Adverse Selection in Subsidized Health Insurance: Evidence from Nepal's Age-70 Threshold

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I study adverse selection in Nepal's National Health Insurance Program using a regression discontinuity design around the age-70 threshold, where premiums are waived and coverage switches from household to individual. Claims per enrollee drop sharply: the probability of any claim falls by 12.2 percentage points, total claimed amounts decline by NPR 1,604 (31%), and the number of claims decreases by 0.86 (33%). An expected cost index constructed from exogenous enrollment-time characteristics drops discontinuously at the threshold, confirming that the composition of enrollees shifts toward healthier individuals. A pre-policy placebo and an event study validate that the pattern is policy-induced. Welfare analysis yields a marginal value of public funds of 0.60 for new enrollees drawn in by the subsidy, with the subsidy correcting underinsurance for small households but generating overinsurance for large ones. These findings demonstrate that adverse selection persists despite household-level bundling and enrollment timing restrictions.

Keywords: Health Insurance, Adverse Selection, Regression Discontinuity, Expected Cost Index, Nepal

JEL-Classification: I13, I18, D82, O15

1 — Introduction

Nepal made health insurance free for citizens over 70—and their claims fell. Using administrative data on 40 million claims from Nepal's National Health Insurance Program (NHIP) and a regression discontinuity design, I find that claims per enrollee drop sharply at the eligibility threshold. Because the data condition on enrollment, this discontinuity reflects a change in the *composition* of the insured pool—not a change in behavior. When insurance requires payment, individuals with higher expected healthcare needs are more likely to enroll (Akerlof 1970; Arrow 1963; Rothschild and Stiglitz 1976); when it becomes free, healthier individuals join, diluting the risk pool.

This finding matters because researchers have proposed specific institutional safeguards to prevent adverse selection in voluntary health insurance: bundling enrollment at the household level and restricting enrollment windows and payment terms (Fischer, Frölich, and Landmann 2023; Banerjee et al. 2021). Nepal's NHIP implements both—premiums are paid per household for the whole year and enrollment is limited to four quarterly start dates per year. Yet adverse selection persists. The core problem is not selection *within* an enrollment period, but selection *across* a predictable eligibility threshold. When individuals can anticipate becoming eligible for free coverage, they time their enrollment accordingly, and standard design fixes do not eliminate this margin. Evidence on adverse selection in developing-country health insurance remains limited and mixed (Asuming, Kim, and Sim 2024; Levine, Polimeni, and Ramage 2016; Thornton et al. 2010; Wagstaff et al. 2016), making this a setting where credible identification is especially valuable.

I exploit the sharp change in insurance terms at age 70 in a regression discontinuity framework. Since 2019, NHIP waives the annual premium (NPR 3,500, approximately USD 26) and provides individual coverage of NPR 100,000 (USD 750) for citizens aged 70 and above. This creates a discrete jump in price at a known threshold, which individuals on either side cannot manipulate. I validate the design using population census data, confirming no discontinuities on important demographic characteristics for the eligible population. To isolate selection from moral hazard, I construct an expected cost index from strictly exogenous enrollment-time characteristics—demographics, geography, and registration type—trained on individuals aged 50–60, well below the policy threshold. Because the index excludes age and any claims history, it is well-defined for both new and renewed enrollees.

The expected cost index drops discontinuously at age 70, confirming that the composition of enrollees shifts toward healthier individuals when insurance becomes free. A placebo test applying the same model to pre-policy enrollees (before April 2019) finds no discontinuity, and an event study shows the effect appears only after the policy was introduced. These results establish that the selection pattern is policy-induced rather than an artifact of the age distribution.

I use the setting to partially discriminate among competing mechanisms. The net decline in claims indicates that selection effects dominate moral hazard. However, the household premium structure creates variation in the implicit per-person price reduction at age 70—from NPR 3,500 for single-person households to NPR 700 for five-member households—which reveals that moral hazard is also present: individuals facing larger price reductions show higher utilization. The utilization decline is nearly identical for renewed enrollees and new entrants, ruling out advantageous selection as the primary channel.

