outcomes from midline (18 months).



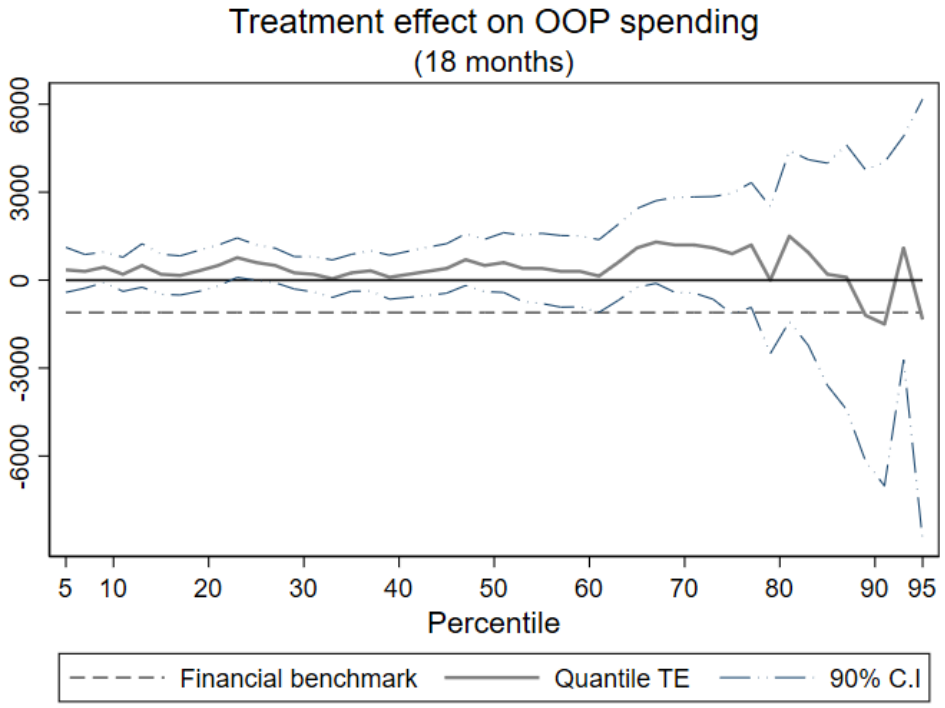
Notes. Figure presents a coefficient plot of estimates of total effects based on CATE coefficients for health outcomes from midline (18 months after treatment). Blue dots are coefficient estimates. Whiskers are 95% confidence intervals. Confidence intervals are based on standard errors that do not correct for multiple testing.

Figure A.5: Estimates of total effects of insurance (CATE) on health outcomes from endline (3.5 years).



Notes. Figure presents a coefficient plot of estimates of total effects based on CATE coefficients for health outcomes from endline (3.5 years after treatment). Blue dots are coefficient estimates. Whiskers are 95% confidence intervals. Confidence intervals are based on standard errors that do not correct for multiple testing.

Figure A.6: Quantile treatment effects on OOP spending



Notes. The solid gray line plots the quantile treatment effects of access to RSBY (a pooled indicator for assignment to treatment arms A, B or C) on midline out-of-pocket (OOP) medical spending from the 5th to 95th percentiles. The dashed line shows the effect on OOP spending which would be expected if insurance had a purely financial benefit: the control mean of medical OOP spending (INR 28,777) multiplied by the pooled treatment effect on RSBY utilization (3.85 percentage points).

Figure A.7: Timeline of study.

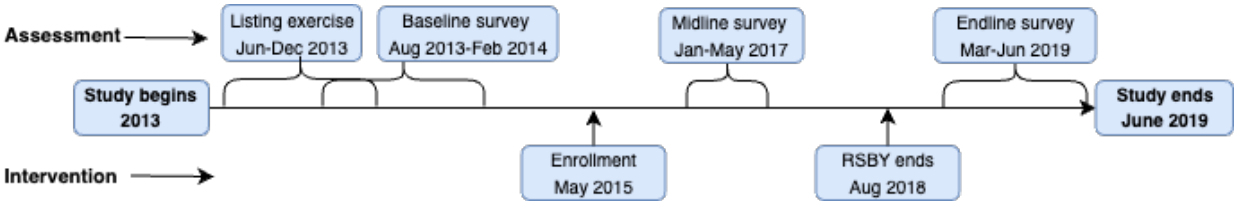
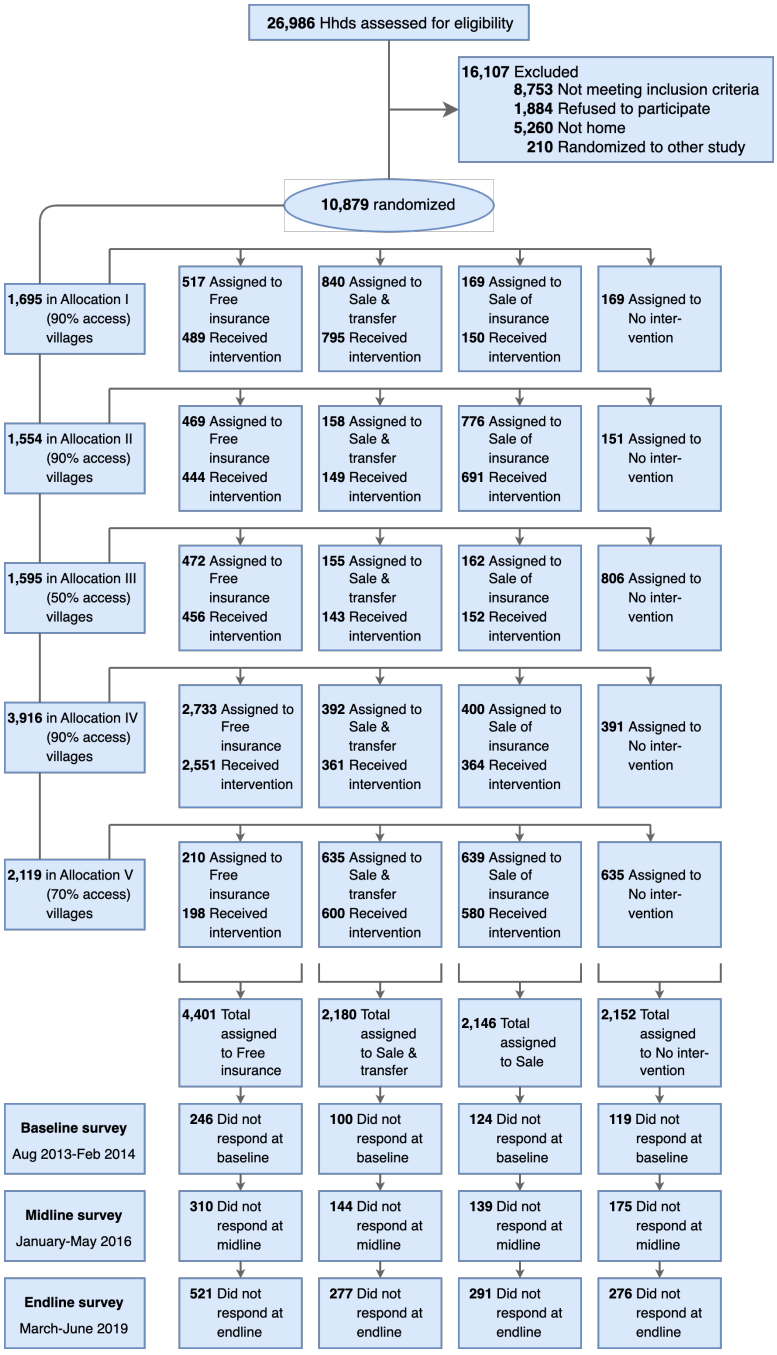
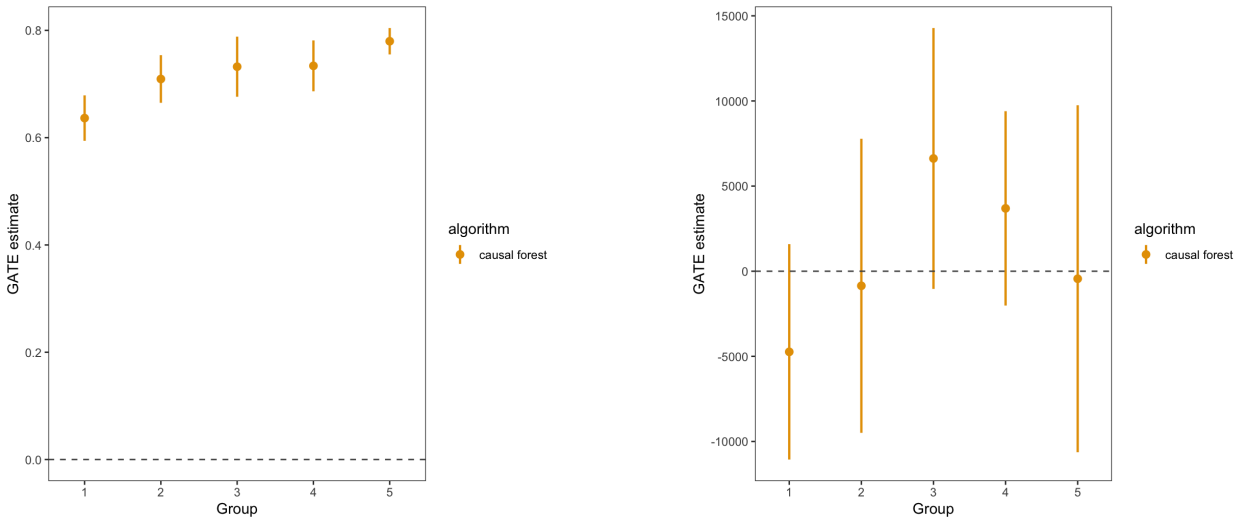


Figure A.8: Subject flowchart, with exclusions and attrition by endline.



Notes. In column 1, X% "access villages" means that in these villages, X% of households were assigned to either groups A, B, or C. In rows 1-5, the difference between N "Assigned to" a group and M "Received intervention" is that our randomization algorithm assigned M to the relevant group but that, when we went to the village to inform households of their method of access and to enroll household, we were only able to contact M our of N of those households.

Figure A.9: GATE predictions of heterogeneity in enrollment and OOP spending.



(a) GATES in enrollment

(b) GATES in OOP spending

Notes. This figure plots the sorted average group treatment effects (GATES) based on the method outlined in Imai and Li (2025). While we find statistically significant heterogeneity in enrollment that can be predicted by baseline covariates (panel a), we do not find such heterogeneity in midline OOP medical expenditure (panel b).

Figure A.10: Predicted medical expenditures

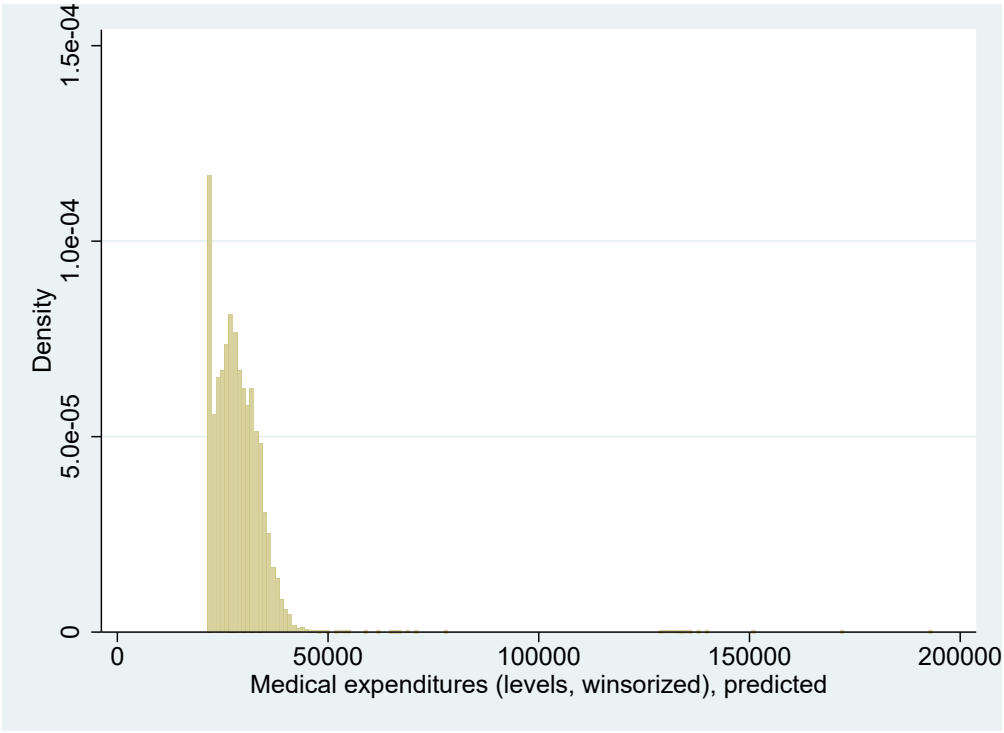
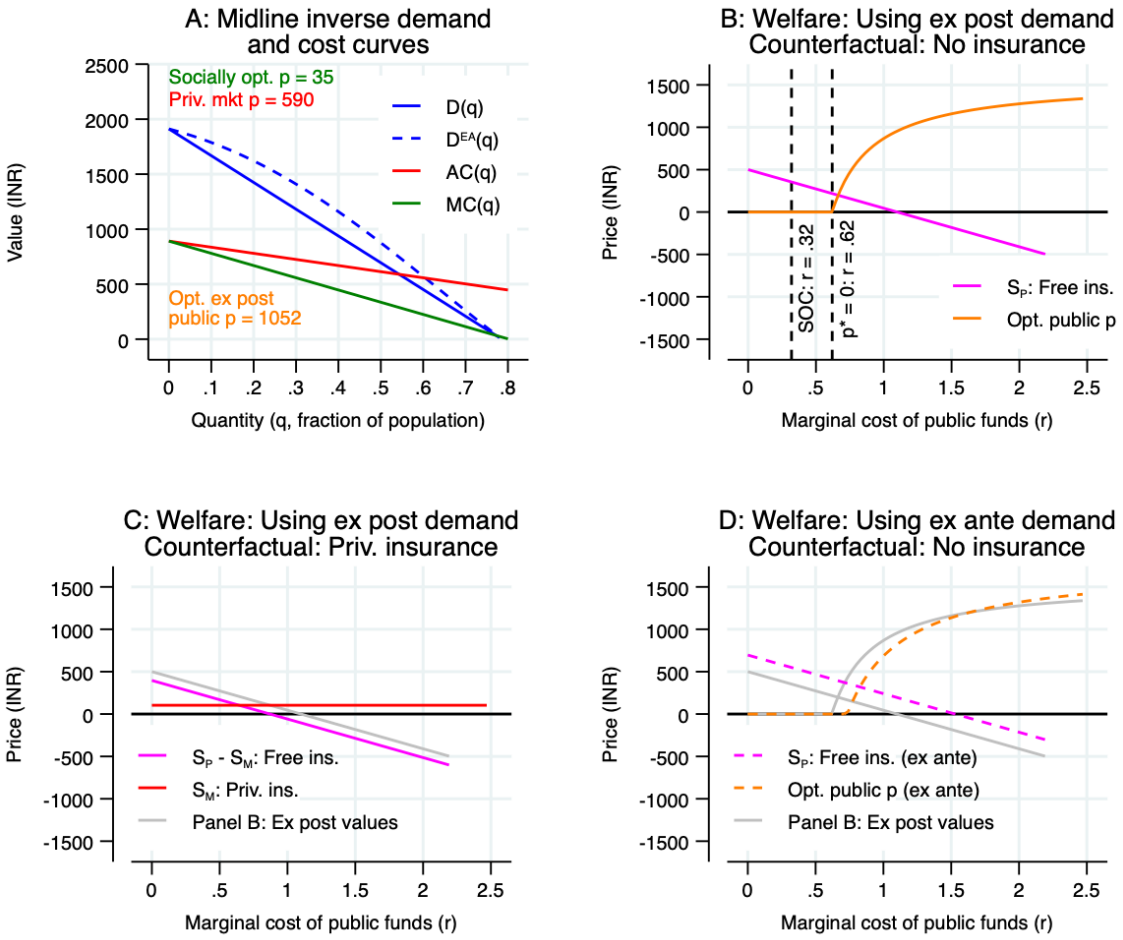
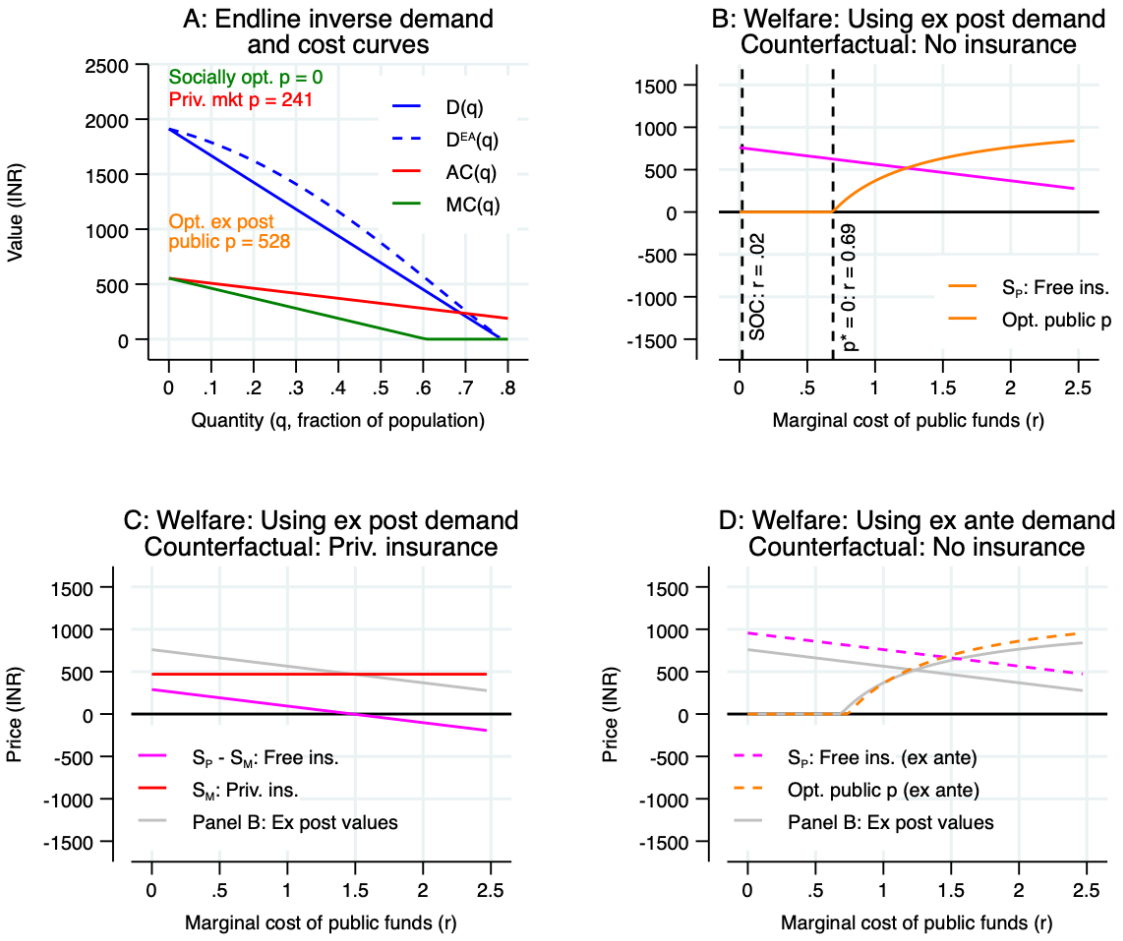


Figure A.11: Inverse demand, cost and welfare calculations at midline.



Note. Midline use equals endline hospital expenditure x midline successful use. Panel A: Demand is an upper bound on Hicksian demand; it is calculated using trial arms A and B. Solid blue line gives ex post demand, dashed blue line gives ex ante demand (Hendren 2021). MC curve is derived from AC curve. Optimal prices are calculated using plotted demand and assuming r = 1.25. Socially optimal price is intersection of plotted demand and MC curve. Private market price is given by intersection of AC line and demand curve. Optimal ex post line is pulled from Panel B at r = 1.25. Panel B: Formulas for MVPF with free insurance (magenta) and optimal price of public insurance (orange) are given in main text. The counterfactual is no insurance in absence of public insurance. Left black dashed line shows highest r at which second-order condition is not satisfied. Right dashed line gives r where p=0 satisfies the first-order condition using ex post demand. Panel C: Value of free insurance when counterfactual is community-rated private insurance without load. Red line shows surplus from private insurance alone. For comparison, gray line shows value of free insurance in panel B, the no insurance counterfactual. Panel D: Value of free insurance and optimal price of insurance using ex ante demand. For comparison, gray line shows value of free insurance in panel B.

Figure A.12: Inverse demand, cost and welfare calculations at endline.



Note. Endline use equals endline hospital use x endline successful use. Panel A: Demand is an upper bound on Hicksian demand; it is calculated using trial arms A and B. Solid blue line gives ex post demand, dashed blue line gives ex ante demand (Hendren 2021). MC curve is derived from AC curve. Optimal prices are calculated using plotted demand and assuming r = 1.25. Socially optimal price is intersection of plotted demand and MC curve. Private market price is given by intersection of AC line and demand curve. Optimal ex post line is pulled from Panel B at r = 1.25. Panel B: Formulas for MVPF with free insurance (magenta) and optimal price of public insurance (orange) are given in main text. The counterfactual is no insurance in absence of public insurance. Left black dashed line shows highest r at which second-order condition is not satisfied. Right dashed line gives r where p=0 satisfies the first-order condition using ex post demand. Panel C: Value of free insurance when counterfactual is community-rated private insurance without load. Red line shows surplus from private insurance alone. For comparison, gray line shows value of free insurance in panel B, the no insurance counterfactual. Panel D: Value of free insurance and optimal price of insurance using ex ante demand. For comparison, gray line shows value of free insurance in panel B.

E Tables

E.1 Design

Table A.1: Trial design in each district.

Village condition label	Percent of villages assigned to condition	Percent of sample households assigned to each household condition in this village condition			
		(A) Free insurance	(B) Sale of insurance + transfer	(C) Sale of insurance	(D) No intervention
I	15	30	50	10	10
II	15	30	10	50	10
III	15	30	10	10	50
IV	35	70	10	10	10
V	20	10	30	30	30
All conds.	100	40	20	20	20

Notes. Table presents the design of the experiment, including percent of sample villages and sample households in each village assigned to each condition. This design was independently and identically applied to each of the 2 districts in the study. Column 1 gives the labels of the village conditions. Column 2 gives the percent of villages assigned to the village condition. The headers of columns 3-6 give the names of the household conditions (i.e., insurance-access arms). Each village condition is defined by the percentage of sample households assigned to each household condition. Numbers in columns 3-6 give the percentage of households assigned to each household condition in the village condition given in column 1. The last row gives totals. The last row of column 2 total shows that all sample villages are assigned to one of the 5 villages condition. The last rows of columns 3-6 give the percentage of all households in the study that were assigned to each of the 4 household conditions. For example, the table reports that 15% of villages were assigned to village condition II, and that in that condition, 30%, 10%, 50% and 10% of households were assigned to household conditions A), (B), (C), and (D), respectively. The last row says that, across all village conditions, 40%, 20%, 20%, 20% of sample households were were assigned to household conditions A), (B), (C), and (D), respectively.

Table A.2: Outcomes measured by topic at midline (18 months post-intervention) and endline (3.5 years post-intervention) surveys.

	Midline (18 months)	Endline (3.5 years)
Utilization		
Inpatient or overnight hospital stay	x	x
Successful RSBY use for treatment	x	x
Other utilization metrics		
Outpatient (day) surgery		x
Failed RSBY use for treatment	x	x
Health value		
Sickness		x
Good or very good health	x	x
Very good health	x	x
Poor or very poor health	x	x
Very poor health	x	x
Chronic disease		
Told had hypertension	x	x
Takes medication for hypertension	x	x
Told had diabetes	x	x
Takes oral medication for diabetes	x	x
Takes insulin for diabetes	x	x
Follows a special diet for diabetes	x	x
Told had cancer	x	x
Treated for cancer past 1 yr.	x	x
Told had lung disease	x	x
Told had heart disease	x	x
Told had stroke	x	x
Told had arthritis or rheumatism	x	x
Had surgery due to arthritis past 1 yr.	x	x
Diagnosed with high cholesterol	x	x
Takes medication to lower cholesterol	x	x
Has eyesight problems		x
Had surgery due to eye problems past 1 yr.		x

Note. Table presents outcomes in first column, and an indicator (x = yes, blank = no) for whether the outcome was measured at midline (column 2) and endline (column 3). Abbreviations: RSBY, Rashtriya Swasthya Bima Yojana; hhld, household.; resp., respondent; yr., year; mo., month; wk., week; kg., kilogram; SF-8, Short-form 8; PCS, physical component score; MCS, mental component score; PSS-10, 10-item Perceived Stress Scale; GHQ-12, 12-item General Health Questionnaire.

Table ?? (continued): Outcomes measured by topic at midline (18 months post-intervention) and endline (3.5 years post-intervention) surveys.

	Midline (18 months)	Endline (3.5 years)
Mental and emotional health		
GHQ-12, Likert scoring		x
GHQ-12, binary scoring		x
PSS-10 score		x
Quality of life		
Number of functional limitations		x
SF-8, PCS		x
SF-8, MCS		x
Had stomach pain past 4 wks.		x
Had back pain past 4 wks.		x
Had chest pain past 4 wks.	x	x
Had joint pain past 4 wks.		x
Had headaches past 4 wks.		x
Had menstrual cramps past 4 wks.		x
Had pain in no specific place past 4 wks.		x
Fainted past 4 wks.		x
Felt dizzy past 4 wks.		x
Shortness of breath past 4 wks.		x
Heart pounded past 4 wks.		x
Childbirth		
Childbirth/stillbirth past 6 mos.	x	x
Childbirth/stillbirth past 3 yrs.	x	x
Number of births in hhld. past 3 yrs.		x
Number of live births in hhld. past 3 yrs.		x
Number of still births in hhld. past 3 yrs.		x
Delivery in hospital past 3 yrs.	x	x
Delivery in facility past 3 yrs.	x	x
Doctor assisted with birth past 3 yrs.	x	x
Doctor or nurse assisted with birth past 3 yrs.	x	x
Delivery complications past 3 yrs.	x	x
Ideal number of children	x	
Biomarkers		
Overweight or obese	x	
Underweight	x	
Abdominally obese	x	
Mid-upper arm circumference	x	
Hypertension, grade 1	x	
Hypertension, grade 2	x	
Skinfolds total	x	
Mortality		
Death in hhld. past 3 yrs.		x
Number of deaths in hhld.		x
Sickness-related death in hhld. past 3 yrs.		x
Number of sickness-related deaths in hhld.		x

Note. Table presents outcomes in first column, and an indicator (x = yes, blank = no) for whether the outcome was measured at midline (column 2) and endline (column 3). Abbreviations: RSBY, Rashtriya Swasthya Bima Yojana; hhld, household.; resp., respondent; yr., year; mo., month; wk., week; kg., kilogram; SF-8, Short-form 8; PCS, physical component score; MCS, mental component score; PSS-10, 10-item Perceived Stress Scale; GHQ-12, 12-item General Health Questionnaire.

E.2 Outcomes

E.2.1 Insurance enrollment

Table A.3: Effects of premium and subsidy combinations on enrollment (intent-to-treat effects)

	Direct effects	Spillover effects	Total effects
	Coefficient (SE) *p*-value	Coefficient (SE) *p*-value	Coefficient (SE) *p*-value
(A) Free insurance	72.419 (4.784) 0.000	6.993 (5.676) 0.219	78.030 (0.821) 0.000
(B) Sale + transfer	65.191 (7.837) 0.000	7.830 (9.340) 0.402	71.474 (1.217) 0.000
(C) Sale of insurance	48.399 (8.078) 0.000	12.788 (9.803) 0.193	58.660 (1.357) 0.000

Notes. Table presents estimates of intent-to-treat effects of access to insurance at different prices and subsidies on enrollment in RSBY. Each observation is a household and has equal weight. Treatment variables are household assignments: free insurance (A), sale of insurance + cash transfer (B), sale of insurance (C). Estimates are intent-to-treat effects; all models estimated with OLS. Each treatment arm was interacted with the share of the village allocated to A, B, or C (combined). Standard errors were clustered at the village level. Coefficients were transformed to show percentage point changes from the control group D. The direct effect only includes the coefficient on treatment A, B, or C. The spillover effect is the estimated effect on a treated household of assigning all other sample households to at least some form of access to RSBY insurance. The total effect is constructed as the sum of the direct effect and 0.8024*(spillover effect), where 0.8024 is the average fraction of households given insurance access in the study. Enrollment in the omitted group D is 0.

Table A.4: Effects of different premium & subsidy combinations, interacted with total household expenditure, on insurance enrollment.

	Direct effects	Spillover effects	Total effects
	Coefficient (SE) P-value	Coefficient (SE) P-value	Coefficient (SE) P-value
(A) Free-insurance	72.96% (7.13%) 0.000	6.88% (8.27%) 0.406	79.15% (1.08%) 0.000
(B) Sale-plus-transfer	65.01% (11.09%) 0.000	5.04% (13.24%) 0.704	69.55% (1.87%) 0.000
(C) Sale-of-insurance	46.80% (13.48%) 0.001	14.03% (16.54%) 0.397	59.43% (2.82%) 0.000
(A) Free-insurance x hhld. expenditure	-0.02% (0.04%) 0.655	0.02% (0.05%) 0.601	0.00% (0.01%) 0.588
(B) Sale-plus-transfer x hhld. expenditure	0.02% (0.07%) 0.756	0.01% (0.08%) 0.879	0.03% (0.01%) 0.003
(C) Sale-of-insurance x hhld. expenditure	0.02% (0.10%) 0.862	0.00% (0.12%) 0.984	0.02% (0.02%) 0.432
N	9080	9080	9080

Notes. Table presents direct and indirect effect of assignment of sample household to different premium and subsidy combinations, interacted with total household expenditures, on enrollment in RSBY insurance. The first column lists the premium/subsidy group. The second column reports direct effects of assigning a household to a premium/subsidy group on enrollment of that same household into RSBY. The third column reports the effect, for a given household assigned to the arm listed in column 1, of assigning other sample households in the village to arms A - C on enrollment of the given household. The fourth columns gives the sum of the direct effect and 90% of the indirect effect. We chose 90% of the indirect effect because in the study the maximum percentage of households assigned to arms A-C in any village was 90%. Each observation is a household. Treatment variables are household assignments: free insurance (A), sale of insurance plus cash transfer (B), and sale of insurance (C). Estimates are intent-to-treat effects; all models estimated with OLS. Each treatment arm was interacted with the share of the village allocated to A, B, or C (combined). Standard errors were clustered at the village level. Coefficients were transformed to show percentage point changes from the control group D. Enrollment rate is 0 in the control group D. The direct effect only includes the coefficient on treatment A, B, or C. The spillover effect is the estimated effect on a treated household of assigning all other sample households to at least some form of access to RSBY insurance. The total effect is constructed as the sum of the direct effect and 0.9*(spillover effect).

Table A.5: Enrollment by health and assets (controlling for education, raven scores and risk aversion)

	(1) Enroll-ment	(2) Enroll-ment	(3) Enroll-ment	(4) Enroll-ment	(5) Enroll-ment	(6) Enroll-ment	(7) Enroll-ment	(8) Enroll-ment	(9) Enroll-ment	(10) Enroll-ment	(11) Enroll-ment
Pay + Cash (B)	-0.15***	-0.14***	-0.15***	-0.13**	-0.14***	-0.16***	-0.13**	-0.13**	-0.14**	-0.14***	-0.15***
	(0.052)	(0.052)	(0.052)	(0.053)	(0.053)	(0.052)	(0.051)	(0.053)	(0.054)	(0.052)	(0.056)
Pay (C)	-0.19***	-0.19***	-0.19***	-0.19***	-0.17***	-0.20***	-0.19***	-0.20***	-0.17***	-0.19***	-0.20***
	(0.058)	(0.058)	(0.058)	(0.059)	(0.057)	(0.059)	(0.059)	(0.059)	(0.058)	(0.057)	(0.062)
Health		0.0079	-0.0069	0.014**	-0.0022	0.0039	-0.020***	-0.018**	0.0035	-0.0058	-0.00045
		(0.0081)	(0.0046)	(0.0071)	(0.0073)	(0.0068)	(0.0070)	(0.0073)	(0.0061)	(0.0080)	(0.0069)
B × health		-0.0070	-0.012	-0.012	-0.014	-0.0023	0.032**	0.028**	-0.027**	0.026**	0.025**
		(0.012)	(0.0088)	(0.013)	(0.012)	(0.012)	(0.013)	(0.012)	(0.013)	(0.011)	(0.010)
C × health		-0.012	-0.017	-0.012	-0.013	0.0097	0.0044	0.0079	-0.0038	0.047***	0.0059
		(0.014)	(0.011)	(0.015)	(0.014)	(0.014)	(0.014)	(0.013)	(0.013)	(0.017)	(0.014)
Asset	0.062***	0.065***	0.063***	0.063***	0.078***	0.065***	0.055***	0.066***	0.078***	0.064***	0.065***
	(0.014)	(0.015)	(0.014)	(0.014)	(0.015)	(0.016)	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)
B × asset	-0.033	-0.035	-0.034	-0.036	-0.041*	-0.034	-0.023	-0.040*	-0.044*	-0.042*	-0.049**
	(0.022)	(0.023)	(0.022)	(0.022)	(0.023)	(0.023)	(0.022)	(0.022)	(0.023)	(0.023)	(0.024)
Dep. var. mean		0.718	0.718	0.733	0.728	0.719	0.719	0.733	0.728	0.718	0.725
Dep. var. SD		0.450	0.450	0.442	0.445	0.450	0.450	0.442	0.445	0.450	0.446
N	8727	8727	8727	7619	7903	8488	8675	7611	7917	8727	7630
Health variable		General health, male, midline pre-dicted	General health, female, midline pre-dicted	General health, male, baseline	General health, female, baseline	Pr(visiting medical facility, male)	Pr(visiting medical facility, female)	Visited medical facility, male	Visited medical facility, female	Medical expendi-ture, pre-dicted	Medical expendi-ture, baseline
C × Health × SD/Mean enrollment		-0.021	-0.031	-0.020	-0.022	0.016	0.007	0.013	-0.006	0.079	0.010

Notes. *** p<0.01, ** p<0.05, * p<0.1. SE clustered at village level. Health variables are standardized by the sample mean and standard deviation. Controls for levels and interactions with education, raven score, and risk aversion are included but not reported. Education is a categorical variable recording the educational attainment of household head (1 = Never attended class 1, 2 = Class 1-5, 3 = Class 6-8, 4 = Class 9-10, 5 = Class 11-12, 6 = Graduate and above). Risk aversion is a dummy variable that equals 1 if respondent had a certain equivalence smaller than 180 in a gamble game. Missing indicators of assets, raven scores, risk aversion and education are included.

Table A.6: Relationship between treatment and cost among enrollees

	(1)	(2)	(3)	(4)
	Predicted midline spending		Predicted endline med spending	
Paid ins.+transfer (B)	0.115	0.084	0.089	0.049
	(0.034)	(0.033)	(0.036)	(0.034)
	[0.001]	[0.010]	[0.013]	[0.144]
Paid ins. (C)	0.058	0.037	0.103	0.077
	(0.037)	(0.035)	(0.039)	(0.037)
	[0.115]	[0.289]	[0.008]	[0.035]
Constant	-0.021	-0.008	-0.011	-0.072
	(0.019)	(0.059)	(0.020)	(0.062)
	[0.256]	[0.889]	[0.579]	[0.243]
Controls	N	Y	N	Y
Observations	6269	6269	6269	6269

Standard errors in parentheses; p-values in brackets. Omitted category is Free insurance (arm A). Sample is households who select into enrollment. Predicted medical spending is defined in Section 3.2. Cols 2 and 4 include controls for assets, education, Raven's scores and risk aversion.

E.2.2 Insurance and hospital utilization

Table A.7: Effects of premium and subsidy combinations (ITT) on insurance and hospital utilization

		Control	(A) Free insurance			(B) Sale of insurance + transfer			(C) Sale of insurance		
			Direct	Spillover	Total	Direct	Spillover	Total	Direct	Spillover	Total
	N	Mean (SD)	Coefficient (SE) p-value	Coefficient (SE) p-value	Coefficient (SE) p-value	Coefficient (SE) p-value	Coefficient (SE) p-value	Coefficient (SE) p-value	Coefficient (SE) p-value	Coefficient (SE) p-value	Coefficient (SE) p-value
Utilization at 18 months											
Successful use (past 6 mos.)	9960	3.856	2.507	4.698	6.276	2.127	5.782	6.766	7.666	-0.251	7.465
		(19.259)	(2.133)	(2.688)	(2.065)	(3.736)	(4.798)	(2.059)	(4.239)	(5.231)	(2.028)
			0.240	0.081	0.003	0.569	0.229	0.001	0.071	0.962	0.000
Failed use (past 6 mos.)	9960	1.337	3.565	-0.285	3.336	3.472	-0.396	3.154	2.571	0.033	2.597
		(11.487)	(1.910)	(2.207)	(1.173)	(2.568)	(3.130)	(1.203)	(2.120)	(2.536)	(1.109)
			0.063	0.897	0.005	0.177	0.899	0.009	0.226	0.990	0.020
Hospitalized on last visit (past 1 yr.)	9053	20.309	4.416	-2.193	2.656	-11.544	19.925	4.444	-0.501	3.903	2.630
		(40.241)	(5.473)	(9.967)	(8.177)	(9.427)	(14.685)	(8.526)	(9.365)	(12.694)	(8.351)
			0.420	0.826	0.745	0.221	0.176	0.602	0.957	0.759	0.753
Utilization at 3.5 years											
Successful use (past 6 mos.)	9458	0.322	2.164	-0.986	1.373	3.360	-2.178	1.612	-1.187	3.063	1.271
		(5.669)	(1.298)	(1.405)	(0.547)	(1.991)	(2.325)	(0.574)	(1.074)	(1.435)	(0.582)
			0.096	0.483	0.013	0.092	0.349	0.005	0.270	0.033	0.030
Successful use (most serious event)	9450	0.107	0.383	0.209	0.551	0.614	-0.148	0.495	-1.301	2.299	0.544
		(3.276)	(0.918)	(0.994)	(0.414)	(0.994)	(1.110)	(0.417)	(0.863)	(1.064)	(0.418)
			0.677	0.833	0.184	0.537	0.894	0.236	0.133	0.031	0.194
Failed used (most serious event)	9451	0.215	2.175	-1.567	0.918	-1.329	1.936	0.224	-1.118	2.179	0.631
		(4.631)	(2.160)	(2.413)	(0.527)	(1.134)	(1.340)	(0.493)	(1.608)	(1.990)	(0.532)
			0.315	0.517	0.082	0.242	0.149	0.650	0.488	0.274	0.237
Overnight stay for treatment	9488	22.579	-5.334	2.284	-3.501	-15.220	14.267	-3.772	-7.561	4.278	-4.129
		(41.821)	(5.534)	(5.748)	(4.466)	(7.428)	(8.035)	(4.454)	(8.025)	(8.535)	(4.548)
			0.336	0.691	0.434	0.041	0.077	0.397	0.347	0.616	0.364
Length of hospital stay	9483	1.266	-0.732	0.588	-0.261	-1.030	1.275	-0.007	-0.192	-0.055	-0.236
		(4.805)	(0.628)	(0.562)	(0.518)	(0.967)	(1.045)	(0.531)	(0.812)	(0.760)	(0.522)
			0.244	0.296	0.615	0.287	0.223	0.990	0.813	0.942	0.651
Outpatient (day) surgery	9474	6.517	-2.068	4.393	1.457	-9.490	12.993	0.935	-5.953	9.477	1.652
		(24.689)	(3.539)	(3.513)	(2.612)	(4.167)	(4.782)	(2.644)	(4.175)	(5.279)	(2.602)
			0.559	0.212	0.577	0.023	0.007	0.724	0.155	0.073	0.526

Notes. Table presents estimates of intent-to-treat effects of access to insurance at different prices and subsidies on use of insurance and visits to medical facilities. Mean and standard deviation in the control group are percentages from group D (no access to insurance). The outcome variables are transformed so coefficients show percentage point changes from group D. Each observation is a household and has equal weight. Treatment variables are household assignments: free insurance (A), sale of insurance + cash transfer (B), sale of insurance (C). Estimates are intent-to-treat effects; all models estimated with OLS. Each treatment arm was interacted with the share of the village allocated to A, B, or C (combined). Standard errors were clustered at the village level. The direct effect only includes the coefficient on treatment A, B, or C. The spillover effect is the estimated effect on a treated household of assigning all other sample households to at least some form of access to RSBY insurance. The total effect is constructed as the sum of the direct effect and 0.8024*(spillover effect), where 0.8024 is the average fraction of households given insurance access in the study. Successful use means the household used RSBY to pay for medical treatment. Failed use means that the household attempted to use RSBY to pay for care but were unable to (for many possible reasons, Table A6). The most serious event is defined as an accident which caused a household member to miss at least two days of work, a childbirth or a stillbirth, or three functional limitations. If none of those occurred, it is defined as the most expensive health event or the one that led to the longest hospital stay. Hospitalized on last visit (past 1 yr.) indicates that the respondent was hospitalized on their most recent visit to a healthcare provider within the past year. This question was administered to both the male or the female respondent within the adult health module. The FWER adjusted 5% critical values are: 0.003 for insurance use at 18 mos; 0.006 for healthcare use at 18 mos; 0.002 for insurance use at 3.5 yrs; 0.002 for healthcare use at 3.5 yrs.

Table A.8: Effects of enrollment (CATE) on insurance and hospital utilization

		Control	Direct effect	Spillover effect	Total effect
	N	Mean (SD)	Coefficient (SE) p-value	Coefficient (SE) p-value	Coefficient (SE) p-value
			Utilization at 18 months		
Successful use (past 6 mos.)	9960	3.856 (19.259)	3.846 (2.728) (0.159)	2.599 (4.467) (0.561)	5.931 (2.580) (0.021)
Failed use (past 6 mos.)	9960	1.337 (11.487)	3.461 (1.872) (0.065)	-0.063 (2.666) (0.981)	3.410 (1.294) (0.008)
Hospitalized on last visit (past 1 yr.)	9053	20.309 (40.241)	0.999 (6.276) (0.873)	6.090 (12.465) (0.625)	5.886 (9.153) (0.520)
			Utilization at 3.5 years		
Successful use (past 6 mos.)	9458	0.322 (5.669)	2.744 (1.165) (0.018)	-1.583 (1.602) (0.323)	1.474 (0.591) (0.013)
Successful use (most serious event)	9450	0.107 (3.276)	0.504 (0.813) (0.535)	0.626 (1.057) (0.554)	1.007 (0.383) (0.009)
Failed used (most serious event)	9451	0.215 (4.631)	1.242 (1.642) (0.450)	0.260 (2.283) (0.909)	1.451 (0.571) (0.011)
Overnight stay for treatment	9488	22.579 (41.821)	-12.384 (5.983) (0.038)	14.486 (7.355) (0.049)	-0.761 (4.183) (0.856)
Length of hospital stay	9483	1.266 (4.805)	-0.872 (0.704) (0.216)	1.257 (0.751) (0.094)	0.137 (0.448) (0.761)
Outpatient (day) surgery	9474	6.517 (24.689)	-4.073 (3.473) (0.241)	10.518 (4.335) (0.015)	4.367 (2.592) (0.092)

Notes. Table presents complier average treatment estimates of the effect of enrollment in RSBY insurance on insurance and healthcare utilization. Each observation is a household and has equal weight. Mean and standard deviation in the control group are percentages from group D (no access to insurance). The outcome variables are transformed so coefficients show percentage point changes the unenrolled group. The direct effect is the estimated effect of enrolling one household, assuming no other sample households in the village are enrolled. The spillover effect is the estimated effect on an enrolled household of enrolling all other sample households in the village. Total effects are the sum of direct and (spillover effects)*(uptake into free insurance). The total effect of free insurance on uptake is estimated as 0.7183, the mean uptake into insurance in arms A-C. Successful use means the household used RSBY to pay for medical treatment. Failed use means that the household attempted to use RSBY to pay for care but were unable to. The most serious event is defined as an accident which caused a household member to miss at least two days of work, a childbirth or a stillbirth, or three functional limitations. If none of those occurred, it is defined as the most expensive health event or the one that led to the longest hospital stay. Hospitalized on last visit (past 1 yr.) indicates that the respondent was hospitalized on their most recent visit to a healthcare provider within the past year. This question was administered to both the male or the female respondent within the adult health module. The FWER adjusted 5% critical values are: 0.009 for insurance use at 18 mos; 0.017 for healthcare use at 18 mos; 0.006 for insurance use at 3.5 yrs; 0.006 for healthcare use at 3.5 yrs.

Table A.9: Relationship between treatment, RSBY enrollment and endline card possession

	(1) RSBY possession (endline)	(2) RSBY possession (endline)	(3) RSBY possession (endline)
Enrolled in RSBY	0.422		
	(43.75)		
Offered ins.		0.432	
		(33.75)	
Free insurance			0.453
			(32.22)
Paid ins.+transfer			0.45
			(25.88)
Paid ins			0.376
			(21.11)
Village-level treat.		0.0453	0.0295
		(0.80)	(0.53)
Constant	0.253	0.119	0.130
	(34.10)	(2.77)	(3.04)
Observations	9206	9206	9206
F-stat	1913.9	672.1	346.8

Notes. t statistics in parentheses. Offered insurance indicates assignment to any treatment group (free, paid+transfer or paid). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.10: Effects of endline RSBY card possession on endline insurance and hospital utilization (complier average treatment effects)

			Direct effect	Spillover effect	Total effect
	Obs.	Control mean (SD)	Coefficient (SE) P-value	Coefficient (SE) P-value	Coefficient (SE) P-value
			Utilization at 3.5 years		
RSBY used for any treatment (endline)	9179	0.322	6.638	-5.728	2.129
		(5.669)	(3.652)	(5.436)	(1.491)
			(0.069)	(0.292)	(0.153)
Successful use (any treatment)	9160	0.107	2.076	0.060	2.124
		(3.276)	(2.308)	(3.380)	(0.997)
			(0.368)	(0.986)	(0.033)
Failed used (any treatment)	9161	0.215	3.836	-0.882	3.141
		(4.631)	(3.721)	(6.187)	(1.718)
			(0.303)	(0.887)	(0.068)
Overnight stay for treatment	9185	22.579	-17.298	33.704	9.233
		(41.821)	(14.294)	(22.653)	(9.337)
			(0.226)	(0.137)	(0.323)
Length of hospital stay	9181	1.266	-2.155	4.088	1.064
		(4.805)	(1.763)	(2.614)	(0.950)
			(0.222)	(0.118)	(0.263)
Outpatient (day) surgery	9169	6.517	-13.327	26.651	7.653
		(24.689)	(8.906)	(14.342)	(6.186)
			(0.135)	(0.063)	(0.216)

Notes. Table presents complier average treatment estimates of the effect possessing an RSBY insurance card on insurance and healthcare utilization. Each observation is a household and has equal weight. Mean and standard deviation in the control group are percentages from group D (no access to insurance). The outcome variables are transformed so coefficients show percentage point changes the unenrolled group. The direct effect is the estimated effect of enrolling one household, assuming no other sample households in the village are enrolled. The spillover effect is the estimated effect on an enrolled household of enrolling all other sample households in the village. Total effects are the sum of direct and (spillover effects)*(uptake into free insurance). The total effect of free insurance on uptake is estimated as 0.7183, the mean uptake into insurance in arms A-C. Successful use means the household used RSBY to pay for medical treatment. Failed use means that the household attempted to use RSBY to pay for care but were unable to. The most serious event is defined as an accident which caused a household member to miss at least two days of work, a childbirth or a stillbirth, or three functional limitations. If none of those occurred, it is defined as the most expensive health event or the one that led to the longest hospital stay. Hospitalized on last visit (past 1 yr.) indicates that the respondent was hospitalized on their most recent visit to a healthcare provider within the past year. This question was administered to both the male or the female respondent within the adult health module.

Table A.11: Effect of insurance access on total and out-of-pocket (OOP) medical expenditures (CATE).

			Direct	Spillover	Total
		Control mean (SD)	Coefficient (SE) P-value	Coefficient (SE) P-value	Coefficient (SE) P-value
Medical spending at 18 months					
Annual medical spending	N = 10030	28717.69 (31601.59)	12848.66 (5148.08) .01	-1.6e+04 (9680.63) .11	515.70 (5047.78) .92
Log annual medical spending	N = 10030	9.57 (1.94)	0.59 (0.31) .06	-1.34 (0.48) .006	-0.47 (0.37) .21
Annual medical non-hospital spending	N = 10030	24072.39 (26111.22)	5794.11 (4200.31) .17	-7181.20 (8399.11) .39	142.23 (4581.71) .98
Log annual medical non-hospital spending	N = 10030	9.35 (2.07)	0.35 (0.32) .28	-1.09 (0.50) .03	-0.51 (0.38) .18
Medical spending at 4 years					
OOP medical spending (most serious event)	N = 9396	20444.06 (1.3e+05)	6670.52 (22178.69) .76	-1.7e+04 (20511.80) .42	-6380.67 (12548.28) .61
Log OOP medical spending (most serious event)	N = 9396	4.74 (4.76)	-0.93 (0.62) .13	1.50 (1.01) .14	0.25 (0.70) .72

Notes. Table presents estimates of the effect of enrollment in RSBY insurance on medical expenditures. Abbreviations: SD, standard deviation; SE, standard error; mos, months; yr, year; hosp., hospital. Each observation is a household. Treatment variable is enrollment. Estimates are complier average treatment effects. Observations are weighted so each household has equal weight. Standard errors were clustered at the village level. Mean and standard deviation in the control group are statistics from the control group D. Coefficients were transformed to show changes relative to the control group D. The direct effect is the estimated effect of enrolling one household, assuming no other sample households in the village are enrolled. The spillover effect is the estimated effect on an enrolled household of enrolling all other sample households in the village. Total effects are the sum of direct and (spillover effects)*(uptake into free insurance). The total effect of free insurance on uptake is estimated as 0.7871 in Table 3.