I quantify the welfare consequences using the sufficient statistics framework of Einav, Finkelstein, and Cullen (2010). The marginal cost of enrollees drawn in by the subsidy is NPR 821—far below the average predicted cost of existing enrollees—confirming that the marginal entrants are substantially healthier. The marginal value of public funds for new enrollees (MVPF) is 0.60: each rupee of fiscal cost delivers only 60 paisa of value to marginal enrollees. Illustrative welfare calculations suggest that the effect varies with household size: for single-person households facing NPR 3,500 per person, the subsidy corrects genuine underinsurance, while for larger households already paying NPR 700 or less per person, it generates overinsurance. A more targeted intervention—reducing premiums for small households below age 70—could capture the welfare gains while avoiding the overinsurance losses that dominate the current blanket policy.

The remainder of the paper is organized as follows. Section 2 describes Nepal's health insurance system and data. Section 3 presents the conceptual framework, empirical strategy, and welfare model. Section 4 details the regression discontinuity design and validates it with covariate balance tests. Section 5 presents the main results, the adverse selection mechanism, and the welfare analysis. Section 6 provides robustness checks including enrollment gap analysis and an event study. Section 7 concludes.

2 — Setting and Data

2.1. Country Context

Nepal is a lower-middle-income country with a population of 29.2 million (National Statistics Office 2021). Gross national income per capita reached USD 1,380 in 2022, and 17 percent of the population are classified as multidimensionally poor (World Bank 2025a; GoN 2021). The healthcare system combines public and private providers organized into three tiers: primary health care centers, district hospitals, and tertiary care hospitals. Out-of-pocket expenditure accounts for more than half of total health spending, at USD 213 per capita in 2022 (WHO 2022). Life expectancy at birth is 70 years, slightly above the lower-middle-income country average of 69 (World Bank 2025b). Reducing financial exposure to health shocks is therefore a central policy priority, motivating the establishment of the National Health Insurance Program.

2.2. The National Health Insurance Program

The National Health Insurance Program (NHIP) is a voluntary, contributory public health insurance program launched by the government of Nepal in 2016 with the objective of reducing out-of-pocket health expenditure and achieving universal health coverage (Ayer et al. 2024). The Health Insurance Board (HIB) was established in 2017 to implement the program nationwide. NHIP was initially piloted in three districts and gradually expanded to all 77 districts by 2022, covering approximately 33 percent of households by the end of 2022.

NHIP operates at the household level. A family of up to five members pays an annual premium of NPR 3,500 (USD 26), with each additional member beyond five costing NPR 700 (USD 5). In return, the household receives coverage of up to NPR 100,000 (USD 750) per year, shared among all members. The program covers preventive, curative, inpatient, emergency, surgical, diagnostic, and rehabilitation services, as well as up to NPR 2,000 (USD 15) for emergency ambulance transport. It operates as a cashless system with no copayments at the point of service (HIB 2024).

Several population groups receive subsidized or free coverage: female community health volunteers receive a 50 percent discount on premiums; ultra-poor households, disabled individuals, and patients with selected terminal diseases are fully exempt. Most relevant for this study, citizens aged 70 and above receive both free premiums and an additional individual coverage of NPR 100,000—a policy introduced in 2019 that forms the basis of the identification strategy described below.

2.3. *The Age-70 Policy*

Since 2019, NHIP waives the premium for citizens aged 70 and above and provides them with individual coverage of NPR 100,000 (USD 750), separate from their household's allocation. This creates a sharp change in both the price and effective coverage of insurance at the age-70 threshold. Table 1 summarizes the change.

Table 1 — Insurance terms below and above age 70

	Below 70	70 and above
Annual premium	NPR 3,500 (USD 26)	Free
Coverage	NPR 100,000 per household	NPR 100,000 per individual
Effective per-person coverage	NPR 100,000 / household size	NPR 100,000