Table A.12: Effect of premium & subsidy combinations on medical expenditures (intent-to-treat effects without accounting for share given access)

	(1) Med Exp	(2) Med Exp (log)	(3) Non-Hosp Exp	(4) Non-Hosp Exp (log)	(5) OOP	(6) OOP (log)
Free insurance	942.37	-0.05	830.22	-0.03	-3363.22	0.05
	(1297.74)	(0.08)	(1161.11)	(0.08)	(3542.37)	(0.16)
Sale + transfer	-494.59	-0.10	6.20	-0.09	-1233.51	-0.10
	(1199.28)	(0.09)	(1025.93)	(0.09)	(4132.25)	(0.17)
Sale	1309.26	0.02	943.25	0.01	-5221.01	-0.43**
	(1123.48)	(0.07)	(972.44)	(0.08)	(3614.42)	(0.18)
Obs.	10,030	10,030	10,030	10,030	9,396	9,396
R-Sqd	0.00	0.00	0.00	0.00	0.00	0.00
Control Mean	28776.72	9.59	23980.96	9.37	21470.36	4.81

Notes. Table presents estimates of intent-to-treat effects of access to insurance at different prices and subsidies on medical expenditures overall and components. Each observation is a household. Treatment variables are household assignments: free insurance (A), sale of insurance + cash transfer (B), sale of insurance (C). Estimates are intent-to-treat effects; all models estimated with OLS. Only indicators for each treatment arm are included. There is no regressor for the share of the village allocated to A, B, or C (combined) or the interaction of the A, B, or C indicator with the share of the village allocated to A, B, or C (combined). Standard errors were clustered at the village level. Standard errors on coefficients are in parentheses. Mean in the control group are statistics from the group without access to insurance. Medical expenditures are defined as the sum of all medical expenditures in the past year. Non-hospital expenditures are defined as the sum of all medical expenditures in the past year excluding in-patient hospital stays. Out-of-pocket expenditures are defined as the sum of all medical expenditures in the past year that were not paid by insurance. */**/*** indicates significance at the 5/1/0.1% level, respectively.

Table A.13: Effect of insurance enrollment on use of insurance for hospital care and on hospital utilization (CATE), by wealth of household.

			Direct			Spillover			Total		
		Control mean (SD)	High wealth Coefficient (SE) P-value	Low wealth Coefficient (SE) P-value	Difference Coefficient (SE) P-value	High wealth Coefficient (SE) P-value	Low wealth Coefficient (SE) P-value	Difference Coefficient (SE) P-value	High wealth Coefficient (SE) P-value	Low wealth Coefficient (SE) P-value	Difference Coefficient (SE) P-value
Insurance use at 18 months											
Successful use (past 6 mos.)	N = 9391	3.88%	8.59%	-1.34%	-9.94%	-2.10%	10.64%	12.74%	6.94%	7.03%	0.09%
		(19.32%)	(4.00%)	(3.54%)	(4.83%)	(5.55%)	(5.66%)	(6.27%)	(3.14%)	(3.07%)	(3.31%)
			.03	.70	.04	.71	.06	.04	.03	.02	.98
Failed use (past 6 mos.)	N = 9391	1.50%	6.11%	0.01%	-6.10%	-2.81%	2.96%	5.77%	3.90%	2.34%	-1.56%
		(12.15%)	(2.73%)	(2.38%)	(3.41%)	(3.63%)	(3.71%)	(4.78%)	(1.75%)	(1.56%)	(2.19%)
			.03	.00	.07	.44	.43	.23	.03	.14	.48
Insurance use at 4 years											
Successful use (past 6 mos.)	N = 8871	0.49%	1.85%	5.08%	3.23%	-1.19%	-4.15%	-2.95%	0.91%	1.81%	0.90%
		(6.99%)	(1.70%)	(1.86%)	(2.57%)	(2.31%)	(2.32%)	(3.27%)	(0.70%)	(0.88%)	(1.05%)
			.28	.006	.21	.61	.07	.37	.19	.04	.39
Successful use (most serious event)	N = 8863	0.13%	-0.88%	1.62%	2.50%	2.92%	-1.33%	-4.25%	1.42%	0.58%	-0.84%
		(3.59%)	(0.65%)	(1.56%)	(1.68%)	(1.14%)	(1.75%)	(2.05%)	(0.31%)	(0.74%)	(0.80%)
			.18	.30	.14	.01	.45	.04	p<.001	.44	.29
Failed used (most serious event)	N = 8864	0.57%	-0.59%	3.68%	4.27%	2.38%	-3.30%	-5.68%	1.29%	1.08%	-0.21%
		(7.52%)	(1.46%)	(2.72%)	(2.52%)	(2.12%)	(3.64%)	(3.31%)	(0.76%)	(0.82%)	(1.07%)
			.69	.18	.09	.26	.36	.09	.09	.19	.85
Healthcare use at 18 months											
Hospitalized on last visit (past 1 yr.)	N = 8559	20.82%	-3.94%	3.31%	7.24%	6.37%	6.88%	0.51%	1.08%	8.72%	7.64%
		(40.61%)	(8.43%)	(10.06%)	(13.22%)	(13.58%)	(15.68%)	(14.14%)	(9.89%)	(10.41%)	(7.83%)
			.64	.74	.58	.64	.66	.97	.91	.40	.33
Healthcare use at 4 years											
Overnight stay for treatment	N = 8892	22.97%	-13.21%	-10.09%	3.12%	14.16%	10.13%	-4.03%	-2.07%	-2.12%	-0.05%
		(42.07%)	(7.49%)	(10.51%)	(13.22%)	(8.30%)	(11.57%)	(12.99%)	(5.36%)	(5.92%)	(7.21%)
			.08	.34	.81	.09	.38	.76	.70	.72	.99
Outpatient (day) surgery	N = 8887	6.76%	-7.22%	0.60%	7.81%	13.16%	6.68%	-6.48%	3.14%	5.85%	2.71%
		(25.11%)	(4.48%)	(5.58%)	(7.24%)	(5.08%)	(6.81%)	(7.78%)	(3.26%)	(3.53%)	(4.16%)
			.11	.91	.28	.010	.33	.40	.33	.10	.52

Notes. Notes. Table presents estimates of the effect of enrollment in RSBY insurance on use of insurance and visits to medical facilities, stratified by level of wealth. Abbreviations: SD, standard deviation; CI, confidence interval; mos, months; yr, year; hosp., hospital. Each observation is a household. Treatment variable is enrollment. Estimates are complier average treatment effects. Observations are weighted so each household has equal weight. Standard errors were clustered at the village level. Coefficients were transformed to show percentage point changes from the control group. Mean and standard deviation in the control group are statistics from the unenrolled group. The direct effect is the estimated effect of enrolling one household, assuming no other sample households in the village are enrolled. The spillover effect is the estimated effect on an enrolled household of enrolling all other sample households in the village. Total effects are the sum of direct and (spillover effects)*(uptake into free insurance). The total effect of free insurance on uptake is estimated as 0.7871 in Table 3. Successful use means the household used RSBY to pay for medical treatment. Failed use means that the household attempted to use RSBY to pay for care but were unable to (for many possible reasons, Table A6). The most serious event is defined as an accident which caused a household member to miss at least two days of work, a childbirth or a stillbirth, or three functional limitations. If none of those occurred, it is defined as the most expensive health event or the one that led to the longest hospital stay. Hospitalized on last visit (past 1 yr.) indicates that the respondent was hospitalized on their most recent visit to a healthcare provider within the past year. This question was administered to both the male or the female respondent within the adult health module. A high (low) wealth household is a household with an above (below) median value of a wealth index created by taking the average of the following: z-score of the value of farm animals, z-score of the amount of silver, z-score of the amount of gold, the average of z-scores of different durable goods (stoves, fridges, etc.), z-score of land, z-score of the number of rooms in the household, and z-score of savings.

Table A.14: OOP Medical Expenditure by predicted success of insurance use

	(1) Midline OOP spending
Free insurance	594.233 (2719.051)
Sale + transfer	354.758 (3017.278)
Sale of insurance	2498.993 (2758.003)
Predicted RSBY success	1956.962 (1666.864)
Free insurance × Pred success	548.604 (1780.019)
Sale + transfer × Pred success	-303.037 (1897.972)
Sale of insurance × Pred success	-565.715 (1713.308)
Share ABC	-3594.050 (5614.056)
Constant	28352.137 (5129.195)
Observations	10028

Notes. Predicted RSBY success is a LASSO prediction of the likelihood of successfully using RSBY, trained in the treatment groups as a function of baseline covariates, used to generate predictions for treatment and control. LHS variable is midline OOP spending. Share ABC is the share of the village allocated to A, B, or C (combined). Standard errors were clustered at the village level.

Table A.15: Reasons given for respondents' inability to use RSBY insurance card, by survey and utilization status.

	Midline (18 months)		Endline (3.5 years)	
	Did not try to use RSBY (N=2551)	Tried but failed to use RSBY (N=160)	Did not try to use RSBY (N=2763)	Tried but failed to use RSBY (N=84)
Forgot papers at home	13%	10%	9%	2%
Has not received papers	5%	3%	21%	1%
Didn't know card could be used for this purpose	15%	13%	20%	2%
Patient wasn't on the card	2%	1%	1%	1%
Card used up	1%	1%	0%	0%
Didn't want to use card for treatment	21%	9%	1%	6%
Doctor didn't accept card	15%	55%	9%	69%
Card machine didn't work	2%	1%	1%	8%
Treatment not covered	5%	8%	2%	7%
Hospital that accepted card was too far	3%	6%	0%	1%
Didn't know card would reduce payments	3%	3%	2%	0%
Didn't know card would make treatment free	12%	6%	3%	0%
Other reasons	2%	0%	2%	10%
Didn't know where to use card			30%	5%
Didn't know how to use card			29%	6%
Insurance company didn't accept card			1%	12%
Didn't need to use card			2%	1%
Didn't trust doctor would accept card			3%	1%
Didn't trust the card would work			3%	0%

Note. Table only includes respondents who enrolled in RSBY insurance. At midline, all respondents who reported having an RSBY card were asked about utilization attempts. At endline, all respondents whose households had a serious health event were asked about utilization attempts. Percentages do not add up to 100 as respondents were allowed to report multiple reasons.

E.2.3 Health outcomes

Table A.16: Effects of premium and subsidy combinations (ITT) on health and health-related outcomes at 18 months

		Control	(A) Free insurance			(B) Sale of insurance + transfer			(C) Sale of insurance		
	N	Mean (SD)	Direct Coefficient (SE) *p*-value	Spillover Coefficient (SE) *p*-value	Total Coefficient (SE) *p*-value	Direct Coefficient (SE) *p*-value	Spillover Coefficient (SE) *p*-value	Total Coefficient (SE) *p*-value	Direct Coefficient (SE) *p*-value	Spillover Coefficient (SE) *p*-value	Total Coefficient (SE) *p*-value
Self-reported measures of health											
Good health	18983	0.662	0.055	-0.091	-0.017	0.061	-0.046	0.025	0.146	-0.192	-0.006
		(0.473)	(0.040)	(0.070)	(0.055)	(0.069)	(0.091)	(0.055)	(0.074)	(0.099)	(0.055)
			0.175	0.193	0.755	0.375	0.615	0.650	0.050	0.053	0.917
Very good health	18983	0.155	0.064	-0.086	-0.004	0.044	-0.038	0.014	0.043	-0.033	0.017
		(0.362)	(0.036)	(0.064)	(0.057)	(0.069)	(0.094)	(0.059)	(0.068)	(0.093)	(0.060)
			0.072	0.178	0.947	0.524	0.683	0.817	0.528	0.720	0.778
Poor or very poor health	18983	0.056	-0.012	-0.022	-0.029	-0.029	-0.006	-0.033	-0.012	-0.020	-0.028
		(0.231)	(0.024)	(0.030)	(0.032)	(0.033)	(0.038)	(0.032)	(0.038)	(0.045)	(0.033)
			0.618	0.462	0.354	0.389	0.874	0.296	0.751	0.658	0.395
Very poor health	18983	0.008	-0.000	-0.004	-0.003	0.008	-0.014	-0.004	0.002	-0.005	-0.002
		(0.090)	(0.010)	(0.010)	(0.006)	(0.011)	(0.010)	(0.006)	(0.012)	(0.013)	(0.006)
			0.996	0.717	0.639	0.466	0.162	0.558	0.863	0.695	0.758
Health value index	18983	-0.000	0.078	-0.066	0.026	0.068	0.000	0.068	0.100	-0.074	0.042
		(0.642)	(0.064)	(0.090)	(0.069)	(0.096)	(0.123)	(0.070)	(0.103)	(0.137)	(0.071)
			0.222	0.465	0.707	0.481	0.999	0.335	0.333	0.589	0.559
Chronic disease											
Told had hypertension	18939	0.190	0.028	-0.098	-0.049	-0.140	0.114	-0.050	-0.026	-0.032	-0.051
		(0.392)	(0.046)	(0.049)	(0.035)	(0.057)	(0.069)	(0.035)	(0.053)	(0.062)	(0.034)
			0.546	0.047	0.157	0.015	0.100	0.156	0.626	0.607	0.139
Takes medication for hypertension	18960	0.131	-0.018	-0.044	-0.052	-0.125	0.089	-0.055	-0.082	0.037	-0.053
		(0.338)	(0.037)	(0.045)	(0.031)	(0.047)	(0.060)	(0.031)	(0.043)	(0.051)	(0.031)
			0.626	0.338	0.087	0.009	0.138	0.081	0.056	0.466	0.092
Told had diabetes	18913	0.068	-0.005	-0.003	-0.007	-0.040	0.047	-0.004	-0.032	0.033	-0.006
		(0.252)	(0.023)	(0.028)	(0.022)	(0.037)	(0.043)	(0.023)	(0.036)	(0.036)	(0.023)
			0.847	0.904	0.741	0.283	0.276	0.874	0.368	0.356	0.788
Takes oral medication for diabetes	18948	0.050	-0.002	-0.000	-0.002	-0.023	0.030	0.001	-0.027	0.025	-0.007
		(0.217)	(0.020)	(0.023)	(0.019)	(0.031)	(0.037)	(0.020)	(0.031)	(0.032)	(0.020)
			0.926	0.988	0.912	0.466	0.417	0.967	0.388	0.434	0.723
Takes insulin for diabetes	18952	0.018	-0.001	0.019	0.014	-0.016	0.042	0.016	-0.006	0.027	0.016
		(0.133)	(0.011)	(0.011)	(0.011)	(0.016)	(0.018)	(0.011)	(0.017)	(0.018)	(0.011)
			0.943	0.088	0.177	0.300	0.023	0.147	0.727	0.131	0.150
Is on a special diet for diabetes	18962	0.046	-0.000	-0.003	-0.003	-0.044	0.055	-0.001	-0.038	0.047	-0.001
		(0.210)	(0.018)	(0.024)	(0.019)	(0.028)	(0.032)	(0.020)	(0.030)	(0.030)	(0.020)
			0.980	0.912	0.895	0.117	0.091	0.949	0.211	0.122	0.973
Told had cancer	18946	0.004	-0.006	0.010	0.001	-0.003	0.009	0.003	-0.005	0.005	-0.000
		(0.064)	(0.005)	(0.006)	(0.004)	(0.009)	(0.010)	(0.003)	(0.008)	(0.009)	(0.003)
			0.224	0.107	0.739	0.691	0.400	0.316	0.555	0.554	0.925
Received cancer treatment past 1 yr.	18998	0.002	0.002	-0.002	0.000	-0.004	0.005	-0.000	0.003	-0.002	0.001
		(0.049)	(0.005)	(0.005)	(0.003)	(0.004)	(0.004)	(0.003)	(0.007)	(0.009)	(0.003)
			0.661	0.668	0.885	0.381	0.280	0.978	0.699	0.807	0.678

Notes. See note at end of table.

Table A.16 (continued): Effects of premium and subsidy combinations (ITT) on health and health-related outcomes at 18 months

		Control	(A) Free insurance			(B) Sale of insurance + transfer			(C) Sale of insurance		
	N	Mean (SD)	Direct Coefficient (SE) *p*-value	Spillover Coefficient (SE) *p*-value	Total Coefficient (SE) *p*-value	Direct Coefficient (SE) *p*-value	Spillover Coefficient (SE) *p*-value	Total Coefficient (SE) *p*-value	Direct Coefficient (SE) *p*-value	Spillover Coefficient (SE) *p*-value	Total Coefficient (SE) *p*-value
Told had lung disease	18907	0.034	-0.017	0.014	-0.006	0.012	-0.022	-0.005	0.002	-0.002	0.000
		(0.181)	(0.020)	(0.017)	(0.016)	(0.028)	(0.028)	(0.017)	(0.028)	(0.030)	(0.017)
			0.388	0.425	0.699	0.663	0.426	0.762	0.952	0.947	0.995
Told had heart disease	18868	0.020	0.009	0.008	0.015	0.023	-0.014	0.012	-0.001	0.018	0.014
		(0.141)	(0.017)	(0.017)	(0.011)	(0.019)	(0.020)	(0.010)	(0.017)	(0.018)	(0.010)
			0.599	0.634	0.166	0.243	0.482	0.254	0.971	0.313	0.174
Told had stroke	18826	0.007	0.003	0.003	0.005	0.009	-0.005	0.005	-0.000	0.006	0.005
		(0.086)	(0.010)	(0.009)	(0.007)	(0.012)	(0.012)	(0.007)	(0.011)	(0.012)	(0.007)
			0.756	0.766	0.433	0.454	0.670	0.445	0.992	0.602	0.478
Told had arthritis	18894	0.176	-0.093	0.060	-0.045	-0.067	0.017	-0.053	-0.127	0.092	-0.055
		(0.381)	(0.038)	(0.065)	(0.050)	(0.076)	(0.094)	(0.053)	(0.058)	(0.072)	(0.051)
			0.014	0.356	0.369	0.379	0.854	0.318	0.029	0.204	0.285
Had surgery for arthritis past 1 yr.	18933	0.018	-0.015	0.004	-0.012	-0.035	0.024	-0.016	-0.053	0.048	-0.015
		(0.135)	(0.014)	(0.018)	(0.013)	(0.019)	(0.022)	(0.013)	(0.017)	(0.019)	(0.013)
			0.286	0.814	0.347	0.072	0.280	0.234	0.002	0.012	0.244
Diagnose with high cholesterol	18871	0.019	-0.001	0.016	0.011	0.010	0.007	0.015	0.005	0.014	0.015
		(0.137)	(0.011)	(0.018)	(0.013)	(0.019)	(0.029)	(0.014)	(0.019)	(0.022)	(0.014)
			0.909	0.374	0.413	0.617	0.811	0.271	0.815	0.529	0.280
Takes medication for high cholesterol	19032	0.014	0.004	0.008	0.010	-0.006	0.019	0.009	-0.009	0.027	0.012
		(0.116)	(0.012)	(0.013)	(0.010)	(0.017)	(0.020)	(0.011)	(0.017)	(0.022)	(0.011)
			0.761	0.558	0.355	0.733	0.347	0.408	0.598	0.217	0.254
Chronic disease index	19113	-0.000	-0.023	0.028	-0.000	-0.096	0.123	0.001	-0.094	0.120	0.000
		(0.433)	(0.041)	(0.053)	(0.043)	(0.068)	(0.084)	(0.044)	(0.063)	(0.077)	(0.043)
			0.583	0.597	0.992	0.160	0.142	0.976	0.137	0.121	0.994
Health-related quality of life, ADLs, and physical health symptoms											
Experiences chest pain	18888	0.081	-0.029	0.021	-0.013	0.003	-0.018	-0.011	-0.008	-0.002	-0.009
		(0.273)	(0.024)	(0.041)	(0.031)	(0.044)	(0.053)	(0.033)	(0.040)	(0.049)	(0.032)
			0.226	0.610	0.680	0.948	0.730	0.732	0.837	0.975	0.767
Phys. symp. index	18888	-0.000	-0.113	0.085	-0.045	0.012	-0.066	-0.040	-0.025	-0.011	-0.033
		(1.000)	(0.089)	(0.150)	(0.114)	(0.160)	(0.195)	(0.122)	(0.146)	(0.179)	(0.116)
			0.204	0.569	0.690	0.940	0.734	0.743	0.865	0.953	0.776
Biomarkers											
Overweight or obese	4853	0.271	-0.034	0.003	-0.031	-0.065	0.073	-0.008	-0.113	0.137	-0.005
		(0.445)	(0.088)	(0.100)	(0.069)	(0.128)	(0.141)	(0.072)	(0.118)	(0.130)	(0.068)
			0.699	0.975	0.649	0.611	0.606	0.915	0.340	0.296	0.937
Underweight	4853	0.084	0.059	-0.123	-0.037	-0.097	0.057	-0.052	-0.045	-0.005	-0.050
		(0.277)	(0.055)	(0.075)	(0.037)	(0.067)	(0.080)	(0.038)	(0.059)	(0.073)	(0.038)
			0.285	0.103	0.322	0.150	0.479	0.173	0.440	0.941	0.198
Abdominally obese	4723	0.713	-0.108	0.204	0.053	-0.046	0.051	-0.006	-0.052	0.091	0.020
		(0.452)	(0.104)	(0.101)	(0.112)	(0.155)	(0.186)	(0.115)	(0.154)	(0.175)	(0.113)
			0.301	0.046	0.634	0.769	0.786	0.960	0.736	0.605	0.863
Mid-Upper Arm Circumference	4815	27.032	-1.680	0.215	-1.510	-2.213	0.504	-1.817	-1.772	0.086	-1.705
		(3.562)	(0.656)	(1.234)	(0.881)	(1.008)	(1.314)	(0.859)	(1.144)	(1.385)	(0.860)
			0.012	0.862	0.089	0.030	0.702	0.037	0.124	0.951	0.050

Notes. See note at end of table.

Table A.16 (continued): Effects of premium and subsidy combinations (ITT) on health and health-related outcomes at 18 months

		Control	(A) Free insurance			(B) Sale of insurance + transfer			(C) Sale of insurance		
	N	Mean (SD)	Direct Coefficient (SE) *p*-value	Spillover Coefficient (SE) *p*-value	Total Coefficient (SE) *p*-value	Direct Coefficient (SE) *p*-value	Spillover Coefficient (SE) *p*-value	Total Coefficient (SE) *p*-value	Direct Coefficient (SE) *p*-value	Spillover Coefficient (SE) *p*-value	Total Coefficient (SE) *p*-value
Hypertension, grade 1	4878	0.449	-0.073	-0.010	-0.081	-0.092	0.000	-0.092	-0.176	0.102	-0.095
		(0.498)	(0.078)	(0.095)	(0.075)	(0.100)	(0.119)	(0.077)	(0.111)	(0.142)	(0.080)
			0.354	0.915	0.288	0.362	0.997	0.234	0.117	0.472	0.235
Hypertension, grade 2	4878	0.191	-0.083	0.086	-0.015	0.030	-0.031	0.005	-0.078	0.070	-0.023
		(0.393)	(0.068)	(0.072)	(0.072)	(0.090)	(0.112)	(0.072)	(0.085)	(0.106)	(0.072)
			0.224	0.231	0.840	0.739	0.780	0.940	0.365	0.511	0.753
Skinfolds total	4065	26.326	-2.131	2.868	0.127	-1.608	1.477	-0.445	-0.994	1.845	0.458
		(9.464)	(2.100)	(3.953)	(3.021)	(3.565)	(4.701)	(3.023)	(3.824)	(5.551)	(3.059)
			0.312	0.470	0.967	0.653	0.754	0.883	0.795	0.740	0.881
Biomarkers index	4935	-0.000	-0.155	0.074	-0.097	-0.202	0.091	-0.130	-0.234	0.150	-0.116
		(0.409)	(0.080)	(0.084)	(0.085)	(0.139)	(0.130)	(0.092)	(0.120)	(0.145)	(0.086)
			0.053	0.381	0.257	0.148	0.488	0.157	0.054	0.302	0.183
Fertility											
Currently pregnant	9262	0.055	0.020	-0.050	-0.020	-0.002	-0.031	-0.026	-0.071	0.078	-0.009
		(0.227)	(0.026)	(0.068)	(0.054)	(0.039)	(0.068)	(0.056)	(0.057)	(0.105)	(0.059)
			0.440	0.455	0.714	0.968	0.647	0.638	0.210	0.456	0.875
Childbirth past 1 yr.	8299	0.049	0.028	-0.056	-0.016	-0.009	-0.006	-0.014	-0.023	-0.009	-0.029
		(0.217)	(0.026)	(0.060)	(0.045)	(0.034)	(0.051)	(0.048)	(0.038)	(0.039)	(0.048)
			0.284	0.348	0.723	0.792	0.900	0.769	0.550	0.827	0.544
Delivered in govt. hosp. past 1 yr.	8297	0.015	0.009	-0.013	-0.001	-0.002	0.014	0.010	-0.016	0.018	-0.002
		(0.120)	(0.017)	(0.015)	(0.012)	(0.022)	(0.023)	(0.012)	(0.017)	(0.019)	(0.012)
			0.572	0.407	0.956	0.941	0.532	0.438	0.343	0.335	0.869
Delivered in facility past 1 yr.	8297	0.047	0.023	-0.051	-0.017	-0.000	-0.016	-0.013	-0.032	0.002	-0.031
		(0.211)	(0.026)	(0.059)	(0.045)	(0.034)	(0.049)	(0.048)	(0.036)	(0.037)	(0.048)
			0.362	0.391	0.709	0.989	0.745	0.783	0.366	0.963	0.522
Doctor assisted with delivery past 1 yr.	8299	0.038	0.023	-0.051	-0.018	0.007	-0.029	-0.016	-0.038	0.014	-0.027
		(0.191)	(0.022)	(0.059)	(0.044)	(0.031)	(0.046)	(0.046)	(0.037)	(0.036)	(0.047)
			0.309	0.382	0.686	0.823	0.529	0.728	0.307	0.707	0.570
Doctor or nurse assisted with delivery past 1 yr.	8299	0.043	0.012	-0.052	-0.029	-0.011	-0.023	-0.029	-0.036	-0.004	-0.040
		(0.203)	(0.026)	(0.059)	(0.045)	(0.032)	(0.047)	(0.047)	(0.037)	(0.039)	(0.048)
			0.640	0.381	0.516	0.730	0.629	0.538	0.335	0.912	0.409
Child delivery complications past 1 yr.	8293	0.015	-0.010	-0.021	-0.027	-0.007	-0.020	-0.022	-0.020	-0.007	-0.025
		(0.122)	(0.013)	(0.026)	(0.019)	(0.018)	(0.031)	(0.020)	(0.017)	(0.018)	(0.020)
			0.436	0.409	0.156	0.719	0.523	0.264	0.249	0.697	0.219
Ideal number of children	7881	2.516	-0.133	0.063	-0.083	-0.136	0.167	-0.004	0.013	-0.086	-0.055
		(1.215)	(0.159)	(0.318)	(0.265)	(0.278)	(0.385)	(0.269)	(0.278)	(0.424)	(0.269)
			0.406	0.842	0.755	0.626	0.665	0.987	0.963	0.840	0.839
Fertility index	9288	0.000	0.061	-0.128	-0.040	-0.021	-0.008	-0.028	-0.107	0.060	-0.060
		(0.495)	(0.063)	(0.124)	(0.091)	(0.082)	(0.107)	(0.096)	(0.089)	(0.105)	(0.097)
			0.335	0.304	0.661	0.799	0.938	0.774	0.230	0.570	0.539

Notes. Table presents estimates of intent-to-treat effects of access to insurance at different prices and subsidies on health and health-related outcomes at 18 months. Each observation is a household and has equal weight. Treatment variables are household assignments: free insurance (A), sale of insurance + cash transfer (B), sale of insurance (C). Estimates are intent-to-treat effects; all models estimated with OLS. Each treatment arm was interacted with the share of the village allocated to A, B, or C (combined). Standard errors were clustered at the village level. Coefficients were transformed to show percentage point changes from the control group D. The direct effect only includes the coefficient on treatment A, B, or C. The spillover effect is the estimated effect on a treated household of assigning all other sample households to at least some form of access to RSBY insurance. The total effect is constructed as the sum of the direct effect and 0.8024*(spillover effect), where 0.8024 is the average fraction of households given insurance access in the study. Mean and standard deviation in the control group are statistics from the group without access to insurance. The FWER adjusted 5% critical values are: 0.00114 for self-reported measures of health; 0.00036 for chronic disease; 0.00285 for quality of life, ADLs, and physical health symptoms; 0.00071 for biomarkers; and 0.00063 for fertility, at 18 months.

Table A.17: Effects of premium and subsidy combinations (ITT) on health and health-related outcomes at 3.5 years

		Control	(A) Free insurance			(B) Sale of insurance + transfer			(C) Sale of insurance		
	N	Mean (SD)	Direct Coefficient (SE) *p*-value	Spillover Coefficient (SE) *p*-value	Total Coefficient (SE) *p*-value	Direct Coefficient (SE) *p*-value	Spillover Coefficient (SE) *p*-value	Total Coefficient (SE) *p*-value	Direct Coefficient (SE) *p*-value	Spillover Coefficient (SE) *p*-value	Total Coefficient (SE) *p*-value
Self-reported measures of health											
Good health	9492	0.516	0.012	-0.010	0.004	-0.169	0.220	0.004	0.012	-0.023	-0.007
		(0.500)	(0.077)	(0.089)	(0.069)	(0.099)	(0.111)	(0.070)	(0.098)	(0.109)	(0.070)
			0.878	0.907	0.958	0.087	0.047	0.955	0.906	0.831	0.926
Very good health	9492	0.076	0.024	-0.120	-0.070	-0.059	-0.020	-0.075	-0.050	-0.041	-0.083
		(0.265)	(0.044)	(0.058)	(0.039)	(0.053)	(0.055)	(0.041)	(0.046)	(0.053)	(0.041)
			0.578	0.041	0.072	0.267	0.710	0.071	0.272	0.446	0.042
Poor health	9492	0.102	-0.032	0.036	-0.003	-0.038	0.037	-0.009	-0.035	0.036	-0.006
		(0.303)	(0.048)	(0.047)	(0.041)	(0.061)	(0.063)	(0.042)	(0.062)	(0.063)	(0.042)
			0.508	0.447	0.938	0.538	0.558	0.834	0.578	0.569	0.880
Very poor health	9492	0.021	-0.042	0.006	-0.037	-0.053	0.022	-0.035	-0.033	-0.008	-0.039
		(0.143)	(0.022)	(0.018)	(0.022)	(0.026)	(0.027)	(0.022)	(0.027)	(0.024)	(0.023)
			0.056	0.752	0.096	0.040	0.426	0.115	0.224	0.736	0.085
Health value index	9492	0.000	0.128	-0.158	0.004	-0.017	0.022	0.001	0.044	-0.066	-0.008
		(0.647)	(0.116)	(0.121)	(0.094)	(0.134)	(0.136)	(0.097)	(0.124)	(0.129)	(0.096)
			0.271	0.192	0.970	0.899	0.869	0.995	0.724	0.610	0.935
Chronic disease											
Told had hypertension	9476	0.233	-0.038	0.013	-0.028	-0.110	0.100	-0.032	-0.168	0.178	-0.028
		(0.423)	(0.057)	(0.059)	(0.051)	(0.076)	(0.080)	(0.053)	(0.083)	(0.085)	(0.054)
			0.501	0.830	0.579	0.149	0.216	0.548	0.043	0.038	0.605
Takes medication for hypertension	9495	0.197	-0.041	0.037	-0.012	-0.062	0.065	-0.011	-0.117	0.141	-0.006
		(0.398)	(0.053)	(0.053)	(0.047)	(0.070)	(0.076)	(0.048)	(0.073)	(0.076)	(0.049)
			0.441	0.487	0.799	0.377	0.395	0.813	0.111	0.063	0.908
Told had diabetes	9479	0.121	-0.052	-0.019	-0.067	-0.128	0.075	-0.069	-0.153	0.108	-0.069
		(0.326)	(0.048)	(0.048)	(0.039)	(0.059)	(0.062)	(0.040)	(0.056)	(0.056)	(0.040)
			0.278	0.702	0.086	0.031	0.227	0.084	0.007	0.057	0.084
Takes oral medication for diabetes	9499	0.107	-0.049	-0.003	-0.051	-0.106	0.067	-0.054	-0.130	0.101	-0.050
		(0.310)	(0.048)	(0.046)	(0.035)	(0.055)	(0.060)	(0.036)	(0.052)	(0.054)	(0.035)
			0.308	0.954	0.147	0.052	0.266	0.131	0.013	0.062	0.152
Takes insulin for diabetes	9489	0.024	0.017	-0.007	0.011	0.019	-0.009	0.012	-0.006	0.022	0.011
		(0.152)	(0.019)	(0.019)	(0.014)	(0.026)	(0.029)	(0.015)	(0.025)	(0.026)	(0.015)
			0.372	0.705	0.439	0.476	0.757	0.425	0.801	0.392	0.445
Follows a special diet for diabetes	9495	0.077	-0.037	0.012	-0.027	-0.073	0.060	-0.026	-0.076	0.066	-0.024
		(0.267)	(0.041)	(0.039)	(0.031)	(0.048)	(0.052)	(0.032)	(0.047)	(0.051)	(0.031)
			0.375	0.752	0.391	0.133	0.251	0.420	0.111	0.195	0.448
Told had cancer	9470	0.004	-0.005	0.012	0.004	0.006	0.001	0.006	0.000	0.002	0.002
		(0.065)	(0.008)	(0.007)	(0.006)	(0.014)	(0.018)	(0.006)	(0.008)	(0.007)	(0.006)
			0.495	0.065	0.489	0.672	0.977	0.271	0.960	0.818	0.764
Treated for cancer past 1 yr.	9496	0.002	-0.000	0.000	0.000	-0.007	0.009	-0.000	-0.002	0.002	-0.000
		(0.046)	(0.006)	(0.006)	(0.004)	(0.005)	(0.005)	(0.004)	(0.006)	(0.006)	(0.004)
			0.994	0.941	0.942	0.145	0.084	0.917	0.729	0.679	0.962

Notes. See note at end of table.

Table A.17 (continued): Effects of premium and subsidy combinations (ITT) on health and health-related outcomes at 3.5 years

		Control	(A) Free insurance			(B) Sale of insurance + transfer			(C) Sale of insurance		
	N	Mean (SD)	Direct Coefficient (SE) *p*-value	Spillover Coefficient (SE) *p*-value	Total Coefficient (SE) *p*-value	Direct Coefficient (SE) *p*-value	Spillover Coefficient (SE) *p*-value	Total Coefficient (SE) *p*-value	Direct Coefficient (SE) *p*-value	Spillover Coefficient (SE) *p*-value	Total Coefficient (SE) *p*-value
Told had lung disease	9479	0.060	-0.036	0.021	-0.019	-0.003	-0.018	-0.018	-0.039	0.018	-0.025
		(0.238)	(0.030)	(0.029)	(0.023)	(0.037)	(0.044)	(0.023)	(0.039)	(0.037)	(0.024)
			0.237	0.464	0.405	0.930	0.680	0.446	0.317	0.622	0.300
Told had heart disease	9473	0.047	0.017	-0.048	-0.021	-0.068	0.047	-0.031	-0.074	0.051	-0.033
		(0.211)	(0.035)	(0.033)	(0.024)	(0.033)	(0.037)	(0.024)	(0.036)	(0.035)	(0.024)
			0.635	0.149	0.386	0.042	0.209	0.190	0.042	0.146	0.172
Told had stroke	9446	0.006	-0.011	0.005	-0.007	-0.022	0.015	-0.010	0.002	-0.016	-0.011
		(0.080)	(0.013)	(0.011)	(0.009)	(0.012)	(0.011)	(0.009)	(0.015)	(0.013)	(0.009)
			0.399	0.632	0.423	0.069	0.173	0.242	0.909	0.221	0.193
Told had arthritis or rheumatism	9482	0.193	-0.061	0.118	0.032	0.035	-0.007	0.030	0.036	-0.001	0.035
		(0.395)	(0.062)	(0.063)	(0.053)	(0.083)	(0.096)	(0.051)	(0.076)	(0.090)	(0.052)
			0.327	0.062	0.549	0.670	0.941	0.559	0.640	0.989	0.509
Had surgery due to arthritis past 1 yr.	9497	0.042	0.025	0.010	0.033	0.004	0.022	0.022	0.028	0.006	0.033
		(0.200)	(0.028)	(0.029)	(0.021)	(0.032)	(0.035)	(0.022)	(0.034)	(0.041)	(0.022)
			0.369	0.735	0.128	0.888	0.525	0.303	0.419	0.877	0.139
Diagnosed with high cholesterol	9449	0.026	0.012	-0.003	0.009	0.004	0.006	0.009	0.014	-0.005	0.010
		(0.160)	(0.021)	(0.020)	(0.016)	(0.024)	(0.022)	(0.016)	(0.023)	(0.022)	(0.016)
			0.578	0.894	0.548	0.871	0.788	0.587	0.555	0.838	0.518
Takes medication to lower cholesterol	9496	0.013	-0.002	-0.004	-0.005	-0.017	0.015	-0.005	-0.006	0.000	-0.006
		(0.115)	(0.014)	(0.009)	(0.012)	(0.014)	(0.011)	(0.011)	(0.014)	(0.010)	(0.012)
			0.872	0.704	0.660	0.229	0.157	0.661	0.643	0.976	0.596
Has eyesight problems	9480	0.329	-0.023	0.145	0.091	-0.033	0.172	0.102	0.019	0.097	0.096
		(0.470)	(0.067)	(0.069)	(0.061)	(0.089)	(0.093)	(0.061)	(0.095)	(0.096)	(0.064)
			0.726	0.036	0.136	0.711	0.066	0.097	0.839	0.311	0.135
Had surgery due to eye problems past 1 yr.	9497	0.074	-0.043	0.091	0.029	0.020	0.012	0.030	-0.022	0.062	0.027
		(0.261)	(0.039)	(0.036)	(0.034)	(0.054)	(0.057)	(0.034)	(0.055)	(0.074)	(0.036)
			0.268	0.012	0.401	0.704	0.827	0.380	0.694	0.400	0.443
Chronic disease index	9504	-0.000	-0.060	0.066	-0.008	-0.117	0.130	-0.014	-0.130	0.145	-0.016
		(0.431)	(0.077)	(0.071)	(0.057)	(0.076)	(0.086)	(0.056)	(0.080)	(0.080)	(0.057)
			0.439	0.353	0.892	0.123	0.129	0.801	0.103	0.070	0.775
			Health-related quality of life, ADLs, and physical health symptoms								
Number of functional limitations	9413	0.674	-0.163	0.034	-0.137	-0.398	0.273	-0.182	-0.367	0.287	-0.141
		(1.523)	(0.191)	(0.247)	(0.208)	(0.273)	(0.325)	(0.215)	(0.282)	(0.333)	(0.216)
			0.393	0.892	0.511	0.146	0.402	0.397	0.194	0.389	0.515
SF-8, PCS	9510	2.260	-0.110	0.272	0.104	-0.076	0.234	0.108	-0.189	0.412	0.136
		(0.930)	(0.173)	(0.151)	(0.137)	(0.183)	(0.202)	(0.135)	(0.177)	(0.198)	(0.135)
			0.525	0.074	0.450	0.680	0.247	0.422	0.287	0.038	0.317
SF-8, MCS	9510	1.491	-0.003	0.041	0.029	0.076	-0.102	-0.004	-0.272	0.365	0.016
		(0.789)	(0.105)	(0.139)	(0.118)	(0.154)	(0.179)	(0.123)	(0.169)	(0.190)	(0.125)
			0.976	0.768	0.806	0.621	0.569	0.976	0.108	0.055	0.899
Had stomach pain past 4 wks.	8999	0.061	0.066	-0.033	0.040	0.002	0.043	0.035	-0.011	0.066	0.041
		(0.240)	(0.039)	(0.044)	(0.024)	(0.042)	(0.048)	(0.025)	(0.047)	(0.054)	(0.025)
			0.091	0.452	0.097	0.964	0.374	0.159	0.816	0.222	0.104

Notes. See note at end of table.

Table A.17 (continued): Effects of premium and subsidy combinations (ITT) on health and health-related outcomes at 3.5 years

		Control	(A) Free insurance			(B) Sale of insurance + transfer			(C) Sale of insurance		
	N	Mean (SD)	Direct Coefficient (SE) *p*-value	Spillover Coefficient (SE) *p*-value	Total Coefficient (SE) *p*-value	Direct Coefficient (SE) *p*-value	Spillover Coefficient (SE) *p*-value	Total Coefficient (SE) *p*-value	Direct Coefficient (SE) *p*-value	Spillover Coefficient (SE) *p*-value	Total Coefficient (SE) *p*-value
Had back pain past 4 wks.	8999	0.254	0.081	0.045	0.117	0.044	0.072	0.101	-0.061	0.212	0.106
		(0.435)	(0.060)	(0.082)	(0.063)	(0.087)	(0.101)	(0.066)	(0.080)	(0.096)	(0.066)
			0.173	0.585	0.066	0.612	0.477	0.128	0.444	0.027	0.110
Had chest pain past 4 wks.	8999	0.074	0.057	-0.020	0.041	0.009	0.032	0.034	-0.014	0.067	0.038
		(0.262)	(0.042)	(0.039)	(0.030)	(0.047)	(0.046)	(0.030)	(0.046)	(0.044)	(0.031)
			0.176	0.610	0.175	0.846	0.490	0.258	0.752	0.130	0.215
Had joint pain past 4 wks.	8999	0.578	-0.062	0.108	0.023	-0.014	0.064	0.037	-0.098	0.193	0.054
		(0.494)	(0.077)	(0.078)	(0.073)	(0.090)	(0.111)	(0.071)	(0.100)	(0.114)	(0.073)
			0.420	0.163	0.747	0.880	0.566	0.607	0.329	0.092	0.459
Had headaches past 4 wks.	8999	0.194	0.010	0.133	0.114	0.091	0.071	0.147	0.047	0.094	0.121
		(0.396)	(0.054)	(0.058)	(0.045)	(0.080)	(0.092)	(0.046)	(0.072)	(0.083)	(0.047)
			0.857	0.021	0.011	0.255	0.438	0.001	0.508	0.256	0.010
Had menstrual cramps past 4 wks.	8999	0.038	0.022	-0.001	0.021	0.021	-0.003	0.019	0.025	0.007	0.030
		(0.190)	(0.023)	(0.030)	(0.019)	(0.031)	(0.036)	(0.020)	(0.036)	(0.043)	(0.020)
			0.348	0.978	0.270	0.485	0.929	0.338	0.492	0.870	0.131
Had pain in no specific place past 4 wks.	8999	0.044	0.015	-0.022	-0.003	-0.013	0.005	-0.009	-0.074	0.073	-0.017
		(0.205)	(0.034)	(0.035)	(0.029)	(0.038)	(0.043)	(0.029)	(0.037)	(0.038)	(0.029)
			0.663	0.521	0.929	0.735	0.915	0.743	0.047	0.053	0.569
Fainted past 4 wks.	9451	0.012	0.011	-0.004	0.008	0.020	-0.015	0.009	0.012	-0.007	0.006
		(0.110)	(0.016)	(0.014)	(0.011)	(0.020)	(0.025)	(0.011)	(0.021)	(0.021)	(0.012)
			0.499	0.800	0.487	0.306	0.558	0.412	0.585	0.751	0.587
Felt dizzy past 4 wks.	9451	0.133	0.062	-0.012	0.052	0.029	0.044	0.064	-0.052	0.155	0.070
		(0.339)	(0.047)	(0.049)	(0.038)	(0.057)	(0.065)	(0.038)	(0.057)	(0.067)	(0.039)
			0.187	0.806	0.169	0.612	0.499	0.099	0.365	0.022	0.077
Shortness of breath past 4 wks.	9451	0.049	0.037	0.011	0.045	0.038	0.005	0.042	-0.028	0.093	0.045
		(0.216)	(0.029)	(0.028)	(0.024)	(0.040)	(0.041)	(0.024)	(0.037)	(0.038)	(0.025)
			0.214	0.703	0.063	0.344	0.903	0.088	0.446	0.016	0.068
Heart pounded past 4 wks.	9451	0.064	0.019	-0.024	0.001	-0.026	0.030	-0.003	-0.057	0.075	0.001
		(0.245)	(0.034)	(0.043)	(0.032)	(0.046)	(0.052)	(0.033)	(0.053)	(0.056)	(0.035)
			0.572	0.582	0.976	0.568	0.565	0.940	0.280	0.186	0.967
Qual. of life index	9510	-0.000	0.073	0.040	0.105	0.033	0.085	0.100	-0.124	0.298	0.111
		(0.454)	(0.071)	(0.075)	(0.065)	(0.086)	(0.098)	(0.066)	(0.087)	(0.098)	(0.066)
			0.301	0.588	0.107	0.700	0.385	0.130	0.157	0.002	0.095
						Mental health					
GHQ-12, Likert scoring	10879	9.329	1.330	-0.367	1.041	-0.014	0.737	0.567	-1.400	2.730	0.749
		(6.728)	(0.871)	(1.198)	(0.985)	(1.272)	(1.428)	(1.032)	(1.249)	(1.396)	(1.046)
			0.127	0.759	0.291	0.991	0.606	0.583	0.263	0.051	0.474
GHQ-12, binary scoring	9510	2.331	0.713	-0.261	0.507	-0.227	0.584	0.232	-0.772	1.532	0.434
		(3.297)	(0.466)	(0.715)	(0.502)	(0.633)	(0.778)	(0.522)	(0.598)	(0.838)	(0.534)
			0.127	0.715	0.314	0.720	0.453	0.657	0.198	0.068	0.417
PSS-10 score	9510	17.785	0.060	0.125	0.159	0.103	-0.172	-0.032	-0.990	1.215	-0.033
		(3.494)	(0.458)	(0.580)	(0.471)	(0.724)	(0.911)	(0.477)	(0.697)	(0.807)	(0.492)
			0.895	0.829	0.735	0.887	0.850	0.946	0.157	0.133	0.946

Notes. See note at end of table.

Table A.17 (continued): Effects of premium and subsidy combinations (ITT) on health and health-related outcomes at 3.5 years

		Control	(A) Free insurance			(B) Sale of insurance + transfer			(C) Sale of insurance		
	N	Mean (SD)	Direct Coefficient (SE) *p*-value	Spillover Coefficient (SE) *p*-value	Total Coefficient (SE) *p*-value	Direct Coefficient (SE) *p*-value	Spillover Coefficient (SE) *p*-value	Total Coefficient (SE) *p*-value	Direct Coefficient (SE) *p*-value	Spillover Coefficient (SE) *p*-value	Total Coefficient (SE) *p*-value
Mental health index	9510	-0.000	0.073	0.040	0.105	0.033	0.085	0.100	-0.124	0.298	0.111
		(0.454)	(0.071)	(0.075)	(0.065)	(0.086)	(0.098)	(0.066)	(0.087)	(0.098)	(0.066)
			0.301	0.588	0.107	0.700	0.385	0.130	0.157	0.002	0.095
						Fertility					
Childbirth/stillbirth past 6 mos.	9493	0.046	0.020	0.002	0.021	-0.016	0.050	0.023	0.033	-0.013	0.023
		(0.210)	(0.031)	(0.032)	(0.020)	(0.038)	(0.041)	(0.020)	(0.035)	(0.040)	(0.020)
			0.525	0.945	0.273	0.668	0.218	0.247	0.343	0.751	0.246
Childbirth/stillbirth past 3 yrs.	9510	0.192	0.031	-0.015	0.019	-0.094	0.118	-0.002	0.067	-0.073	0.010
		(0.394)	(0.058)	(0.064)	(0.046)	(0.072)	(0.078)	(0.047)	(0.070)	(0.087)	(0.047)
			0.593	0.814	0.674	0.188	0.131	0.973	0.339	0.397	0.838
Number of births in hhld. past 3 years	9510	0.315	0.118	-0.111	0.031	0.069	-0.108	-0.016	0.149	-0.153	0.029
		(0.920)	(0.134)	(0.238)	(0.119)	(0.159)	(0.236)	(0.122)	(0.164)	(0.275)	(0.130)
			0.378	0.643	0.795	0.665	0.649	0.897	0.364	0.578	0.824
Number of live births in hhld. past 3 years	9510	0.205	0.049	-0.027	0.028	-0.153	0.196	0.002	0.059	-0.054	0.016
		(0.487)	(0.069)	(0.079)	(0.055)	(0.083)	(0.088)	(0.056)	(0.086)	(0.093)	(0.057)
			0.482	0.733	0.616	0.066	0.027	0.976	0.493	0.556	0.781
Number of still births in hhld. past 3 years	9510	0.110	0.069	-0.084	0.003	0.222	-0.304	-0.017	0.091	-0.098	0.013
		(0.777)	(0.102)	(0.211)	(0.108)	(0.140)	(0.224)	(0.110)	(0.135)	(0.239)	(0.121)
			0.497	0.691	0.975	0.115	0.177	0.874	0.502	0.681	0.913
Delivery in hospital past 3 yrs	9510	0.141	-0.008	-0.034	-0.035	-0.078	0.041	-0.045	-0.028	-0.021	-0.044
		(0.349)	(0.052)	(0.049)	(0.043)	(0.065)	(0.067)	(0.044)	(0.062)	(0.066)	(0.044)
			0.872	0.492	0.417	0.234	0.539	0.305	0.655	0.755	0.322
Delivery in facility past 3 yrs	9510	0.152	-0.008	-0.031	-0.032	-0.127	0.109	-0.042	-0.008	-0.047	-0.045
		(0.359)	(0.052)	(0.052)	(0.043)	(0.067)	(0.069)	(0.044)	(0.063)	(0.071)	(0.044)
			0.880	0.552	0.455	0.058	0.115	0.350	0.898	0.511	0.309
Doctor assisted with birth past 3 yrs.	9510	0.156	-0.001	0.011	0.007	-0.101	0.124	-0.003	0.011	-0.020	-0.005
		(0.363)	(0.052)	(0.053)	(0.040)	(0.067)	(0.069)	(0.042)	(0.056)	(0.067)	(0.041)
			0.986	0.841	0.855	0.136	0.076	0.938	0.846	0.768	0.908
Doctor or nurse assisted with birth past 3 yrs.	9510	0.164	0.007	-0.003	0.005	-0.123	0.142	-0.011	0.031	-0.047	-0.007
		(0.371)	(0.056)	(0.056)	(0.043)	(0.067)	(0.069)	(0.043)	(0.061)	(0.072)	(0.043)
			0.898	0.962	0.906	0.067	0.041	0.793	0.618	0.513	0.875
Delivery complications past 3 yrs.	9510	0.039	-0.006	0.018	0.008	0.048	-0.048	0.010	-0.005	0.023	0.013
		(0.194)	(0.027)	(0.024)	(0.023)	(0.038)	(0.038)	(0.023)	(0.034)	(0.032)	(0.023)
			0.839	0.465	0.715	0.204	0.205	0.675	0.879	0.470	0.574
Fertility index	9510	-0.000	0.049	-0.056	0.005	-0.170	0.183	-0.027	0.076	-0.114	-0.014
		(0.660)	(0.098)	(0.116)	(0.078)	(0.120)	(0.132)	(0.079)	(0.113)	(0.142)	(0.080)
			0.616	0.627	0.953	0.157	0.166	0.738	0.499	0.421	0.864
						Mortality					
Death in hhld. past 3 yrs	9482	0.121	0.010	0.043	0.044	-0.018	0.068	0.035	0.091	-0.069	0.036
		(0.327)	(0.049)	(0.046)	(0.029)	(0.051)	(0.057)	(0.029)	(0.062)	(0.067)	(0.030)
			0.836	0.344	0.132	0.717	0.236	0.232	0.146	0.308	0.222
Deaths in the HH past 3 yrs	9474	0.125	0.022	0.049	0.061	0.003	0.064	0.053	0.111	-0.068	0.058
		(0.345)	(0.051)	(0.048)	(0.030)	(0.052)	(0.059)	(0.030)	(0.068)	(0.075)	(0.031)
			0.667	0.308	0.044	0.948	0.280	0.079	0.102	0.371	0.062

Notes. See note at end of table.