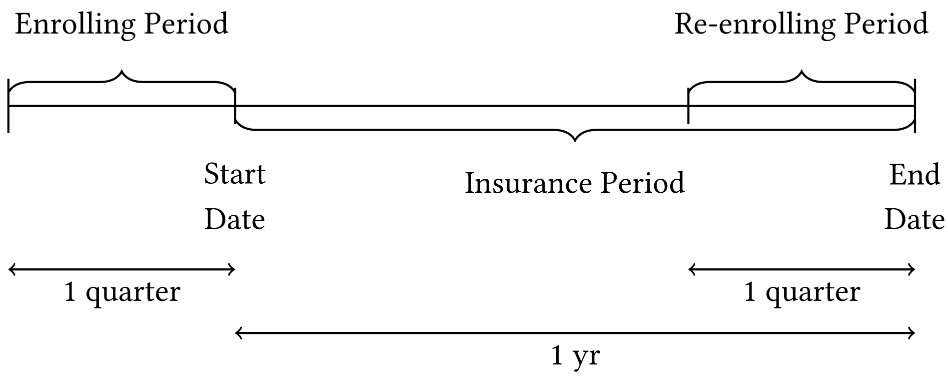
Note: Premium of NPR 3,500 applies to households of up to five members. Each additional member costs NPR 700. At age 70, the individual is removed from the household plan and receives a separate free policy.

The key implication is that the magnitude of the price and coverage change varies with household size. A single-person household experiences the largest price drop (NPR 3,500) but no change in coverage. A five-member household experiences a smaller per-person price reduction (NPR 700) but a large coverage expansion (from NPR 20,000 to NPR 100,000 per person). This variation is central to disentangling selection from moral hazard.

2.4. *Enrollment Mechanics*

NHIP operates on a quarterly enrollment cycle (Figure 1). There are four start dates per year: February, May, August, and November. Registration opens one quarter before each start date, and all individuals who enroll during that window share the same start date. Renewal is permitted only during the quarter before the current spell expires; the new spell begins the day after the previous one ends. This structure prevents individuals from re-enrolling mid-spell, ensuring that each enrollee is limited to their annual coverage allocation. Critically, eligibility for the free premium is determined by whether the individual is aged 70 or above at the start date of their insurance spell.

Figure 1 — Process of getting into NHIP



Note: Insurance timeline has remained the same since its inception.

2.5. Data

I use administrative data from the Health Insurance Board covering the universe of NHIP enrollees and their insurance claims from the program's inception through May 2025. The data contain two linked files: a registration file recording each enrollment spell (individual and household identifiers, date of birth, gender, enrollment and insurance period dates, premium paid, and first point of contact facility) and a claims file recording each reimbursed service (claim date, amount, ICD-10 diagnosis code, hospital visited, and type of service).

I construct the analysis sample by selecting all enrollment spells with start dates between May 2023 and May 2025 whose full insurance period is observed in the data. For each spell, I aggregate claims into spell-level outcomes: number of claims, total amount claimed, mean claim amount, number of unique diagnoses, and number of unique hospitals visited. Individuals with no claims during their spell are assigned zeros.

3 — Conceptual Framework

3.1. Why Free Insurance Could Raise or Lower Claims

The age-70 policy creates a sharp reduction in the price of insurance. The effect of this price change on claims per enrollee is theoretically ambiguous, depending on which of four mechanisms dominates.

Adverse selection. When insurance is costly, individuals with higher expected healthcare needs are more likely to find enrollment worthwhile (Rothschild and Stiglitz 1976; Akerlof 1970). When insurance becomes free, lower-risk individuals who previously opted out now enroll, shifting the pool toward healthier enrollees. Claims per enrollee fall.

Selection on moral hazard. Individuals differ not only in baseline health but in how much they respond to having insurance. If high-response types—those who would use insurance most intensively—are also more likely to enroll when insurance is costly, then free insurance attracts lower-response types. Claims per enrollee fall.

Ex-post moral hazard. Insurance reduces the effective price of care at the point of service, inducing greater utilization among all enrollees regardless of their health status (Arrow 1963). Claims per enrollee rise.

Advantageous selection. If healthier, more risk-averse individuals are more likely to purchase insurance when it is costly (Fang, Keane, and Silverman 2008), then free insurance may attract less risk-averse (and not necessarily healthier) individuals. The direction of the effect is ambiguous.

A simple comparison of claims above and below the threshold reveals only the net effect of these competing mechanisms. The sign of the discontinuity identifies which force dominates: if claims fall, selection effects outweigh moral hazard; if claims rise, moral hazard dominates. Disentangling the specific channels requires additional evidence, which I describe next.

3.2. Empirical Strategy

I use a regression discontinuity design exploiting the age-70 threshold to estimate the net effect of free insurance on claims. The sign of the discontinuity reveals which force dominates: claims falling indicates that selection effects outweigh moral hazard. However, a negative discontinuity alone does not identify the specific type of selection or rule out competing explanations. I pursue three additional strategies.