Table A.17 (continued): Effects of premium and subsidy combinations (ITT) on health and health-related outcomes at 3.5 years

		Control	(A) Free insurance			(B) Sale of insurance + transfer			(C) Sale of insurance		
	N	Mean (SD)	Direct Coefficient (SE) *p*-value	Spillover Coefficient (SE) *p*-value	Total Coefficient (SE) *p*-value	Direct Coefficient (SE) *p*-value	Spillover Coefficient (SE) *p*-value	Total Coefficient (SE) *p*-value	Direct Coefficient (SE) *p*-value	Spillover Coefficient (SE) *p*-value	Total Coefficient (SE) *p*-value
Sickness-related death in hhld. past 3 yrs	9482	0.079	-0.009	0.049	0.030	-0.013	0.055	0.031	0.102	-0.097	0.025
		(0.270)	(0.042)	(0.036)	(0.026)	(0.043)	(0.046)	(0.026)	(0.052)	(0.055)	(0.026)
			0.836	0.176	0.243	0.764	0.227	0.228	0.053	0.078	0.332
Number of sickness-related deaths in hhld.	9482	0.081	-0.005	0.053	0.036	-0.008	0.055	0.035	0.104	-0.090	0.033
		(0.281)	(0.044)	(0.038)	(0.026)	(0.044)	(0.046)	(0.026)	(0.055)	(0.059)	(0.026)
			0.903	0.162	0.165	0.862	0.237	0.174	0.058	0.126	0.206
Mortality index	9482	0.000	0.011	0.161	0.138	-0.030	0.198	0.126	0.337	-0.272	0.122
		(0.942)	(0.144)	(0.129)	(0.086)	(0.144)	(0.158)	(0.086)	(0.185)	(0.200)	(0.087)
			0.940	0.211	0.109	0.833	0.212	0.145	0.069	0.173	0.160

Notes. Table presents estimates of intent-to-treat effects of access to insurance at different prices and subsidies on health and health-related outcomes at 3.5 years. Each observation is a household and has equal weight. Treatment variables are household assignments: free insurance (A), sale of insurance + cash transfer (B), sale of insurance (C). Estimates are intent-to-treat effects; all models estimated with OLS. Each treatment arm was interacted with the share of the village allocated to A, B, or C (combined). Standard errors were clustered at the village level. Coefficients were transformed to show percentage point changes from the control group D. The direct effect only includes the coefficient on treatment A, B, or C. The spillover effect is the estimated effect on a treated household of assigning all other sample households to at least some form of access to RSBY insurance. The total effect is constructed as the sum of the direct effect and 0.8024*(spillover effect), where 0.8024 is the average fraction of households given insurance access in the study. Mean and standard deviation in the control group are statistics from the group without access to insurance. The FWER adjusted 5% critical values are: 0.00114 for self-reported measures of health; 0.00032 for chronic disease; 0.00038 for quality of life, ADLs, and physical health symptoms; 0.00142 for mental health; 0.00052 for fertility; and 0.00114 for mortality, at 3.5 yrs.

Table A.18: Effects of enrollment (CATE) on health and health-related outcomes at 18 months

		Control	Direct effect	Spillover effect	Total effect
	N	Mean (SD)	Coefficient (SE) *p*-value	Coefficient (SE) *p*-value	Coefficient (SE) *p*-value
Self-reported measures of health					
Good health	18983	0.662	0.084	-0.165	-0.046
		(0.473)	(0.049)	(0.092)	(0.062)
			(0.087)	(0.074)	(0.458)
Very good health	18983	0.155	0.100	-0.169	-0.034
		(0.362)	(0.048)	(0.080)	(0.060)
			(0.037)	(0.035)	(0.576)
Poor or very poor health	18983	0.056	-0.013	-0.028	-0.035
		(0.231)	(0.029)	(0.036)	(0.031)
			(0.648)	(0.438)	(0.247)
Very poor health	18983	0.008	0.003	-0.014	-0.008
		(0.090)	(0.010)	(0.013)	(0.006)
			(0.756)	(0.282)	(0.175)
Health value index	18983	-0.000	0.109	-0.121	0.014
		(0.642)	(0.073)	(0.121)	(0.075)
			(0.136)	(0.317)	(0.857)
Chronic disease					
Told had hypertension	18939	0.190	-0.028	-0.029	-0.051
		(0.392)	(0.047)	(0.062)	(0.036)
			(0.556)	(0.639)	(0.160)
Takes medication for hypertension	18960	0.131	-0.059	0.026	-0.039
		(0.338)	(0.037)	(0.052)	(0.032)
			(0.108)	(0.611)	(0.224)
Told had diabetes	18913	0.068	-0.013	0.020	0.003
		(0.252)	(0.026)	(0.032)	(0.021)
			(0.620)	(0.534)	(0.900)
Takes oral medication for diabetes	18948	0.050	-0.010	0.018	0.004
		(0.217)	(0.022)	(0.027)	(0.018)
			(0.640)	(0.509)	(0.830)
Takes insulin for diabetes	18952	0.018	-0.003	0.026	0.017
		(0.133)	(0.012)	(0.014)	(0.010)
			(0.799)	(0.057)	(0.076)
Is on a special diet for diabetes	18962	0.046	-0.010	0.023	0.008
		(0.210)	(0.020)	(0.025)	(0.018)
			(0.620)	(0.347)	(0.644)
Told had cancer	18946	0.004	-0.007	0.013	0.003
		(0.064)	(0.006)	(0.008)	(0.004)
			(0.271)	(0.116)	(0.378)
Received cancer treatment past 1 yr.	18998	0.002	0.002	-0.004	-0.001
		(0.049)	(0.005)	(0.005)	(0.003)
			(0.640)	(0.489)	(0.823)
Told had lung disease	18907	0.034	-0.003	-0.008	-0.009
		(0.181)	(0.023)	(0.025)	(0.015)
			(0.909)	(0.741)	(0.542)
Told had heart disease	18868	0.020	0.015	-0.003	0.013
		(0.141)	(0.016)	(0.020)	(0.010)
			(0.346)	(0.877)	(0.203)
Told had stroke	18826	0.007	0.005	-0.002	0.003
		(0.086)	(0.010)	(0.012)	(0.006)
			(0.612)	(0.848)	(0.561)
Told had arthritis	18894	0.176	-0.102	0.122	-0.006
		(0.381)	(0.048)	(0.082)	(0.055)
			(0.033)	(0.137)	(0.907)
Had surgery for arthritis past 1 yr.	18933	0.018	-0.024	0.026	-0.004
		(0.135)	(0.015)	(0.020)	(0.012)
			(0.121)	(0.194)	(0.757)
Diagnose with high cholesterol	18871	0.019	0.013	-0.003	0.011
		(0.137)	(0.014)	(0.022)	(0.014)
			(0.338)	(0.891)	(0.449)

Notes. See note at end of table.

Table A.18 (continued): Effects of enrollment (CATE) on health and health-related outcomes at 18 months

		Control	Direct effect	Spillover effect	Total effect
	N	Mean (SD)	Coefficient (SE) *p*-value	Coefficient (SE) *p*-value	Coefficient (SE) *p*-value
Takes medication for high cholesterol	19032	0.014	0.008	0.003	0.010
		(0.116)	(0.015)	(0.018)	(0.011)
			(0.583)	(0.879)	(0.339)
Chronic disease index	19113	-0.000	-0.034	0.069	0.020
		(0.433)	(0.048)	(0.068)	(0.045)
			(0.478)	(0.314)	(0.659)
		Health-related quality of life, ADLs, and physical health symptoms			
Experiences chest pain	18888	0.081	-0.023	0.005	-0.019
		(0.273)	(0.029)	(0.048)	(0.034)
			(0.425)	(0.914)	(0.568)
Phys. symp. index	18888	-0.000	-0.092	0.029	-0.069
		(1.000)	(0.107)	(0.174)	(0.124)
			(0.393)	(0.868)	(0.579)
		Biomarkers			
Overweight or obese	4853	0.271	0.014	0.031	0.038
		(0.445)	(0.096)	(0.134)	(0.073)
			(0.886)	(0.819)	(0.604)
Underweight	4853	0.084	-0.001	-0.042	-0.034
		(0.277)	(0.050)	(0.082)	(0.043)
			(0.977)	(0.612)	(0.428)
Abdominally obese	4723	0.713	-0.158	0.233	0.025
		(0.452)	(0.134)	(0.180)	(0.126)
			(0.237)	(0.195)	(0.844)
Mid-Upper Arm Circumference	4815	27.032	-2.363	1.363	-1.290
		(3.562)	(0.889)	(1.676)	(0.995)
			(0.008)	(0.416)	(0.195)
Hypertension, grade 1	4878	0.449	-0.113	0.067	-0.060
		(0.498)	(0.087)	(0.120)	(0.078)
			(0.193)	(0.576)	(0.438)
Hypertension, grade 2	4878	0.191	-0.075	0.090	-0.005
		(0.393)	(0.067)	(0.092)	(0.075)
			(0.261)	(0.332)	(0.952)
Skinfolds total	4065	26.326	-0.884	2.357	0.972
		(9.464)	(2.627)	(5.267)	(3.504)
			(0.737)	(0.654)	(0.782)
Biomarkers index	4935	-0.000	-0.203	0.193	-0.051
		(0.409)	(0.102)	(0.130)	(0.091)
			(0.046)	(0.138)	(0.573)
		Fertility			
Currently pregnant	9262	0.055	0.036	-0.085	-0.030
		(0.227)	(0.037)	(0.065)	(0.057)
			(0.325)	(0.196)	(0.596)
Childbirth past 1 yr.	8299	0.049	0.010	-0.044	-0.025
		(0.217)	(0.029)	(0.050)	(0.046)
			(0.741)	(0.377)	(0.588)
Delivered in govt. hosp. past 1 yr.	8297	0.015	0.006	-0.010	-0.003
		(0.120)	(0.016)	(0.018)	(0.011)
			(0.729)	(0.559)	(0.818)
Delivered in facility past 1 yr.	8297	0.047	0.005	-0.035	-0.022
		(0.211)	(0.028)	(0.048)	(0.046)
			(0.854)	(0.469)	(0.625)
Doctor assisted with delivery past 1 yr.	8299	0.038	0.008	-0.040	-0.023
		(0.191)	(0.026)	(0.048)	(0.044)
			(0.756)	(0.409)	(0.601)
Doctor or nurse assisted with delivery past 1 yr.	8299	0.043	-0.004	-0.035	-0.032
		(0.203)	(0.028)	(0.049)	(0.045)
			(0.882)	(0.475)	(0.480)
Child delivery complications past 1 yr.	8293	0.015	-0.013	-0.020	-0.029
		(0.122)	(0.016)	(0.026)	(0.020)
			(0.409)	(0.445)	(0.150)
Ideal number of children	7881	2.516	-0.005	-0.060	-0.052
		(1.215)	(0.207)	(0.393)	(0.291)
			(0.981)	(0.879)	(0.858)
Fertility index	9288	0.000	0.049	-0.131	-0.054
		(0.495)	(0.067)	(0.110)	(0.092)
			(0.470)	(0.235)	(0.553)

Notes. Table presents complier average treatment estimates of the effect of enrollment in RSBY insurance on health and health-related outcomes at 18 months. Each observation is a household and has equal weight. Coefficients were transformed to show percentage point changes from the control group. Mean and standard deviation in the control group are statistics from the unenrolled group. The direct effect is the estimated effect of enrolling one household, assuming no other sample households in the village are enrolled. The spillover effect is the estimated effect on an enrolled household of enrolling all other sample households in the village. The total effect of enrollment is estimated as the direct effect, plus the spillover effects times 0.7183, the mean uptake into insurance in arms A-C. The FWER adjusted 5% critical values are: 0.00341 for self-reported measures of health; 0.00107 for chronic disease; 0.00851 for quality of life, ADLs, and physical health symptoms; 0.00213 for biomarkers; and 0.00190 for fertility, at 18 mos.

Table A.19: Effects of enrollment (CATE) on health and health-related outcomes at 3.5 years

		Control	Direct effect	Spillover effect	Total effect
	N	Mean (SD)	Coefficient (SE) p-value	Coefficient (SE) p-value	Coefficient (SE) p-value
Self-reported measures of health					
Good health	9492	0.516	-0.001	0.041	0.031
		(0.500)	(0.080)	(0.106)	(0.069)
			(0.995)	(0.700)	(0.647)
Very good health	9492	0.076	-0.024	-0.069	-0.079
		(0.265)	(0.041)	(0.053)	(0.038)
			(0.564)	(0.189)	(0.040)
Poor health	9492	0.102	-0.039	0.061	0.010
		(0.303)	(0.051)	(0.056)	(0.038)
			(0.446)	(0.272)	(0.798)
Very poor health	9492	0.021	-0.050	0.032	-0.024
		(0.143)	(0.025)	(0.024)	(0.020)
			(0.044)	(0.177)	(0.216)
Health value index	9492	0.000	0.096	-0.152	-0.024
		(0.647)	(0.116)	(0.132)	(0.088)
			(0.406)	(0.247)	(0.790)
Chronic disease					
Told had hypertension	9476	0.233	-0.074	0.090	-0.003
		(0.423)	(0.063)	(0.068)	(0.046)
			(0.239)	(0.187)	(0.941)
Takes medication for hypertension	9495	0.197	-0.066	0.086	0.002
		(0.398)	(0.058)	(0.059)	(0.042)
			(0.257)	(0.150)	(0.971)
Told had diabetes	9479	0.121	-0.078	0.063	-0.029
		(0.326)	(0.049)	(0.052)	(0.035)
			(0.108)	(0.227)	(0.406)
Takes oral medication for diabetes	9499	0.107	-0.072	0.067	-0.019
		(0.310)	(0.047)	(0.051)	(0.031)
			(0.124)	(0.192)	(0.542)
Takes insulin for diabetes	9489	0.024	0.019	-0.013	0.009
		(0.152)	(0.020)	(0.022)	(0.013)
			(0.332)	(0.539)	(0.494)
Follows a special diet for diabetes	9495	0.077	-0.045	0.053	-0.004
		(0.267)	(0.041)	(0.045)	(0.029)
			(0.277)	(0.240)	(0.898)
Told had cancer	9470	0.004	-0.001	0.008	0.006
		(0.065)	(0.008)	(0.009)	(0.005)
			(0.924)	(0.364)	(0.292)
Treated for cancer past 1 yr.	9496	0.002	-0.003	0.005	0.001
		(0.046)	(0.006)	(0.006)	(0.003)
			(0.581)	(0.367)	(0.811)
Told had lung disease	9479	0.060	-0.049	0.046	-0.013
		(0.238)	(0.031)	(0.036)	(0.021)
			(0.118)	(0.202)	(0.537)
Told had heart disease	9473	0.047	-0.029	0.016	-0.016
		(0.211)	(0.034)	(0.039)	(0.021)
			(0.400)	(0.670)	(0.461)
Told had stroke	9446	0.006	-0.012	0.010	-0.004
		(0.080)	(0.013)	(0.012)	(0.007)
			(0.337)	(0.405)	(0.522)
Told had arthritis or rheumatism	9482	0.193	-0.051	0.117	0.041
		(0.395)	(0.064)	(0.085)	(0.054)
			(0.429)	(0.170)	(0.444)
Had surgery due to arthritis past 1 yr.	9497	0.042	0.019	0.003	0.022
		(0.200)	(0.029)	(0.034)	(0.022)
			(0.498)	(0.926)	(0.319)
Diagnosed with high cholesterol	9449	0.026	0.003	-0.007	-0.002
		(0.160)	(0.022)	(0.023)	(0.014)
			(0.876)	(0.764)	(0.883)

Notes. See note at end of table.

Table A.18 (continued): Effects of enrollment (CATE) on health and health-related outcomes at 18 months

		Control	Direct effect	Spillover effect	Total effect
	N	Mean (SD)	Coefficient (SE) *p*-value	Coefficient (SE) *p*-value	Coefficient (SE) *p*-value
Takes medication to lower cholesterol	9496	0.013	-0.014	0.006	-0.009
		(0.115)	(0.015)	(0.012)	(0.009)
			(0.364)	(0.622)	(0.307)
Has eyesight problems	9480	0.329	0.011	0.115	0.102
		(0.470)	(0.075)	(0.082)	(0.055)
			(0.884)	(0.158)	(0.064)
Had surgery due to eye problems past 1 yr.	9497	0.074	-0.013	0.065	0.039
		(0.261)	(0.045)	(0.052)	(0.032)
			(0.779)	(0.207)	(0.235)
Chronic disease index	9504	-0.000	-0.093	0.141	0.018
		(0.431)	(0.074)	(0.078)	(0.051)
			(0.204)	(0.070)	(0.727)
		Health-related quality of life, ADLs, and physical health symptoms			
Number of functional limitations	9413	0.674	-0.240	0.269	-0.028
		(1.523)	(0.207)	(0.269)	(0.204)
			(0.245)	(0.316)	(0.889)
SF-8, PCS	9510	2.260	-0.064	0.293	0.166
		(0.930)	(0.172)	(0.186)	(0.124)
			(0.710)	(0.115)	(0.178)
SF-8, MCS	9510	1.491	-0.024	0.081	0.040
		(0.789)	(0.120)	(0.153)	(0.115)
			(0.843)	(0.599)	(0.730)
Had stomach pain past 4 wks.	8999	0.061	0.051	-0.026	0.031
		(0.240)	(0.038)	(0.051)	(0.024)
			(0.176)	(0.609)	(0.201)
Had back pain past 4 wks.	8999	0.254	0.072	0.050	0.111
		(0.435)	(0.065)	(0.091)	(0.063)
			(0.269)	(0.579)	(0.078)
Had chest pain past 4 wks.	8999	0.074	0.038	-0.008	0.032
		(0.262)	(0.043)	(0.046)	(0.026)
			(0.376)	(0.869)	(0.212)
Had joint pain past 4 wks.	8999	0.578	-0.034	0.100	0.044
		(0.494)	(0.078)	(0.097)	(0.070)
			(0.660)	(0.306)	(0.526)
Had headaches past 4 wks.	8999	0.194	0.054	0.069	0.108
		(0.396)	(0.060)	(0.078)	(0.044)
			(0.372)	(0.375)	(0.015)
Had menstrual cramps past 4 wks.	8999	0.038	0.034	-0.029	0.011
		(0.190)	(0.024)	(0.034)	(0.020)
			(0.165)	(0.394)	(0.580)
Had pain in no specific place past 4 wks.	8999	0.044	-0.006	0.018	0.008
		(0.205)	(0.035)	(0.039)	(0.025)
			(0.873)	(0.650)	(0.736)
Fainted past 4 wks.	9451	0.012	0.014	-0.012	0.004
		(0.110)	(0.016)	(0.018)	(0.010)
			(0.378)	(0.491)	(0.661)
Felt dizzy past 4 wks.	9451	0.133	0.083	-0.047	0.046
		(0.339)	(0.047)	(0.057)	(0.036)
			(0.076)	(0.405)	(0.204)
Shortness of breath past 4 wks.	9451	0.049	0.035	0.011	0.044
		(0.216)	(0.032)	(0.034)	(0.022)
			(0.275)	(0.734)	(0.044)
Heart pounded past 4 wks.	9451	0.064	0.012	-0.003	0.010
		(0.245)	(0.035)	(0.045)	(0.031)
			(0.735)	(0.954)	(0.747)
Qual. of life index	9510	-0.000	0.075	0.047	0.112
		(0.454)	(0.076)	(0.091)	(0.063)
			(0.323)	(0.606)	(0.077)
		Mental health			
GHQ-12, Likert scoring	10879	9.329	0.830	0.139	0.940
		(6.728)	(1.002)	(1.309)	(0.968)
			(0.407)	(0.916)	(0.332)

Notes. See note at end of table.

Table A.18 (continued): Effects of enrollment (CATE) on health and health-related outcomes at 18 months

		Control	Direct effect	Spillover effect	Total effect
	N	Mean (SD)	Coefficient (SE) *p*-value	Coefficient (SE) *p*-value	Coefficient (SE) *p*-value
GHQ-12, binary scoring	9510	2.331	0.437	0.070	0.492
		(3.297)	(0.480)	(0.741)	(0.525)
			(0.363)	(0.924)	(0.349)
PSS-10 score	9510	17.785	-0.154	0.653	0.360
		(3.494)	(0.514)	(0.747)	(0.477)
			(0.764)	(0.383)	(0.451)
Mental health index	9510	-0.000	0.075	0.047	0.112
		(0.454)	(0.076)	(0.091)	(0.063)
			(0.323)	(0.606)	(0.077)
			Fertility		
Childbirth/stillbirth past 6 mos.	9493	0.046	0.009	0.010	0.017
		(0.210)	(0.029)	(0.034)	(0.018)
			(0.745)	(0.780)	(0.349)
Childbirth/stillbirth past 3 yrs.	9510	0.192	-0.005	0.003	-0.003
		(0.394)	(0.059)	(0.073)	(0.045)
			(0.927)	(0.963)	(0.951)
Number of births in hhld. past 3 years	9510	0.315	0.096	-0.200	-0.062
		(0.920)	(0.133)	(0.274)	(0.149)
			(0.473)	(0.465)	(0.678)
Number of live births in hhld. past 3 years	9510	0.205	-0.006	0.021	0.010
		(0.487)	(0.067)	(0.079)	(0.051)
			(0.925)	(0.794)	(0.846)
Number of still births in hhld. past 3 years	9510	0.110	0.102	-0.221	-0.072
		(0.777)	(0.106)	(0.243)	(0.136)
			(0.335)	(0.365)	(0.598)
Delivery in hospital past 3 yrs	9510	0.141	-0.040	-0.007	-0.045
		(0.349)	(0.054)	(0.055)	(0.039)
			(0.461)	(0.899)	(0.251)
Delivery in facility past 3 yrs	9510	0.152	-0.054	0.026	-0.033
		(0.359)	(0.053)	(0.055)	(0.040)
			(0.308)	(0.632)	(0.400)
Doctor assisted with birth past 3 yrs.	9510	0.156	-0.038	0.050	0.001
		(0.363)	(0.052)	(0.058)	(0.037)
			(0.462)	(0.391)	(0.983)
Doctor or nurse assisted with birth past 3 yrs.	9510	0.164	-0.036	0.043	-0.003
		(0.371)	(0.054)	(0.059)	(0.039)
			(0.503)	(0.467)	(0.943)
Delivery complications past 3 yrs.	9510	0.039	0.011	-0.015	-0.001
		(0.194)	(0.029)	(0.030)	(0.019)
			(0.715)	(0.616)	(0.948)
Fertility index	9510	-0.000	-0.027	-0.002	-0.029
		(0.660)	(0.096)	(0.124)	(0.078)
			(0.778)	(0.987)	(0.711)
			Mortality		
Death in hhld. past 3 yrs	9482	0.121	-0.005	0.029	0.018
		(0.327)	(0.047)	(0.053)	(0.026)
			(0.918)	(0.582)	(0.488)
Deaths in the HH past 3 yrs	9474	0.125	0.018	0.016	0.031
		(0.345)	(0.050)	(0.057)	(0.028)
			(0.714)	(0.776)	(0.263)
Sickness-related death in hhld. past 3 yrs	9482	0.079	-0.018	0.040	0.013
		(0.270)	(0.041)	(0.044)	(0.022)
			(0.660)	(0.366)	(0.541)
Number of sickness-related deaths in hhld.	9482	0.081	-0.012	0.040	0.019
		(0.281)	(0.043)	(0.046)	(0.022)
			(0.770)	(0.376)	(0.386)
Mortality index	9482	0.000	-0.019	0.107	0.066
		(0.942)	(0.140)	(0.155)	(0.076)
			(0.895)	(0.488)	(0.384)

Notes. Table presents complier average treatment estimates of the effect of enrollment in RSBY insurance on health and health-related outcomes at 3.5 years. Each observation is a household and has equal weight. Coefficients were transformed to show percentage point changes from the control group. Mean and standard deviation in the control group are statistics from the unenrolled group. The direct effect is the estimated effect of enrolling one household, assuming no other sample households in the village are enrolled. The spillover effect is the estimated effect on an enrolled household of enrolling all other sample households in the village. The total effect of enrollment is estimated as the direct effect, plus the spillover effects times 0.7183, the mean uptake into insurance in arms A-C. The FWER adjusted 5% critical values are: 0.00341 for self-reported measures of health; 0.00095 for chronic disease; 0.00114 for quality of life, ADLs, and physical health symptoms; 0.00426 for mental health; 0.00155 for fertility; and 0.00341 for mortality, at 3.5 yrs.

Table A.20: Effect of different premium & subsidy combinations on midline (18 mos.) health outcomes (intent to treat estimate).

			Free insurance			Sale of insurance + transfer			Sale of insurance		
	N	Control mean (SD)	Direct Coefficient (SE) P-value	Spillover Coefficient (SE) P-value	Total Coefficient (SE) P-value	Direct Coefficient (SE) P-value	Spillover Coefficient (SE) P-value	Total Coefficient (SE) P-value	Direct Coefficient (SE) P-value	Spillover Coefficient (SE) P-value	Total Coefficient (SE) P-value
Health value											
Good health	18983	0.662	0.055	-0.091	-0.027	0.061	-0.046	0.020	0.146	-0.192	-0.027
		(0.473)	(0.040)	(0.070)	(0.061)	(0.069)	(0.091)	(0.061)	(0.074)	(0.099)	(0.060)
			.18	.19	.65	.38	.62	.74	.05	.05	.65
Very good health	18983	0.155	0.064	-0.086	-0.014	0.044	-0.038	0.009	0.043	-0.033	0.013
		(0.362)	(0.036)	(0.064)	(0.063)	(0.069)	(0.094)	(0.065)	(0.068)	(0.093)	(0.066)
			.07	.18	.83	.52	.68	.89	.53	.72	.84
Poor or very poor health	18983	0.056	-0.012	-0.022	-0.032	-0.029	-0.006	-0.034	-0.012	-0.020	-0.030
		(0.231)	(0.024)	(0.030)	(0.034)	(0.033)	(0.038)	(0.034)	(0.038)	(0.045)	(0.035)
			.62	.46	.35	.39	.87	.32	.75	.66	.39
Very poor health	18983	0.008	-0.000	-0.004	-0.003	0.008	-0.014	-0.005	0.002	-0.005	-0.003
		(0.090)	(0.010)	(0.010)	(0.007)	(0.011)	(0.010)	(0.006)	(0.012)	(0.013)	(0.007)
			.00	.72	.60	.47	.16	.40	.86	.69	.69
Chronic disease											
Told had hypertension	18939	0.190	0.028	-0.098	-0.060	-0.140	0.114	-0.038	-0.026	-0.032	-0.055
		(0.392)	(0.046)	(0.049)	(0.036)	(0.057)	(0.069)	(0.038)	(0.053)	(0.062)	(0.037)
			.55	.05	.10	.02	.10	.32	.63	.61	.14
Takes medication for hypertension	18960	0.131	-0.018	-0.044	-0.057	-0.125	0.089	-0.045	-0.082	0.037	-0.048
		(0.338)	(0.037)	(0.045)	(0.033)	(0.047)	(0.060)	(0.034)	(0.043)	(0.051)	(0.033)
			.63	.34	.08	.009	.14	.19	.06	.47	.15
Told had diabetes	18913	0.068	-0.005	-0.003	-0.008	-0.040	0.047	0.002	-0.032	0.033	-0.002
		(0.252)	(0.023)	(0.028)	(0.023)	(0.037)	(0.043)	(0.024)	(0.036)	(0.036)	(0.023)
			.85	.90	.75	.28	.28	.95	.37	.36	.92
Takes oral medication for diabetes	18948	0.050	-0.002	-0.000	-0.002	-0.023	0.030	0.004	-0.027	0.025	-0.004
		(0.217)	(0.020)	(0.023)	(0.020)	(0.031)	(0.037)	(0.021)	(0.031)	(0.032)	(0.020)
			.93	.99	.92	.47	.42	.84	.39	.43	.84
Takes insulin for diabetes	18952	0.018	-0.001	0.019	0.016	-0.016	0.042	0.021	-0.006	0.027	0.019
		(0.133)	(0.011)	(0.011)	(0.011)	(0.016)	(0.018)	(0.012)	(0.017)	(0.018)	(0.011)
			.94	.09	.14	.30	.02	.08	.73	.13	.10
Is on a special diet for diabetes	18962	0.046	-0.000	-0.003	-0.003	-0.044	0.055	0.005	-0.038	0.047	0.005
		(0.210)	(0.018)	(0.024)	(0.021)	(0.028)	(0.032)	(0.021)	(0.030)	(0.030)	(0.021)
			.98	.91	.89	.12	.09	.82	.21	.12	.83
Told had cancer	18946	0.004	-0.006	0.010	0.002	-0.003	0.009	0.004	-0.005	0.005	0.000
		(0.064)	(0.005)	(0.006)	(0.004)	(0.009)	(0.010)	(0.004)	(0.008)	(0.009)	(0.004)
			.22	.11	.54	.69	.40	.23	.55	.55	.94

Notes. Table presents (in all panels but the last one) estimates of intent-to-treat effects of access to insurance at different prices and subsidies on specific midline (18 mos.) health outcomes. The outcomes are listed in the first column. The last panel provides critical p-values that control the false discovery rate for different groups of outcomes listed in the first column. Each observation in our regressions is a household. Treatment variables are household assignments: free insurance (A), sale of insurance + cash transfer (B), sale of insurance (C). Estimates are intent-to-treat effects; all models estimated with OLS. Each treatment arm was interacted with the share of the village allocated to A, B, or C (combined). The omitted category is the control group (D). Standard errors were clustered at the village level. The direct effect only includes the coefficient on treatment A, B, or C. The spillover effect is the estimated effect on a treated household of assigning all other sample households to at least some form of access to RSBY insurance. The total effect is constructed as the sum of the direct effect and 0.9*(spillover effect). Mean and standard deviation in the control group are statistics from group D without access to insurance. Abbreviations: SD, standard deviation; SE, standard error; mos, months; yr, year.

Table A.20 (cont'd): Effect of different premium & subsidy combinations on midline (18 mos.) health outcomes (intent to treat estimate).

			Free insurance			Sale of insurance + transfer			Sale of insurance		
	N	Control mean (SD)	Direct Coefficient (SE) P-value	Spillover Coefficient (SE) P-value	Total Coefficient (SE) P-value	Direct Coefficient (SE) P-value	Spillover Coefficient (SE) P-value	Total Coefficient (SE) P-value	Direct Coefficient (SE) P-value	Spillover Coefficient (SE) P-value	Total Coefficient (SE) P-value
Received cancer treatment past 1 yr.	18998	0.002	0.002	-0.002	0.000	-0.004	0.005	0.000	0.003	-0.002	0.001
		(0.049)	(0.005)	(0.005)	(0.003)	(0.004)	(0.004)	(0.003)	(0.007)	(0.009)	(0.003)
			.66	.67	.95	.38	.28	.87	.70	.81	.75
Told had lung disease	18907	0.034	-0.017	0.014	-0.005	0.012	-0.022	-0.008	0.002	-0.002	-0.000
		(0.181)	(0.020)	(0.017)	(0.017)	(0.028)	(0.028)	(0.017)	(0.028)	(0.030)	(0.017)
			.39	.42	.78	.66	.43	.66	.95	.95	.99
Told had heart disease	18868	0.020	0.009	0.008	0.016	0.023	-0.014	0.010	-0.001	0.018	0.016
		(0.141)	(0.017)	(0.017)	(0.011)	(0.019)	(0.020)	(0.010)	(0.017)	(0.018)	(0.011)
			.60	.63	.15	.24	.48	.33	.97	.31	.13
Told had stroke	18826	0.007	0.003	0.003	0.006	0.009	-0.005	0.004	-0.000	0.006	0.005
		(0.086)	(0.010)	(0.009)	(0.007)	(0.012)	(0.012)	(0.007)	(0.011)	(0.012)	(0.007)
			.76	.77	.42	.45	.67	.50	.99	.60	.42
Told had arthritis	18894	0.176	-0.093	0.060	-0.038	-0.067	0.017	-0.051	-0.127	0.092	-0.044
		(0.381)	(0.038)	(0.065)	(0.056)	(0.076)	(0.094)	(0.057)	(0.058)	(0.072)	(0.055)
			.01	.36	.49	.38	.85	.38	.03	.20	.42
Had surgery for arthritis past 1 yr.	18933	0.018	-0.015	0.004	-0.011	-0.035	0.024	-0.013	-0.053	0.048	-0.010
		(0.135)	(0.014)	(0.018)	(0.014)	(0.019)	(0.022)	(0.014)	(0.017)	(0.019)	(0.014)
			.29	.81	.41	.07	.28	.35	.002	.01	.47
Diagnose with high cholesterol	18871	0.019	-0.001	0.016	0.013	0.010	0.007	0.016	0.005	0.014	0.017
		(0.137)	(0.011)	(0.018)	(0.015)	(0.019)	(0.029)	(0.016)	(0.019)	(0.022)	(0.015)
			.91	.37	.39	.62	.81	.31	.81	.53	.26
Takes medication for high cholesterol	19032	0.014	0.004	0.008	0.010	-0.006	0.019	0.011	-0.009	0.027	0.015
		(0.116)	(0.012)	(0.013)	(0.011)	(0.017)	(0.020)	(0.012)	(0.017)	(0.022)	(0.012)
			.76	.56	.34	.73	.35	.34	.60	.22	.20
Health-related quality of life, ADLs, and physical health symptoms											
Experiences chest pain	18888	0.081	-0.029	0.021	-0.011	0.003	-0.018	-0.014	-0.008	-0.002	-0.010
		(0.273)	(0.024)	(0.041)	(0.035)	(0.044)	(0.053)	(0.036)	(0.040)	(0.049)	(0.034)
			.23	.61	.76	.95	.73	.71	.84	.97	.78
Fertility											
Currently pregnant	9262	0.055	0.020	-0.050	-0.025	-0.002	-0.031	-0.030	-0.071	0.078	-0.000
		((0.227))	(0.026)	(0.068)	(0.061)	(0.039)	(0.068)	(0.062)	(0.057)	(0.105)	(0.068)
			.44	.46	.68	.97	.65	.63	.21	.46	.99
Childbirth past 1 yr.	8299	0.049	0.028	-0.056	-0.022	-0.009	-0.006	-0.015	-0.023	-0.009	-0.030
		((0.217))	(0.026)	(0.060)	(0.051)	(0.034)	(0.051)	(0.052)	(0.038)	(0.039)	(0.051)
			.28	.35	.66	.79	.90	.78	.55	.83	.55
Delivered in govt. hosp. past 1 yr.	8297	0.015	0.009	-0.013	-0.002	-0.002	0.014	0.011	-0.016	0.018	0.000
		((0.120))	(0.017)	(0.015)	(0.012)	(0.022)	(0.023)	(0.013)	(0.017)	(0.019)	(0.013)
			.57	.41	.86	.94	.53	.38	.34	.34	.00
Delivered in facility past 1 yr.	8297	0.047	0.023	-0.051	-0.023	-0.000	-0.016	-0.015	-0.032	0.002	-0.031
		((0.211))	(0.026)	(0.059)	(0.051)	(0.034)	(0.049)	(0.052)	(0.036)	(0.037)	(0.051)
			.36	.39	.66	.99	.75	.77	.37	.96	.55
Doctor assisted with delivery past 1 yr.	8299	0.038	0.023	-0.051	-0.023	0.007	-0.029	-0.019	-0.038	0.014	-0.025
		((0.191))	(0.022)	(0.059)	(0.050)	(0.031)	(0.046)	(0.050)	(0.037)	(0.036)	(0.050)
			.31	.38	.64	.82	.53	.70	.31	.71	.61

Table A.20 (cont'd): Effect of different premium & subsidy combinations on midline (18 mos.) health outcomes (intent to treat estimate).

			Free insurance			Sale of insurance + transfer			Sale of insurance		
	N	Control mean (SD)	Direct Coefficient (SE) P-value	Spillover Coefficient (SE) P-value	Total Coefficient (SE) P-value	Direct Coefficient (SE) P-value	Spillover Coefficient (SE) P-value	Total Coefficient (SE) P-value	Direct Coefficient (SE) P-value	Spillover Coefficient (SE) P-value	Total Coefficient (SE) P-value
Doctor or nurse assisted with delivery past 1 yr.	8299	0.043	0.012	-0.052	-0.035	-0.011	-0.023	-0.031	-0.036	-0.004	-0.040
		((0.203))	(0.026)	(0.059)	(0.050)	(0.032)	(0.047)	(0.051)	(0.037)	(0.039)	(0.051)
			.64	.38	.49	.73	.63	.54	.33	.91	.43
Child delivery complications past 1 yr.	8293	0.015	-0.010	-0.021	-0.029	-0.007	-0.020	-0.024	-0.020	-0.007	-0.026
		((0.122))	(0.013)	(0.026)	(0.021)	(0.018)	(0.031)	(0.022)	(0.017)	(0.018)	(0.022)
			.44	.41	.17	.72	.52	.28	.25	.70	.23
Ideal number of children	7881	2.516	-0.133	0.063	-0.076	-0.136	0.167	0.015	0.013	-0.086	-0.064
		((1.215))	(0.159)	(0.318)	(0.295)	(0.278)	(0.385)	(0.294)	(0.278)	(0.424)	(0.299)
			.41	.84	.80	.63	.66	.96	.96	.84	.83
					Biomarkers						
Overweight or obese	4853	0.271	-0.034	0.003	-0.031	-0.065	0.073	0.001	-0.113	0.137	0.010
		(0.445)	(0.088)	(0.100)	(0.073)	(0.128)	(0.141)	(0.075)	(0.118)	(0.130)	(0.071)
			.70	.97	.67	.61	.61	.99	.34	.30	.89
Underweight	4853	0.084	0.059	-0.123	-0.051	-0.097	0.057	-0.046	-0.045	-0.005	-0.050
		(0.277)	(0.055)	(0.075)	(0.041)	(0.067)	(0.080)	(0.041)	(0.059)	(0.073)	(0.042)
			.28	.10	.22	.15	.48	.26	.44	.94	.23
Abdominally obese	4723	0.713	-0.108	0.204	0.076	-0.046	0.051	-0.000	-0.052	0.091	0.030
		(0.452)	(0.104)	(0.101)	(0.118)	(0.155)	(0.186)	(0.124)	(0.154)	(0.175)	(0.120)
			.30	.05	.52	.77	.79	.00	.74	.60	.80
Mid-Upper Arm Circumference	4815	27.032	-1.680	0.215	-1.486	-2.213	0.504	-1.760	-1.772	0.086	-1.695
		(3.562)	(0.656)	(1.234)	(0.990)	(1.008)	(1.314)	(0.935)	(1.144)	(1.385)	(0.923)
			.01	.86	.14	.03	.70	.06	.12	.95	.07
Hypertension, grade 1	4878	0.449	-0.073	-0.010	-0.082	-0.092	0.000	-0.092	-0.176	0.102	-0.084
		(0.498)	(0.078)	(0.095)	(0.081)	(0.100)	(0.119)	(0.082)	(0.111)	(0.142)	(0.087)
			.35	.91	.31	.36	.00	.27	.12	.47	.34
Hypertension, grade 2	4878	0.191	-0.083	0.086	-0.005	0.030	-0.031	0.002	-0.078	0.070	-0.015
		(0.393)	(0.068)	(0.072)	(0.077)	(0.090)	(0.112)	(0.078)	(0.085)	(0.106)	(0.077)
			.22	.23	.95	.74	.78	.98	.36	.51	.85
Skinfolds total	4065	26.326	-2.131	2.868	0.450	-1.608	1.477	-0.279	-0.994	1.845	0.666
		(9.464)	(2.100)	(3.953)	(3.374)	(3.565)	(4.701)	(3.297)	(3.824)	(5.551)	(3.425)
			.31	.47	.89	.65	.75	.93	.80	.74	.85
					FWER crit. values						
Health value			0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013
Chronic disease			0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003
Health-related quality of life, ADLs, and physical health symptoms			0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Fertility			0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006

Notes. Table presents (in all panels but the last one) estimates of intent-to-treat effects of access to insurance at different prices and subsidies on specific midline (18 mos.) health outcomes. The outcomes are listed in the first column. The last panel provides critical p-values that control the false discovery rate for different groups of outcomes listed in the first column. Each observation in our regressions is a household. Treatment variables are household assignments: free insurance (A), sale of insurance + cash transfer (B), sale of insurance (C). Estimates are intent-to-treat effects; all models estimated with OLS. Each treatment arm was interacted with the share of the village allocated to A, B, or C (combined). The omitted category is the control group (D). Standard errors were clustered at the village level. The direct effect only includes the coefficient on treatment A, B, or C. The spillover effect is the estimated effect on a treated household of assigning all other sample households to at least some form of access to RSBY insurance. The total effect is constructed as the sum of the direct effect and 0.9*(spillover effect). Mean and standard deviation in the control group are statistics from group D without access to insurance. Abbreviations: SD, standard deviation; SE, standard error; mos, months; yr, year.

Table A.21: Effect of different premium & subsidy combinations on endline (3.5 yrs.) health outcomes (intent to treat estimate).

			Free insurance			Sale of insurance + transfer			Sale of insurance		
	N	Control mean (SD)	Direct Coefficient (SE) P-value	Spillover Coefficient (SE) P-value	Total Coefficient (SE) P-value	Direct Coefficient (SE) P-value	Spillover Coefficient (SE) P-value	Total Coefficient (SE) P-value	Direct Coefficient (SE) P-value	Spillover Coefficient (SE) P-value	Total Coefficient (SE) P-value
Health value											
		(0.340)	(0.043)	(0.047)	(0.042)	(0.058)	(0.068)	(0.043)	(0.060)	(0.079)	(0.044)
			.67	.77	.89	.65	.88	.69	.62	.65	.95
Good health	9492	0.516	0.014	-0.011	0.005	-0.172	0.225	0.031	0.015	-0.026	-0.008
		(0.500)	(0.077)	(0.089)	(0.073)	(0.098)	(0.110)	(0.074)	(0.097)	(0.108)	(0.074)
			.86	.90	.95	.08	.04	.67	.87	.81	.91
Very good health	9492	0.076	0.027	-0.120	-0.081	-0.061	-0.016	-0.075	-0.047	-0.043	-0.086
		(0.265)	(0.044)	(0.058)	(0.042)	(0.052)	(0.054)	(0.043)	(0.046)	(0.053)	(0.043)
			.54	.04	.05	.24	.77	.08	.30	.41	.04
Poor health	9492	0.102	-0.033	0.036	-0.001	-0.036	0.033	-0.006	-0.037	0.038	-0.003
		(0.303)	(0.048)	(0.048)	(0.043)	(0.061)	(0.063)	(0.044)	(0.062)	(0.063)	(0.043)
			.49	.45	.99	.55	.60	.89	.54	.54	.94
Very poor health	9492	0.021	-0.042	0.006	-0.037	-0.052	0.021	-0.033	-0.033	-0.007	-0.040
		(0.143)	(0.022)	(0.018)	(0.023)	(0.025)	(0.027)	(0.024)	(0.027)	(0.023)	(0.023)
			.05	.75	.11	.04	.44	.16	.22	.75	.08
Chronic disease											
Told had hypertension	9476	0.233	-0.039	0.013	-0.027	-0.110	0.099	-0.021	-0.169	0.178	-0.008
		(0.423)	(0.057)	(0.060)	(0.053)	(0.076)	(0.080)	(0.055)	(0.083)	(0.085)	(0.056)
			.50	.83	.61	.15	.22	.70	.04	.04	.88
Takes medication for hypertension	9495	0.197	-0.041	0.037	-0.008	-0.062	0.064	-0.004	-0.117	0.141	0.010
		(0.398)	(0.053)	(0.053)	(0.049)	(0.070)	(0.076)	(0.050)	(0.073)	(0.076)	(0.051)
			.44	.49	.87	.38	.40	.93	.11	.06	.84
Told had diabetes	9479	0.121	-0.049	-0.019	-0.066	-0.131	0.082	-0.058	-0.149	0.104	-0.055
		(0.326)	(0.048)	(0.048)	(0.040)	(0.059)	(0.061)	(0.041)	(0.057)	(0.056)	(0.041)
			.30	.70	.10	.03	.18	.16	.009	.06	.18
Takes oral medication for diabetes	9499	0.107	-0.046	-0.003	-0.049	-0.109	0.073	-0.044	-0.126	0.098	-0.037
		(0.310)	(0.048)	(0.046)	(0.036)	(0.055)	(0.059)	(0.037)	(0.052)	(0.054)	(0.036)
			.33	.95	.18	.05	.22	.24	.02	.07	.30
Takes insulin for diabetes	9489	0.024	0.018	-0.007	0.011	0.018	-0.007	0.011	-0.005	0.022	0.014
		(0.152)	(0.019)	(0.019)	(0.015)	(0.026)	(0.029)	(0.015)	(0.025)	(0.026)	(0.015)
			.35	.70	.46	.49	.80	.46	.84	.41	.35
Follows a special diet for diabetes	9495	0.077	-0.035	0.012	-0.024	-0.075	0.064	-0.017	-0.073	0.064	-0.015
		(0.267)	(0.041)	(0.039)	(0.032)	(0.048)	(0.051)	(0.033)	(0.048)	(0.051)	(0.033)
			.40	.76	.47	.12	.21	.61	.13	.21	.65

Notes. Table presents (in all panels but the last one) estimates of intent-to-treat effects of access to insurance at different prices and subsidies on specific endline (3.5 yrs.) health outcomes. The outcomes are listed in the first column. The last panel provides critical p-values that control the false discovery rate for different groups of outcomes listed in the first column. Each observation in our regressions is a household. Treatment variables are household assignments: free insurance (A), sale of insurance + cash transfer (B), sale of insurance (C). Estimates are intent-to-treat effects; all models estimated with OLS. Each treatment arm was interacted with the share of the village allocated to A, B, or C (combined). The omitted category is the control group (D). Standard errors were clustered at the village level. The direct effect only includes the coefficient on treatment A, B, or C. The spillover effect is the estimated effect on a treated household of assigning all other sample households to at least some form of access to RSBY insurance. The total effect is constructed as the sum of the direct effect and 0.9*(spillover effect). Mean and standard deviation in the control group are statistics from group D without access to insurance. Abbreviations: SD, standard deviation; SE, standard error; mos, months; yr, year.

Table A.21 (cont'd): Effect of different premium & subsidy combinations on endline (3.5 yrs.) health outcomes (intent to treat estimate).

			Free insurance			Sale of insurance + transfer			Sale of insurance		
	N	Control mean (SD)	Direct Coefficient (SE) P-value	Spillover Coefficient (SE) P-value	Total Coefficient (SE) P-value	Direct Coefficient (SE) P-value	Spillover Coefficient (SE) P-value	Total Coefficient (SE) P-value	Direct Coefficient (SE) P-value	Spillover Coefficient (SE) P-value	Total Coefficient (SE) P-value
Told had cancer	9470	0.004	-0.005	0.012	0.006	0.006	0.001	0.007	0.001	0.001	0.002
		(0.065)	(0.008)	(0.006)	(0.006)	(0.014)	(0.018)	(0.007)	(0.008)	(0.007)	(0.006)
			.51	.06	.35	.68	.96	.32	.93	.84	.73
Treated for cancer past 1 yr.	9496	0.002	0.000	0.000	0.000	-0.007	0.009	0.001	-0.002	0.002	0.000
		(0.046)	(0.006)	(0.006)	(0.004)	(0.005)	(0.005)	(0.004)	(0.006)	(0.006)	(0.004)
			.99	.94	.91	.14	.08	.87	.75	.69	.97
Told had lung disease	9479	0.060	-0.035	0.021	-0.016	-0.004	-0.017	-0.019	-0.038	0.017	-0.022
		(0.238)	(0.030)	(0.029)	(0.024)	(0.037)	(0.045)	(0.025)	(0.039)	(0.037)	(0.024)
			.25	.46	.50	.91	.71	.45	.34	.64	.35
Told had heart disease	9473	0.047	0.018	-0.048	-0.026	-0.069	0.049	-0.025	-0.072	0.050	-0.027
		(0.211)	(0.035)	(0.033)	(0.025)	(0.033)	(0.037)	(0.025)	(0.036)	(0.035)	(0.025)
			.62	.15	.30	.04	.19	.32	.05	.16	.28
Told had stroke	9446	0.006	-0.011	0.005	-0.006	-0.022	0.016	-0.008	0.002	-0.017	-0.013
		(0.080)	(0.013)	(0.011)	(0.009)	(0.012)	(0.011)	(0.009)	(0.015)	(0.014)	(0.009)
			.41	.63	.48	.06	.15	.36	.88	.21	.13
Told had arthritis or rheumatism	9482	0.193	-0.064	0.118	0.043	0.038	-0.013	0.026	0.031	0.002	0.033
		(0.395)	(0.062)	(0.063)	(0.055)	(0.082)	(0.096)	(0.054)	(0.076)	(0.090)	(0.056)
			.31	.06	.44	.64	.89	.63	.68	.99	.56
Had surgery due to arthritis past 1 yr.	9497	0.042	0.024	0.010	0.033	0.005	0.021	0.024	0.027	0.007	0.033
		(0.200)	(0.028)	(0.029)	(0.022)	(0.032)	(0.035)	(0.023)	(0.034)	(0.041)	(0.024)
			.38	.74	.14	.87	.55	.29	.44	.86	.16
Diagnosed with high cholesterol	9449	0.026	0.012	-0.003	0.010	0.003	0.007	0.010	0.015	-0.005	0.010
		(0.160)	(0.021)	(0.020)	(0.016)	(0.024)	(0.022)	(0.016)	(0.024)	(0.022)	(0.016)
			.56	.89	.55	.89	.75	.55	.54	.82	.53
Takes medication to lower cholesterol	9496	0.013	-0.002	-0.004	-0.005	-0.017	0.015	-0.003	-0.006	0.000	-0.006
		(0.115)	(0.014)	(0.009)	(0.011)	(0.014)	(0.011)	(0.012)	(0.014)	(0.010)	(0.012)
			.88	.70	.65	.23	.15	.79	.66	.00	.61
Has eyesight problems	9480	0.329	-0.025	0.145	0.106	-0.031	0.168	0.120	0.017	0.099	0.106
		(0.470)	(0.067)	(0.069)	(0.064)	(0.088)	(0.093)	(0.064)	(0.095)	(0.096)	(0.065)
			.71	.04	.10	.72	.07	.06	.86	.30	.11
Had surgery due to eye problems past 1 yr.	9497	0.074	-0.042	0.091	0.040	0.020	0.014	0.032	-0.020	0.061	0.035
		(0.261)	(0.039)	(0.036)	(0.035)	(0.054)	(0.056)	(0.036)	(0.055)	(0.074)	(0.040)
			.28	.01	.26	.72	.80	.36	.71	.41	.38
Health-related quality of life, ADLs, and physical health symptoms											
Number of functional limitations	9413	0.674	-0.170	0.034	-0.139	-0.389	0.257	-0.158	-0.378	0.295	-0.112
		(1.523)	(0.192)	(0.247)	(0.224)	(0.271)	(0.323)	(0.230)	(0.281)	(0.333)	(0.230)
			.38	.89	.53	.15	.43	.49	.18	.38	.63
SF-8, PCS	9510	2.260	-0.120	0.273	0.125	-0.066	0.212	0.125	-0.206	0.425	0.176
		(0.930)	(0.172)	(0.151)	(0.140)	(0.180)	(0.200)	(0.141)	(0.176)	(0.197)	(0.143)
			.48	.07	.37	.71	.29	.38	.24	.03	.22
SF-8, MCS	9510	1.491	-0.012	0.042	0.025	0.085	-0.121	-0.024	-0.287	0.377	0.052
		(0.789)	(0.107)	(0.140)	(0.129)	(0.153)	(0.176)	(0.131)	(0.168)	(0.190)	(0.134)
			.91	.77	.84	.58	.49	.85	.09	.05	.70
Had stomach pain past 4 wks.	8999	0.061	0.065	-0.034	0.035	0.005	0.037	0.039	-0.014	0.070	0.049
		(0.240)	(0.039)	(0.045)	(0.025)	(0.041)	(0.048)	(0.026)	(0.047)	(0.054)	(0.027)
			.10	.45	.17	.90	.43	.14	.76	.20	.07

Table A.21 (cont'd): Effect of different premium & subsidy combinations on endline (3.5 yrs.) health outcomes (intent to treat estimate).