First, I construct an expected healthcare cost index using pre-determined characteristics: gender, household head status, ethnicity, education, profession, district, and registration category. I estimate the prediction model on a training sample of individuals aged 50–60—well below the age-70 threshold, ensuring that the training sample is free from treatment contamination. I then generate predicted costs for all individuals in the study sample. If adverse selection is present, this index should drop discontinuously at age 70, indicating that the composition of enrollees shifts toward healthier individuals when insurance becomes free. Because the index is based on pre-determined characteristics rather than contemporaneous utilization, it is not contaminated by ex-post moral hazard. As a robustness check, I verify that the results hold when the prediction model is trained on alternative age groups.

Second, I compare the treatment effect across new enrollees and individuals who renewed their insurance. If the decline in claims were driven by advantageous selection—healthier individuals entering when insurance becomes free—the effect should be concentrated among new entrants. If instead the decline is similar for both groups, it reflects a broader selection pattern that operates at both the entry and renewal margins.

Third, I systematically rule out alternative explanations for the decline in claims. I show that claims fall even among individuals who make at least one claim, ruling out a mechanical artifact from an influx of zero-claim enrollees. I show that the treatment effect is unchanged when controlling for distance to the nearest health facility, ruling out selection on transaction costs. I show that coverage ceilings are non-binding, establishing that the price reduction—not the coverage expansion—is the operative margin. And I show that enrollment gaps do not increase at age 70, ruling out strategic timing of enrollment around the threshold.

3.3. Welfare Framework

I adapt the demand-cost framework of Einav, Finkelstein, and Cullen (2010) to evaluate the welfare consequences of the age-70 subsidy. In this framework, an insurance market is characterized by three objects: the demand curve $D(Q)$, giving the willingness to pay for insurance at each coverage level Q; the average cost curve $AC(Q)$, giving the average insured cost per enrollee; and the marginal cost curve $MC(Q)$, giving the expected cost of the marginal enrollee. When

MC lies below AC—the defining feature of adverse selection—competitive insurers who price at average cost exclude individuals whose willingness to pay exceeds their expected cost, generating a deadweight loss (Einav and Finkelstein 2011).

Two features distinguish my setting from the canonical framework. First, the government sets the price P rather than the market pricing at average cost; consequently, the welfare calculation evaluates the cost of the administered price relative to marginal-cost pricing, rather than the deadweight loss of competitive average-cost pricing. Second, I observe only two price points—the premium P and zero—rather than continuous price variation. Following Chetty (2009), the welfare effects of the price change can be computed from three sufficient statistics recoverable from the regression discontinuity, without estimating the full demand and cost curves.

The three sufficient statistics are: (i) the change in coverage ΔQ, measured as the discontinuous jump in enrollment at age 70; (ii) the marginal cost of the new enrollees MC_{marginal}, obtained from the accounting identity below; and (iii) the per-person premium P waived at age 70. Under the policy rule, $P =$ NPR $3{,}500/N$ for households of size $N \leq 5$ and NPR 700 for $N > 5$, so P ranges from NPR 700 to 3,500 depending on household size.

The marginal cost is recovered from the accounting identity: total predicted cost above the threshold equals the predicted cost of inframarginal enrollees (who would have enrolled at price P) plus the predicted cost of marginal enrollees (who enroll only because insurance is free):

$$MC_{\text{marginal}} = \frac{AC_{\text{above}} \times Q_{\text{above}} - AC_{\text{below}} \times Q_{\text{below}}}{\Delta Q} \tag{1}$$

where AC_{above} and AC_{below} are mean predicted costs per enrollee above and below age 70, generated from the expected cost index trained on ages 50–60, and Q_{above} and Q_{below} are coverage rates. Using predicted costs rather than actual claims isolates the selection channel: because the index depends only on pre-determined characteristics, it is not contaminated by any moral hazard response to the subsidy. If inframarginal enrollees increase utilization when insurance becomes free, actual claims would overstate MC_{marginal}, biasing the welfare gain downward.