			Free insurance			Sale of insurance + transfer			Sale of insurance		
	N	Control mean (SD)	Direct Coefficient (SE) P-value	Spillover Coefficient (SE) P-value	Total Coefficient (SE) P-value	Direct Coefficient (SE) P-value	Spillover Coefficient (SE) P-value	Total Coefficient (SE) P-value	Direct Coefficient (SE) P-value	Spillover Coefficient (SE) P-value	Total Coefficient (SE) P-value
Had back pain past 4 wks.	8999	0.254	0.079	0.044	0.119	0.052	0.060	0.106	-0.068	0.219	0.129
		(0.435)	(0.060)	(0.083)	(0.069)	(0.085)	(0.099)	(0.070)	(0.079)	(0.096)	(0.071)
			.19	.59	.09	.54	.54	.13	.38	.02	.07
Had chest pain past 4 wks.	8999	0.074	0.056	-0.020	0.038	0.011	0.029	0.037	-0.016	0.069	0.045
		(0.262)	(0.042)	(0.039)	(0.031)	(0.047)	(0.046)	(0.031)	(0.046)	(0.044)	(0.031)
			.18	.61	.22	.81	.53	.23	.72	.12	.15
Had joint pain past 4 wks.	8999	0.578	-0.065	0.108	0.032	-0.004	0.049	0.040	-0.107	0.202	0.075
		(0.494)	(0.076)	(0.078)	(0.076)	(0.090)	(0.112)	(0.077)	(0.099)	(0.115)	(0.077)
			.39	.17	.68	.96	.66	.60	.28	.08	.33
Had headaches past 4 wks.	8999	0.194	0.007	0.132	0.126	0.099	0.059	0.152	0.040	0.101	0.131
		(0.396)	(0.053)	(0.057)	(0.047)	(0.079)	(0.090)	(0.048)	(0.071)	(0.083)	(0.050)
			.90	.02	.008	.21	.51	.002	.57	.23	.009
Had menstrual cramps past 4 wks.	8999	0.038	0.021	-0.001	0.020	0.025	-0.009	0.017	0.022	0.010	0.031
		(0.190)	(0.023)	(0.029)	(0.021)	(0.030)	(0.036)	(0.021)	(0.036)	(0.043)	(0.021)
			.36	.97	.34	.41	.81	.41	.55	.81	.15
Had pain in no specific place past 4 wks.	8999	0.044	0.016	-0.022	-0.004	-0.015	0.008	-0.008	-0.073	0.071	-0.008
		(0.205)	(0.034)	(0.035)	(0.030)	(0.039)	(0.043)	(0.030)	(0.037)	(0.038)	(0.030)
			.65	.52	.89	.70	.86	.79	.05	.06	.78
Fainted past 4 wks.	9451	0.012	0.010	-0.004	0.007	0.021	-0.015	0.007	0.011	-0.006	0.005
		(0.110)	(0.016)	(0.014)	(0.012)	(0.020)	(0.025)	(0.012)	(0.021)	(0.021)	(0.011)
			.51	.80	.53	.30	.54	.56	.60	.76	.65
Felt dizzy past 4 wks.	9451	0.133	0.058	-0.012	0.047	0.032	0.036	0.064	-0.058	0.159	0.085
		(0.339)	(0.047)	(0.049)	(0.040)	(0.057)	(0.064)	(0.040)	(0.057)	(0.067)	(0.042)
			.22	.81	.23	.57	.58	.11	.30	.02	.04
Shortness of breath past 4 wks.	9451	0.049	0.036	0.011	0.045	0.038	0.004	0.042	-0.029	0.094	0.055
		(0.216)	(0.029)	(0.028)	(0.025)	(0.040)	(0.041)	(0.025)	(0.037)	(0.039)	(0.026)
			.22	.70	.07	.34	.93	.10	.43	.02	.03
Heart pounded past 4 wks.	9451	0.064	0.018	-0.023	-0.003	-0.025	0.027	-0.001	-0.060	0.076	0.009
		(0.245)	(0.034)	(0.043)	(0.035)	(0.046)	(0.052)	(0.036)	(0.053)	(0.057)	(0.037)
			.60	.59	.93	.59	.60	.99	.26	.18	.81
Mental and emotional health and cognitive function											
GHQ-12, Likert scoring	9510	9.329	0.385	0.165	0.533	-0.428	0.711	0.212	-2.151	3.292	0.812
		(6.728)	(0.895)	(1.270)	(1.061)	(1.219)	(1.480)	(1.072)	(1.144)	(1.467)	(1.101)
			.67	.90	.62	.73	.63	.84	.06	.03	.46
GHQ-12, binary scoring	9510	2.331	0.679	-0.258	0.447	-0.195	0.512	0.265	-0.828	1.573	0.588
		(3.297)	(0.467)	(0.714)	(0.557)	(0.633)	(0.771)	(0.562)	(0.603)	(0.844)	(0.589)
			.15	.72	.42	.76	.51	.64	.17	.06	.32
PSS-10 score	9510	17.785	0.036	0.128	0.151	0.127	-0.225	-0.076	-1.031	1.245	0.089
		(3.494)	(0.458)	(0.580)	(0.511)	(0.722)	(0.913)	(0.523)	(0.695)	(0.809)	(0.527)
			.94	.83	.77	.86	.81	.88	.14	.12	.87
Fertility											
Childbirth/stillbirth past 6 mos.	9493	0.046	0.020	0.002	0.022	-0.016	0.050	0.029	0.033	-0.013	0.021
		(0.210)	(0.031)	(0.032)	(0.020)	(0.038)	(0.041)	(0.020)	(0.034)	(0.040)	(0.021)
			.53	.95	.28	.67	.22	.16	.34	.75	.31

Table A.21 (cont'd): Effect of different premium & subsidy combinations on endline (3.5 yrs.) health outcomes (intent to treat estimate).

			Free insurance			Sale of insurance + transfer			Sale of insurance		
	N	Control mean (SD)	Direct Coefficient (SE) P-value	Spillover Coefficient (SE) P-value	Total Coefficient (SE) P-value	Direct Coefficient (SE) P-value	Spillover Coefficient (SE) P-value	Total Coefficient (SE) P-value	Direct Coefficient (SE) P-value	Spillover Coefficient (SE) P-value	Total Coefficient (SE) P-value
Childbirth/stillbirth past 3 yrs.	9510	0.192	0.032	-0.015	0.018	-0.095	0.120	0.013	0.069	-0.075	0.002
		(0.394)	(0.058)	(0.064)	(0.048)	(0.072)	(0.078)	(0.048)	(0.070)	(0.086)	(0.050)
			.58	.81	.70	.18	.12	.80	.33	.39	.97
Number of births in hhld. past 3 years	9510	0.315	0.124	-0.111	0.024	0.063	-0.094	-0.022	0.160	-0.161	0.016
		(0.920)	(0.133)	(0.237)	(0.139)	(0.159)	(0.235)	(0.136)	(0.162)	(0.273)	(0.152)
			.35	.64	.86	.69	.69	.87	.32	.56	.92
Number of live births in hhld. past 3 years	9510	0.205	0.049	-0.027	0.025	-0.153	0.197	0.024	0.060	-0.055	0.010
		(0.487)	(0.069)	(0.079)	(0.058)	(0.083)	(0.088)	(0.059)	(0.086)	(0.092)	(0.059)
			.48	.73	.67	.06	.03	.68	.48	.55	.86
Number of still births in hhld. past 3 years	9510	0.110	0.075	-0.084	-0.001	0.216	-0.291	-0.046	0.100	-0.106	0.005
		(0.777)	(0.102)	(0.210)	(0.127)	(0.140)	(0.223)	(0.127)	(0.133)	(0.237)	(0.140)
			.46	.69	.00	.12	.19	.72	.45	.66	.97
Delivery in hospital past 3 yrs	9510	0.141	-0.008	-0.034	-0.039	-0.078	0.042	-0.040	-0.027	-0.021	-0.046
		(0.349)	(0.052)	(0.049)	(0.045)	(0.065)	(0.067)	(0.045)	(0.062)	(0.066)	(0.046)
			.87	.49	.39	.23	.54	.37	.66	.75	.32
Delivery in facility past 3 yrs	9510	0.152	-0.008	-0.031	-0.036	-0.128	0.109	-0.029	-0.008	-0.047	-0.050
		(0.359)	(0.052)	(0.052)	(0.045)	(0.067)	(0.069)	(0.046)	(0.063)	(0.071)	(0.047)
			.88	.55	.43	.06	.11	.53	.90	.51	.28
Doctor assisted with birth past 3 yrs.	9510	0.156	-0.001	0.011	0.009	-0.101	0.125	0.011	0.012	-0.020	-0.007
		(0.363)	(0.052)	(0.053)	(0.042)	(0.067)	(0.069)	(0.043)	(0.055)	(0.067)	(0.044)
			.99	.84	.83	.13	.07	.79	.84	.76	.88
Doctor or nurse assisted with birth past 3 yrs.	9510	0.164	0.007	-0.003	0.005	-0.123	0.142	0.005	0.031	-0.048	-0.012
		(0.371)	(0.056)	(0.056)	(0.044)	(0.067)	(0.069)	(0.045)	(0.061)	(0.072)	(0.046)
			.90	.96	.91	.07	.04	.91	.61	.51	.79
Delivery complications past 3 yrs.	9510	0.039	-0.005	0.018	0.011	0.047	-0.047	0.005	-0.004	0.023	0.016
		(0.194)	(0.027)	(0.024)	(0.023)	(0.037)	(0.038)	(0.023)	(0.034)	(0.032)	(0.023)
			.86	.46	.64	.21	.21	.84	.90	.48	.50
Mortality											
Death in hhld. past 3 yrs	9482	0.121	0.010	0.043	0.049	-0.018	0.067	0.043	0.090	-0.068	0.029
		(0.327)	(0.049)	(0.046)	(0.029)	(0.051)	(0.057)	(0.031)	(0.062)	(0.067)	(0.030)
			.84	.34	.09	.72	.24	.17	.15	.31	.35
Deaths in the HH past 3 yrs	9474	0.125	0.022	0.049	0.066	0.004	0.063	0.060	0.111	-0.067	0.050
		(0.345)	(0.051)	(0.048)	(0.030)	(0.052)	(0.059)	(0.032)	(0.068)	(0.075)	(0.032)
			.67	.31	.03	.94	.28	.06	.10	.37	.12
Sickness-related death in hhld. past 3 yrs	9482	0.079	-0.009	0.049	0.035	-0.013	0.055	0.037	0.102	-0.097	0.014
		(0.270)	(0.042)	(0.036)	(0.025)	(0.043)	(0.046)	(0.026)	(0.052)	(0.055)	(0.026)
			.84	.18	.16	.77	.23	.16	.05	.08	.59
Number of sickness-related deaths in hhld.	9482	0.081	-0.005	0.053	0.042	-0.008	0.055	0.042	0.104	-0.090	0.023
		(0.281)	(0.044)	(0.038)	(0.026)	(0.044)	(0.046)	(0.027)	(0.055)	(0.059)	(0.027)
			.90	.16	.10	.86	.24	.12	.06	.13	.39

Table A.21 (cont'd): Effect of different premium & subsidy combinations on endline (3.5 yrs) health outcomes (intent to treat estimate).

			Free insurance			Sale of insurance + transfer			Sale of insurance		
	N	Control mean (SD)	Direct Coefficient (SE) P-value	Spillover Coefficient (SE) P-value	Total Coefficient (SE) P-value	Direct Coefficient (SE) P-value	Spillover Coefficient (SE) P-value	Total Coefficient (SE) P-value	Direct Coefficient (SE) P-value	Spillover Coefficient (SE) P-value	Total Coefficient (SE) P-value
FWER crit. values											
Health value			0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Chronic disease			0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003
Health-related quality of life, ADLs, and physical health symptoms			0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004
Mental and emotional health and cognitive function			0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017
Fertility			0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005
Mortality			0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013

Notes. Table presents (in all panels but the last one) estimates of intent-to-treat effects of access to insurance at different prices and subsidies on specific endline (3.5 yrs.) health outcomes. The outcomes are listed in the first column. The last panel provides critical p-values that control the false discovery rate for different groups of outcomes listed in the first column. Each observation in our regressions is a household. Treatment variables are household assignments: free insurance (A), sale of insurance + cash transfer (B), sale of insurance (C). Estimates are intent-to-treat effects; all models estimated with OLS. Each treatment arm was interacted with the share of the village allocated to A, B, or C (combined). The omitted category is the control group (D). Standard errors were clustered at the village level. The direct effect only includes the coefficient on treatment A, B, or C. The spillover effect is the estimated effect on a treated household of assigning all other sample households to at least some form of access to RSBY insurance. The total effect is constructed as the sum of the direct effect and 0.9*(spillover effect). Mean and standard deviation in the control group are statistics from group D without access to insurance. Abbreviations: SD, standard deviation; SE, standard error; mos, months; yr, year.

Table A.22: Effect of insurance enrollment on midline (18 mos.) health outcomes (complier average treatment effect estimates).

			Direct	Spillover	Total
		Control mean (SD)	Coefficient (SE) P-value	Coefficient (SE) P-value	Coefficient (SE) P-value
Health value					
Good health	18983	0.657	0.084	-0.165	-0.046
		(0.475)	(0.049)	(0.092)	(0.062)
			.09	.07	.46
Very good health	18983	0.155	0.100	-0.169	-0.034
		(0.362)	(0.048)	(0.080)	(0.060)
			.04	.04	.58
Poor or very poor health	18983	0.053	-0.013	-0.028	-0.035
		(0.225)	(0.029)	(0.036)	(0.031)
			.65	.44	.25
Very poor health	18983	0.008	0.003	-0.014	-0.008
		(0.088)	(0.010)	(0.013)	(0.006)
			.76	.28	.18
Chronic disease					
Told had hypertension	18939	0.189	-0.028	-0.029	-0.051
		(0.392)	(0.047)	(0.062)	(0.036)
			.56	.64	.16
Takes medication for hypertension	18960	0.130	-0.059	0.026	-0.039
		(0.336)	(0.037)	(0.052)	(0.032)
			.11	.61	.22
Told had diabetes	18913	0.069	-0.013	0.020	0.003
		(0.253)	(0.026)	(0.032)	(0.021)
			.62	.53	.90
Takes oral medication for diabetes	18948	0.051	-0.010	0.018	0.004
		(0.220)	(0.022)	(0.027)	(0.018)
			.64	.51	.83
Takes insulin for diabetes	18952	0.019	-0.003	0.026	0.017
		(0.135)	(0.012)	(0.014)	(0.010)
			.80	.06	.08
Is on a special diet for diabetes	18962	0.048	-0.010	0.023	0.008
		(0.214)	(0.020)	(0.025)	(0.018)
			.62	.35	.64
Told had cancer	18946	0.005	-0.007	0.013	0.003
		(0.071)	(0.006)	(0.008)	(0.004)
			.27	.12	.38
Received cancer treatment past 1 yr.	18998	0.003	0.002	-0.004	-0.001
		(0.051)	(0.005)	(0.005)	(0.003)
			.64	.49	.82
Told had lung disease	18907	0.035	-0.003	-0.008	-0.009
		(0.185)	(0.023)	(0.025)	(0.015)
			.91	.74	.54
Told had heart disease	18868	0.022	0.015	-0.003	0.013
		(0.147)	(0.016)	(0.020)	(0.010)
			.35	.88	.20
Told had stroke	18826	0.008	0.005	-0.002	0.003
		(0.091)	(0.010)	(0.012)	(0.006)
			.61	.85	.56
Told had arthritis	18894	0.177	-0.102	0.122	-0.006
		(0.381)	(0.048)	(0.082)	(0.055)
			.03	.14	.91

Notes. Table presents (in all panels but the last one) estimates of complier average treatment effects of enrollment in insurance at different prices and subsidies on specific midline (18 mos.) health outcomes. The outcomes are listed in the first column. The last panel provides critical p-values that control the false discovery rate for different groups of outcomes listed in the first column. Each observation in our regressions is a household. Treatment variables are enrollment in insurance, the share of sample households in the village that enrolled in insurance, and the interaction of these variables. Enrollment is instrumented with household assignments: free insurance (A), sale of insurance + cash transfer (B), sale of insurance (C). Share enrolled is instrumented with the share of study households assigned to arms (A)-(C) in the same village. The interaction is instrumented with the interaction of household assignment and share of households assigned to (A)-(C). Standard errors were clustered at the village level. The direct effect only includes the coefficient on enrollment. The spillover effect is the estimated effect on an enrolled household of enrolling all other sample households in RSBY insurance. The total effect is constructed as the sum of the direct effect and 0.787*(spillover effect), since 78.7% is the maximum share of households that enroll in insurance in any arm. Mean and standard deviation in the control group are statistics from group D without access to insurance. Abbreviations: SD, standard deviation; SE, standard error; mos, months; yr, year.

Table A.22 (cont'd): Effect of insurance enrollment on midline (18 mos.) health outcomes (complier average treatment effect estimates).

			Direct	Spillover	Total
		Control mean (SD)	Coefficient (SE) P-value	Coefficient (SE) P-value	Coefficient (SE) P-value
Had surgery for arthritis past 1 yr.	18933	0.020 (0.140)	-0.024 (0.015) .12	0.026 (0.020) .19	-0.004 (0.012) .76
Diagnose with high cholesterol	18871	0.022 (0.145)	0.013 (0.014) .34	-0.003 (0.022) .89	0.011 (0.014) .45
Takes medication for high cholesterol	19032	0.016 (0.124)	0.008 (0.015) .58	0.003 (0.018) .88	0.010 (0.011) .34
Health-related quality of life, ADLs, and physical health symptoms					
Experiences chest pain	18888	0.078 (0.268)	-0.023 (0.029) .42	0.005 (0.048) .91	-0.019 (0.034) .57
Fertility					
Currently pregnant	9262	0.058 (0.233)	0.036 (0.037) .33	-0.085 (0.065) .20	-0.030 (0.057) .60
Childbirth past 1 yr.	8299	0.040 (0.195)	0.010 (0.029) .74	-0.044 (0.050) .38	-0.025 (0.046) .59
Delivered in govt. hosp. past 1 yr.	8297	0.013 (0.115)	0.006 (0.016) .73	-0.010 (0.018) .56	-0.003 (0.011) .82
Delivered in facility past 1 yr.	8297	0.038 (0.191)	0.005 (0.028) .85	-0.035 (0.048) .47	-0.022 (0.046) .63
Doctor assisted with delivery past 1 yr.	8299	0.031 (0.174)	0.008 (0.026) .76	-0.040 (0.048) .41	-0.023 (0.044) .60
Doctor or nurse assisted with delivery past 1 yr.	8299	0.036 (0.187)	-0.004 (0.028) .88	-0.035 (0.049) .48	-0.032 (0.045) .48
Child delivery complications past 1 yr.	8293	0.011 (0.105)	-0.013 (0.016) .41	-0.020 (0.026) .44	-0.029 (0.020) .15
Ideal number of children	7881	2.479 (1.235)	-0.005 (0.207) .98	-0.060 (0.393) .88	-0.052 (0.291) .86
Biomarkers					
Overweight or obese	4853	0.282 (0.450)	0.014 (0.096) .89	0.031 (0.134) .82	0.038 (0.073) .60
Underweight	4853	0.088 (0.283)	-0.001 (0.050) .98	-0.042 (0.082) .61	-0.034 (0.043) .43
Abdominally obese	4723	0.700 (0.458)	-0.158 (0.134) .24	0.233 (0.180) .20	0.025 (0.126) .84
Mid-Upper Arm Circumference	4815	26.883 (3.507)	-2.363 (0.889) .008	1.363 (1.676) .42	-1.291 (0.995) .19
Hypertension, grade 1	4878	0.449 (0.498)	-0.113 (0.087) .19	0.067 (0.120) .58	-0.060 (0.078) .44
Hypertension, grade 2	4878	0.201 (0.401)	-0.075 (0.067) .26	0.090 (0.092) .33	-0.005 (0.075) .95
Skinfolds total	4065	26.851 (9.859)	-0.884 (2.627) .74	2.357 (5.267) .65	0.972 (3.504) .78
FWER crit. values					
Health value			0.013	0.013	0.013
Chronic disease			0.003	0.003	0.003
Health-related quality of life, ADLs, and physical health symptoms			0.05	0.05	0.05
Fertility			0.006	0.006	0.006

Notes. See Table A.22

Table A.23: Effect of insurance enrollment on endline (3.5 yrs.) health outcomes (complier average treatment effect estimates).

			Direct	Spillover	Total
		Control mean (SD)	Coefficient (SE) P-value	Coefficient (SE) P-value	Coefficient (SE) P-value
Health value					
Good health	9492	0.516 (0.500)	0.000 (0.080) .00	0.041 (0.106) .70	0.033 (0.068) .63
Very good health	9492	0.068 (0.252)	-0.023 (0.041) .57	-0.069 (0.052) .19	-0.078 (0.038) .04
Poor health	9492	0.104 (0.305)	-0.039 (0.051) .44	0.061 (0.056) .28	0.009 (0.038) .81
Very poor health	9492	0.019 (0.136)	-0.050 (0.025) .04	0.032 (0.024) .18	-0.025 (0.020) .21
Chronic disease					
Told had hypertension	9476	0.235 (0.424)	-0.074 (0.063) .24	0.089 (0.068) .19	-0.004 (0.046) .94
Takes medication for hypertension	9495	0.196 (0.397)	-0.066 (0.058) .26	0.086 (0.059) .15	0.002 (0.042) .97
Told had diabetes	9479	0.119 (0.324)	-0.077 (0.049) .11	0.063 (0.051) .22	-0.027 (0.034) .43
Takes oral medication for diabetes	9499	0.106 (0.308)	-0.071 (0.047) .13	0.067 (0.051) .18	-0.018 (0.031) .57
Takes insulin for diabetes	9489	0.027 (0.161)	0.020 (0.020) .33	-0.013 (0.022) .54	0.009 (0.013) .48
Follows a special diet for diabetes	9495	0.078 (0.268)	-0.044 (0.042) .29	0.053 (0.044) .23	-0.003 (0.029) .93
Told had cancer	9470	0.005 (0.068)	-0.001 (0.008) .93	0.008 (0.009) .36	0.006 (0.005) .29
Treated for cancer past 1 yr.	9496	0.002 (0.048)	-0.003 (0.006) .58	0.005 (0.006) .36	0.001 (0.003) .80
Told had lung disease	9479	0.055 (0.229)	-0.049 (0.031) .12	0.046 (0.036) .20	-0.012 (0.021) .55
Told had heart disease	9473	0.043 (0.202)	-0.028 (0.034) .41	0.017 (0.039) .67	-0.015 (0.021) .47
Told had stroke	9446	0.006 (0.077)	-0.012 (0.013) .34	0.010 (0.012) .40	-0.004 (0.007) .54
Told had arthritis or rheumatism	9482	0.199 (0.399)	-0.052 (0.064) .42	0.116 (0.086) .17	0.040 (0.054) .46
Had surgery due to arthritis past 1 yr.	9497	0.042 (0.201)	0.019 (0.029) .50	0.003 (0.035) .93	0.022 (0.022) .32

Notes. Table presents (in all panels but the last one) estimates of complier average treatment effects of enrollment in insurance at different prices and subsidies on specific mendline (3.5 yrs.) health outcomes. The outcomes are listed in the first column. The last panel provides critical p-values that control the false discovery rate for different groups of outcomes listed in the first column. Each observation in our regressions is a household. Treatment variables are enrollment in insurance, the share of sample households in the village that enrolled in insurance, and the interaction of these variables. Enrollment is instrumented with household assignments: free insurance (A), sale of insurance + cash transfer (B), sale of insurance (C). Share enrolled is instrumented with the share of study households assigned to arms (A)-(C) in the same village. The interaction is instrumented with the interaction of household assignment and share of households assigned to (A)-(C). Standard errors were clustered at the village level. The direct effect only includes the coefficient on enrollment. The spillover effect is the estimated effect on an enrolled household of enrolling all other sample households in RSBY insurance. The total effect is constructed as the sum of the direct effect and 0.787*(spillover effect), since 78.7% is the maximum share of households that enroll in insurance in any arm. Mean and standard deviation in the control group are statistics from group D without access to insurance. Abbreviations: SD, standard deviation; SE, standard error; mos, months; yr, year.

Table A.23 (cont'd): Effect of insurance enrollment on endline (3.5 yrs.) health outcomes (complier average treatment effect estimates).

			Direct	Spillover	Total
		Control mean (SD)	Coefficient (SE) P-value	Coefficient (SE) P-value	Coefficient (SE) P-value
Diagnosed with high cholesterol	9449	0.022	0.004	-0.007	-0.002
		(0.147)	(0.022)	(0.023)	(0.014)
			.87	.77	.90
Takes medication to lower cholesterol	9496	0.010	-0.014	0.006	-0.009
		(0.097)	(0.015)	(0.012)	(0.009)
			.37	.62	.31
Has eyesight problems	9480	0.324	0.011	0.115	0.101
		(0.468)	(0.075)	(0.082)	(0.055)
			.89	.16	.07
Had surgery due to eye problems past 1 yr.	9497	0.080	-0.012	0.065	0.039
		(0.272)	(0.045)	(0.051)	(0.033)
			.78	.20	.23
Health-related quality of life, ADLs, and physical health symptoms					
Number of functional limitations	9413	0.681	-0.241	0.266	-0.032
		(1.528)	(0.207)	(0.268)	(0.203)
			.24	.32	.88
SF-8, PCS	9510	2.250	-0.068	0.291	0.161
		(0.899)	(0.171)	(0.186)	(0.124)
			.69	.12	.19
SF-8, MCS	9510	1.508	-0.027	0.079	0.035
		(0.789)	(0.121)	(0.153)	(0.116)
			.82	.61	.76
Had stomach pain past 4 wks.	8999	0.071	0.052	-0.028	0.031
		(0.256)	(0.038)	(0.051)	(0.024)
			.16	.59	.21
Had back pain past 4 wks.	8999	0.264	0.074	0.047	0.111
		(0.441)	(0.064)	(0.090)	(0.063)
			.25	.61	.08
Had chest pain past 4 wks.	8999	0.075	0.038	-0.009	0.032
		(0.264)	(0.043)	(0.046)	(0.026)
			.37	.85	.22
Had joint pain past 4 wks.	8999	0.586	-0.031	0.095	0.044
		(0.493)	(0.077)	(0.098)	(0.070)
			.68	.33	.53
Had headaches past 4 wks.	8999	0.202	0.056	0.065	0.108
		(0.401)	(0.060)	(0.076)	(0.044)
			.34	.39	.01
Had menstrual cramps past 4 wks.	8999	0.044	0.035	-0.030	0.011
		(0.206)	(0.024)	(0.033)	(0.020)
			.14	.36	.58
Had pain in no specific place past 4 wks.	8999	0.041	-0.006	0.019	0.009
		(0.198)	(0.035)	(0.039)	(0.025)
			.86	.63	.73
Fainted past 4 wks.	9451	0.012	0.014	-0.012	0.004
		(0.108)	(0.016)	(0.018)	(0.010)
			.38	.49	.67
Felt dizzy past 4 wks.	9451	0.132	0.082	-0.048	0.044
		(0.338)	(0.047)	(0.057)	(0.036)
			.08	.40	.22
Shortness of breath past 4 wks.	9451	0.056	0.035	0.011	0.044
		(0.230)	(0.032)	(0.034)	(0.022)
			.28	.74	.05
Heart pounded past 4 wks.	9451	0.071	0.011	-0.003	0.009
		(0.256)	(0.035)	(0.045)	(0.031)
			.75	.95	.77
Mental and emotional health and cognitive function					
GHQ-12, Likert scoring	9510	9.259	0.091	0.863	0.771
		(6.821)	(0.926)	(1.348)	(0.990)
			.92	.52	.44
GHQ-12, binary scoring	9510	2.451	0.424	0.065	0.476
		(3.323)	(0.482)	(0.739)	(0.524)
			.38	.93	.36
PSS-10 score	9510	17.842	-0.162	0.648	0.348
		(3.502)	(0.515)	(0.751)	(0.481)
			.75	.39	.47

Notes. See Table A.23

Table A.23 (cont'd): Effect of insurance enrollment on endline (3.5 yrs.) health outcomes (complier average treatment effect estimates).

			Direct	Spillover	Total
		Control mean (SD)	Coefficient (SE) P-value	Coefficient (SE) P-value	Coefficient (SE) P-value
Fertility					
Childbirth/stillbirth past 6 mos.	9493	0.045 (0.207)	0.009 (0.029) .74	0.010 (0.034) .78	0.017 (0.018) .35
Childbirth/stillbirth past 3 yrs.	9510	0.187 (0.390)	-0.005 (0.059) .93	0.003 (0.073) .96	-0.002 (0.045) .96
Number of births in hhld. past 3 years	9510	0.310 (0.927)	0.097 (0.133) .46	-0.199 (0.273) .47	-0.059 (0.148) .69
Number of live births in hhld. past 3 years	9510	0.202 (0.491)	-0.006 (0.067) .93	0.020 (0.079) .80	0.010 (0.051) .84
Number of still births in hhld. past 3 years	9510	0.109 (0.778)	0.103 (0.105) .33	-0.219 (0.242) .37	-0.069 (0.136) .61
Delivery in hospital past 3 yrs	9510	0.136 (0.343)	-0.039 (0.054) .46	-0.007 (0.055) .90	-0.045 (0.039) .25
Delivery in facility past 3 yrs	9510	0.149 (0.356)	-0.054 (0.053) .31	0.026 (0.055) .63	-0.033 (0.040) .40
Doctor assisted with birth past 3 yrs.	9510	0.152 (0.359)	-0.038 (0.052) .47	0.049 (0.058) .39	0.001 (0.037) .98
Doctor or nurse assisted with birth past 3 yrs.	9510	0.161 (0.368)	-0.036 (0.054) .51	0.043 (0.059) .47	-0.003 (0.039) .95
Delivery complications past 3 yrs.	9510	0.038 (0.192)	0.011 (0.029) .71	-0.015 (0.030) .62	-0.001 (0.019) .96
Mortality					
Death in hhld. past 3 yrs	9482	0.127 (0.333)	-0.005 (0.047) .92	0.029 (0.053) .58	0.018 (0.026) .49
Deaths in the HH past 3 yrs	9474	0.133 (0.362)	0.018 (0.050) .72	0.016 (0.057) .78	0.031 (0.028) .26
Sickness-related death in hhld. past 3 yrs	9482	0.080 (0.271)	-0.018 (0.041) .66	0.040 (0.044) .37	0.013 (0.022) .54
Number of sickness-related deaths in hhld.	9482	0.084 (0.290)	-0.012 (0.043) .77	0.040 (0.046) .38	0.019 (0.022) .39
FWER crit. values					
Health value			0.01	0.01	0.01
Chronic disease			0.003	0.003	0.003
Health-related quality of life, ADLs, and physical health symptoms			0.004	0.004	0.004
Mental and emotional health and cognitive function			0.017	0.017	0.017
Fertility			0.005	0.005	0.005
Mortality			0.013	0.013	0.013

Notes. See Table A.23

Table A.24: Number of significant health outcomes per category, without multiple testing adjustments.

	18 months (midline)				3.5 years (endline)			
	ITT			CATE	ITT			CATE
	(A) Free insurance	(B) Sale of insurance + transfer	(C) Sale of insurance	Enrollment	(A) Free insurance	(B) Sale of insurance + transfer	(C) Sale of insurance	Enrollment
Self-reported health								
Total outcomes	2	2	2	2	3	3	3	3
Significant direct effect	0	0	0	1	0	1	0	1
Significant spillover effect	0	0	0	1	1	0	0	0
Significant total	0	0	0	0	0	0	1	1
Chronic disease								
Total outcomes	15	15	15	15	17	17	17	17
Significant direct effect	1	2	2	1	0	3	4	0
Significant spillover effect	1	1	1	0	2	0	1	0
Significant total	0	1	0	1	0	1	0	1
Quality of life								
Total outcomes	1	1	1	1	14	14	14	14
Significant direct effect	0	0	0	0	0	0	0	0
Significant spillover effect	0	0	0	0	1	0	5	0
Significant total	0	0	0	0	1	1	4	2
Mental and behavioral health								
Total outcomes	0	0	0	0	3	3	3	3
Significant direct effect					0	0	0	0
Significant spillover effect					0	0	1	0
Significant total					0	0	0	0
Childbirth								
Total outcomes	8	8	8	8	10	10	10	10
Significant direct effect	0	0	0	0	0	0	0	0
Significant spillover effect	0	0	0	0	0	2	0	0
Significant total	0	0	0	0	0	0	0	0
Biomarkers								
Total outcomes	7	7	7	7	0	0	0	0
Significant direct effect	1	1	0	1				
Significant spillover effect	1	0	0	0				
Significant total	0	0	0	0				
Mortality								
Total outcomes	0	0	0	0	4	4	4	4
Significant direct effect					0	0	0	0
Significant spillover effect					0	0	0	0
Significant total					1	0	0	0

Notes. Treatment variables in intent-to-treat (ITT) analysis are household assignments: free insurance (A), sale of insurance + cash transfer (B), sale of insurance (C). Treatment variables in complier averate treatment effect (CATE) analyses are enrollment in insurance; enrollment is instrumented with assignment to groups A, B or C. All models estimated with OLS. Each treatment arm was interacted with the share of the village allocated to A, B, or C (combined) to estimate spillover effects in ITT analysis. Each treatment arm was interacted with the share of the village enrolled to estimate spillover effects in CATE analysis; the instrument for the share enrolled is the fraction allocated to groups A, B, or C. Standard errors were clustered at the village level. Significant health outcomes are identified using traditional critical p-value at the 5% significance level without making any multiple testing adjustments.

E.2.4 Expenditures

Table A.25: Effects of premium and subsidy combinations (ITT) on medical spending

		Control	(A) Free insurance			(B) Sale of insurance + transfer			(C) Sale of insurance		
	N	Mean (SD)	Direct Coefficient (SE) *p*-value	Spillover Coefficient (SE) *p*-value	Total Coefficient (SE) *p*-value	Direct Coefficient (SE) *p*-value	Spillover Coefficient (SE) *p*-value	Total Coefficient (SE) *p*-value	Direct Coefficient (SE) *p*-value	Spillover Coefficient (SE) *p*-value	Total Coefficient (SE) *p*-value
Spending at 18 months											
Annual medical spending (INR, thous.)	10030	28.777	13.621	-10.050	5.557	6.980	-4.069	3.715	10.526	-6.242	5.518
		(31.206)	(5.891)	(8.509)	(4.215)	(6.325)	(8.612)	(4.232)	(6.093)	(7.872)	(4.154)
			0.021	0.238	0.188	0.270	0.637	0.380	0.085	0.428	0.185
Log annual medical spending	10030	9.594	0.390	-0.681	-0.156	0.793	-1.266	-0.223	0.624	-0.915	-0.110
		(1.912)	(0.241)	(0.403)	(0.356)	(0.424)	(0.533)	(0.369)	(0.356)	(0.439)	(0.362)
			0.106	0.091	0.661	0.062	0.018	0.547	0.080	0.038	0.762
Annual medical non-hospital spending (INR, thous.)	10030	23.981	7.260	-5.553	2.804	3.161	-1.758	1.751	5.431	-3.413	2.692
		(24.866)	(4.486)	(7.034)	(3.839)	(5.471)	(7.562)	(3.833)	(5.025)	(6.824)	(3.778)
			0.106	0.430	0.465	0.564	0.816	0.648	0.280	0.617	0.476
Spending at 3.5 years											
Log annual medical non-hospital spending	10030	9.374	0.228	-0.618	-0.268	0.625	-1.212	-0.347	0.550	-0.994	-0.248
		(2.036)	(0.256)	(0.412)	(0.365)	(0.427)	(0.566)	(0.380)	(0.359)	(0.513)	(0.373)
			0.373	0.134	0.463	0.144	0.033	0.362	0.126	0.054	0.508
OOP medical spending (most serious event, INR, thous.)	9396	21.470	-1.120	-5.093	-5.207	30.035	-41.002	-2.865	2.169	-11.668	-7.194
		(144.220)	(18.940)	(11.620)	(15.837)	(36.761)	(39.959)	(15.857)	(20.799)	(15.004)	(15.966)
			0.953	0.661	0.742	0.414	0.305	0.857	0.917	0.437	0.653
Log OOP medical spending (most serious event)	4821	2.343	-0.081	-0.295	-0.318	-0.258	-0.064	-0.309	-0.155	-0.221	-0.332
		(1.615)	(0.384)	(0.385)	(0.266)	(0.464)	(0.528)	(0.266)	(0.512)	(0.542)	(0.275)
			0.833	0.444	0.233	0.578	0.903	0.245	0.762	0.684	0.228

Notes. Table presents estimates of intent-to-treat effects of access to insurance at different prices and subsidies on medical spending. Each observation is a household and has equal weight. Treatment variables are household assignments: free insurance (A), sale of insurance + cash transfer (B), sale of insurance (C). Estimates are intent-to-treat effects; all models estimated with OLS. Each treatment arm was interacted with the share of the village allocated to A, B, or C (combined). Standard errors were clustered at the village level. Coefficients were transformed to show percentage point changes from the control group D. The direct effect only includes the coefficient on treatment A, B, or C. The spillover effect is the estimated effect on a treated household of assigning all other sample households to at least some form of access to RSBY insurance. The total effect is constructed as the sum of the direct effect and 0.8024*(spillover effect), where 0.8024 is the average fraction of households given insurance access in the study. Mean and standard deviation in the control group are statistics from the group without access to insurance. The FWER adjusted 5% critical values are: 0.001 for spending at 18 mos; 0.003 for spending at 3.5 yrs.

Table A.26: Effects of enrollment (CATE) on medical spending

		Control	Direct effect	Spillover effect	Total effect
	N	Mean (SD)	Coefficient (SE) *p*-value	Coefficient (SE) *p*-value	Coefficient (SE) *p*-value
			Utilization at 18 months		
Annual medical spending (INR, thous.)	10030	28.777	12.849	-15.670	0.275
		(31.206)	(5.148)	(9.681)	(5.159)
			(0.013)	(0.106)	(0.957)
Log annual medical spending	10030	9.594	0.586	-1.336	-0.487
		(1.912)	(0.309)	(0.483)	(0.374)
			(0.058)	(0.006)	(0.193)
Annual medical non-hospital spending (INR, thous.)	10030	23.981	5.794	-7.181	0.032
		(24.866)	(4.200)	(8.399)	(4.683)
			(0.168)	(0.393)	(0.995)
			Utilization at 3.5 years		
Log annual medical non-hospital spending	10030	9.374	0.347	-1.093	-0.530
		(2.036)	(0.321)	(0.503)	(0.389)
			(0.280)	(0.030)	(0.174)
OOP medical spending (most serious event, INR, thous.)	9396	21.470	6.671	-16.583	-6.635
		(144.220)	(22.179)	(20.512)	(12.495)
			(0.764)	(0.419)	(0.595)
Log OOP medical spending (most serious event)	4821	2.343	-0.223	-0.141	-0.336
		(1.615)	(0.381)	(0.463)	(0.247)
			(0.558)	(0.761)	(0.174)

Notes. Table presents complier average treatment estimates of the effect of enrollment in RSBY insurance on medical spending. Each observation is a household and has equal weight. Coefficients were transformed to show percentage point changes from the control group. Mean and standard deviation in the control group are statistics from the unenrolled group. The direct effect is the estimated effect of enrolling one household, assuming no other sample households in the village are enrolled. The spillover effect is the estimated effect on an enrolled household of enrolling all other sample households in the village. Total effects are the sum of direct and (spillover effects)*(uptake into free insurance). The total effect of free insurance on uptake is estimated as 0.7183, the mean uptake into insurance in arms A-C. The FWER adjusted 5% critical values are: 0.004 for spending at 18 mos; 0.009 for spending at 3.5 yrs.

E.2.5 Adverse selection

Table A.27: Estimates of demand and average cost using multiple different measures of cost.

	(1) Predicted	(2) Midline	(3) Mixed	(4) Endline	(5) ML attempt	(6) Mix attempt	(7) EL attempt
Price	0.3024	0.0219	0.6208	0.5095	0.1228	0.6260	0.6577
	(0.597)	(0.961)	(0.809)	(0.592)	(1.217)	(1.066)	(1.064)
Constant	754.9922	625.4481	455.1337	195.5689	1018.1084	779.6266	662.2843
	(60.463)	(97.754)	(81.974)	(60.045)	(123.958)	(108.652)	(107.910)
Observations	5008	4709	4988	4446	4685	4668	4447
AC curve:							
Constant	1332.916	667.235	1641.703	1169.459	1252.814	1976.070	1919.300
Quantity	-735.525	-53.182	-1510.150	-1239.472	-298.711	-1522.718	-1599.807
Welfare							
Demand LB: Group C (p)							
Free ins.	-1347.255	-1055.780	-672.573	-88.552	-1939.266	-1402.682	-1138.662
	0.000	0.000	0.001	0.504	0.000	0.000	0.000
Opt. price	981.233	661.854	1303.684	424.839	1009.435	2404.939	2458.271
	0.280	0.079	0.826	0.007	0.368	0.879	0.898
SOC	-0.475	-0.756	-0.157	-0.268	-0.655	-0.152	-0.120
	0.504	0.437	0.874	0.689	0.571	0.897	0.914
Demand UB: Group B (p)							
Free ins.	-743.078	-451.604	-68.397	515.624	-1335.090	-798.506	-534.486
	0.004	0.151	0.792	0.014	0.001	0.016	0.077
Opt. price	1302.995	1088.416	1052.488	528.483	1408.625	2124.629	1944.579
	0.008	0.000	0.084	0.639	0.068	0.812	0.827
SOC	-0.475	-0.756	-0.157	-0.268	-0.655	-0.152	-0.120
	0.504	0.437	0.874	0.689	0.571	0.897	0.914

Note. Top panel presents regressions of average cost (measured 7 ways, corresponding to column headings) on price. Each cell provides coefficient estimate and standard error in parentheses. Units of price and cost are INR. The 7 measures of cost are:

1. Predicted midline medical expenditures (same as outcome in Table 6) × midline successful use over 6 months × 2
2. Midline medical expend. × hospital share of endline medical expend. × midline successful use over 6 months × 2
3. Hospital expend. at endline × midline successful use over 6 months × 2 (same as column 1 in Table A.30)
4. Hospital expend. at endline × endline successful use over 6 months × 2 (same as column 2 in Table A.30)
5. Midline medical expend. × hospital share of endline medical expend. × midline attempted (successful or failed) use over 6 months × 2
6. Hospital expend. at endline × midline attempted use over 6 months × 2 (same as column 3 in Table A.30)
7. Hospital expend. at endline × endline attempted use over 6 months × 2 (same as column 4 in Table A.30)

Second panel presents estimates of a linear average cost curve: AC = Constant - β Quantity, where Constant and β are derived from estimates from top panel. Each cell provides a coefficient estimate. Third panel presents welfare calculations associated with a lower bound estimate of the Hicksian demand curve and each measure of cost. Calculations include the net welfare benefit of free insurance, the price of insurance that satisfies the first-order condition (FOC) for optimal premium, and the value of the second-order condition (SOC). If the SOC is negative, then the price that satisfied the FOC is the welfare-maximizing price. Units are INR. Demand is estimated using data on households in the free-insurance arm (A) and the sale-of-insurance arm (C) only. The demand curve is assumed to be linear. This demand curve is a Marshallian demand because arm C is not compensated; if there are income effects, this is a lower-bound on Hicksian demand. Fourth panel provides same calculations as the thurd panel, except that it employs an estimate of an upper bound on the demand curve. Specifically, demand is estimated using data on arm A and the sale-plus-transfer arm (B). The demand curve is assumed to be linear. This demand curve shows demand that is greater than the Hicksian demand curve. The Hicksian demand curve would compensate those household who purchase insurance; however, this demand curve compensates all households, even those who do not purchase insurance. Those non-complier households experience a raw income effect.

Table A.28: Sample size per insurance access group and response rates by survey and insurance access group.

	Insurance access group						
	(A) Free-insurance	(B) Sale-plus-transfer	(C) Sale-of-insurance	(D) No access (control)	Total	Non-response	Attrition
			Initial sample				
Main surveys	4,401	2,180	2,146	2,152	10,879		
Biomarker surveys	1,363	718	737	833	3,651		
			Baseline survey				
Main survey	4,155	2,080	2,022	2,033	10,290	558	31
	(94%)	(95%)	(94%)	(94%)	(95%)	(5%)	(0.2%)
Biomarker survey	1145	588	615	692	3040	611	
	(84%)	(82%)	(83%)	(83%)	(83%)	(17%)	
			Midline (18 mos.) survey				
Main survey	4,091	2,036	2,007	1,977	10,111	439	329
	(93%)	(93%)	(94%)	(92%)	(93%)	(4%)	(3%)
Biomarker survey	1043	546	555	628	2772	879	
	(77%)	(76%)	(75%)	(75%)	(76%)	(24%)	
			Endline (3.5 yr.) survey				
Main survey	3,879	1,902	1,855	1,874	9,510	1,369	
	(88%)	(87%)	(86%)	(87%)	(87%)	(13%)	

Note. Table presents number of households in initial sample (top panel) and the number of households that respond to each survey (remaining panels), by insurance access arm (columns 1-4) and in total across arms (column 5). Column 6 provides the number of households that do not respond to a survey. Column 7 presents numbner of households that attrited out of the study at each survey. Abbreviations: mos., months; yr., year. Cells in top panel report the number of households. Cells in remaining panels report the number of households and (in parentheses) the percent of initial sample in an arm or in total sample that respond to a given survey. Percentages for non-response are number of households that do not respond to a survey devided by the total sample for that survey (from top panel), times 100.

Table A.29: Respondent and response rate by module and insurance access group.

	Insurance (access) group				
	(A) Free-Insurance	(B) Sale-plus-Insurance	(C) Sale-of-Insurance	(D) No access (control)	Total
Initial sample					
Main survey	4,401	2,180	2,146	2,152	10,879
Biomarker survey	1,363	718	737	833	3,651
Module & Respondent					
Baseline survey					
1. Most knowledgeable female.	4,063 (92%)	2,033 (93%)	1,980 (92%)	1,979 (92%)	10,055 (92%)
2. Most knowledgeable female. If none present, most knowledgeable male.	4,125 (94%)	2,070 (95%)	2,007 (94%)	2,010 (93%)	10,212 (94%)
3. Most knowledgeable male. If none present, most knowledgeable female.	3,831 (87%)	1,955 (90%)	1,873 (87%)	1,892 (88%)	9,551 (88%)
4. Female respondent.	1114 (82%)	566 (79%)	603 (82%)	656 (79%)	2939 (80%)
5. Male respondent.	1053 (77%)	545 (76%)	565 (77%)	634 (76%)	2797 (77%)
Midline (18 months) survey					
1. Baseline respondent. Otherwise, most knowledgeable male.	3,972 (90%)	1,977 (91%)	1,930 (90%)	1,922 (89%)	9,801 (90%)
2. Baseline respondent.	4,091 (93%)	2,034 (93%)	2,006 (93%)	1,977 (92%)	10,108 (93%)
3. Baseline respondent.	3,887 (88%)	1,913 (88%)	1,913 (89%)	1,868 (87%)	9,581 (88%)
4. Baseline respondent. Otherwise, male respondent.	970 (71%)	514 (72%)	525 (71%)	574 (69%)	2583 (71%)
5. Baseline respondent. Otherwise, female respondent.	928 (68%)	483 (67%)	473 (64%)	526 (63%)	2410 (66%)

Note. Different modules of the baseline and midline surveys are directed towards different household members. This table presents number of households in initial sample (top panel) and the respondent to whom each module is directed (remaining panels). Columns 2-7 present number of households where respondent answered the survey module (in parentheses) the implied response rate, for each of the 4 study arms and overall. Respondent and response rates are reported for baseline and midline surveys only since the endline survey was administered to a single respondent. Module 1 measures intra-household allocation, fertility and family planning, maternal and newborn health, child care and development, child health and investment, adult health behavior, adult health, cognitive survey, expectations (midline only). Module 2 measures household composition, household characteristics, household income, household expenditures, household indebtedness, savings, demonetization (midline only). Module 3 measures cognitive task, trust, cognitive survey, adult health behavior, adult health, risk unincentivized, expectations (midline only). Module 4 measures female biomarkers, child biomarkers. Module 5 measures male biomarkers.

Table A.30: Welfare calculations using four different measures of cost.

	(1) Midline use	(2) Endline use	(3) Midline attempt	(4) Endline attempt
Ex post demand and no insurance counterfactual (p)				
Free ins. value	-68.397	515.624	-798.506	-534.486
Opt. price	1052.488	528.483	2124.629	1944.579
SOC	-0.157	-0.268	-0.152	-0.120
Ex post demand and private insurance counterfactual (p)				
Private ins. value	1150.894	912.341	1488.042	1361.131
Free ins. value	-1219.290	-396.718	-2286.548	-1895.617
Ex ante demand and no insurance counterfactual (p)				
Free ins. value	1888.483	2472.504	1158.374	1422.394
Opt. price	238.883	864.175	1216.728	280.769
Observations	4988	4446	4668	4447

Note. Table presents welfare calculations associated with demand based on (1) uptake in groups A and B and (2) four different measures of cost. Welfare calculations in the first panel focus on ex post demand and assume no insurance in the absence of public insurance. This panel presents the net welfare benefit of free insurance, the price of insurance that satisfies the first-order condition (FOC) for optimal premium, and the value of the second-order condition (SOC). If the SOC is negative, then the price that satisfied the FOC is the welfare-maximizing price. Welfare calculations in the second panel focus on ex post demand and assume private insurance is the alternative to public insurance. The panel presents social surplus under private insurance and the net gain from public insurance (assuming public insurance prevents private insurance). The third panel focuses on ex ante demand (Hendren 2021) and assumes no insurance absent public insurance. It presents the net welfare benefit of free insurance and the price of insurance that satisfies the first-order condition (FOC) for optimal premium. The four measures of cost are: (1) ML use = endline hospital use * midline successful use for most serious event over 6 months * 2; (2) EL use = endline hospital use * endline successful use for most serious event over 6 months * 2; (3) ML attempt = endline hospital use * midline (successful or failed) use for most serious event over 6 months * 2; (2) EL use = endline hospital use * endline (successful or failed) use for most serious event over 6 months * 2.