Because the subsidy moves the price all the way to zero, it overshoots the efficient quantity Q^* (where willingness to pay equals marginal cost). Under a linear demand assumption—the demand curve runs from (Q_{below}, P) to $(Q_{\text{above}}, 0)$—the welfare decomposition depends on whether

$P \geq MC$.[1]

When $P \geq MC$, the efficient quantity Q^* lies between Q_{below} and Q_{above}, and the welfare effect decomposes into two triangles:

$$\text{Welfare gain} = \frac{(P - MC)^2}{2P} \times \Delta Q \times \text{Pop}_{70} \tag{2}$$

$$\text{Overinsurance cost} = \frac{MC^2}{2P} \times \Delta Q \times \text{Pop}_{70} \tag{3}$$

$$\text{Net welfare} = \left(\frac{P}{2} - MC\right) \times \Delta Q \times \text{Pop}_{70} \tag{4}$$

The net welfare is positive whenever $P > 2 \times MC_{\text{marginal}}$: the midpoint of the demand curve must lie above MC for the welfare gain to exceed the overinsurance cost.

When $P < MC$, the marginal cost exceeds willingness to pay for every new enrollee. The welfare gain is zero and the entire coverage expansion represents overinsurance:

$$\text{Welfare gain} = 0$$

$$\text{Overinsurance cost} = \left(MC - \frac{P}{2}\right) \times \Delta Q \times \text{Pop}_{70}$$

This case applies to large households (size 5+), where $P = \text{NPR } 700 < MC = 821$.

I also compute the **marginal value of public funds** (MVPF) following Hendren and Sprung-Keyser (2020). Under linear demand, the average willingness to pay of marginal enrollees is $P/2$, while the fiscal cost per marginal enrollee is MC. The MVPF for marginal enrollees is therefore:

$$\text{MVPF}_{\text{marginal}} = \frac{P}{2 \times MC} \tag{5}$$

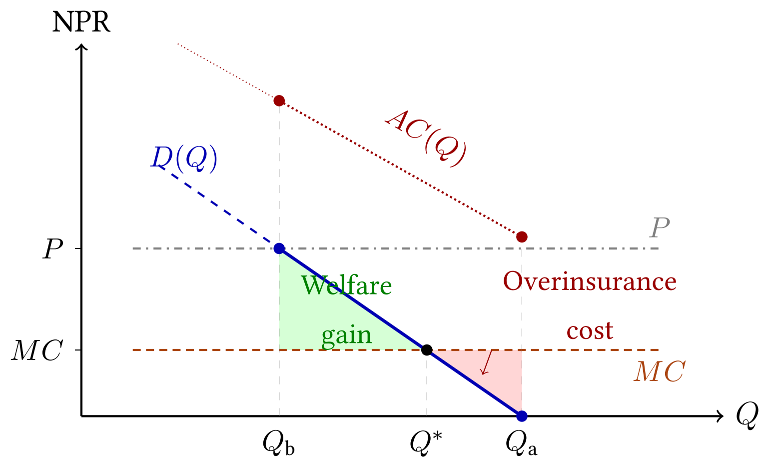
An MVPF below 1 indicates that marginal enrollees value the subsidy at less than its fiscal cost—the government could improve welfare by redirecting spending elsewhere.

Figure 2 illustrates the welfare geometry. Under the premium P, coverage is Q_{below}. The subsidy to zero expands coverage to Q_{above}. The green triangle represents the welfare gain from

1. With only two observed price points (P and zero), a linear interpolation is the only functional form identifiable without further assumptions. The constant-MC assumption is conservative: adverse selection implies that MC declines with Q (healthier individuals enroll at lower prices), which would shrink the overinsurance triangle and increase the net welfare gain.

correcting underinsurance: marginal enrollees between Q_{below} and Q^* have willingness to pay above their marginal cost but were priced out by the premium. The red triangle represents the overinsurance cost: enrollees beyond Q^* have marginal cost exceeding their willingness to pay.

Figure 2 — Welfare effects of the age-70 subsidy



Note: Q_{b} and Q_{a} denote coverage rates below and above age 70. $D(Q)$ is the demand curve (willingness to pay), $AC(Q)$ is average cost, MC is marginal cost of new enrollees. The green region is the welfare gain from correcting underinsurance; the red region is the overinsurance cost from zero pricing. Adapted from Einav, Finkelstein, and Cullen (2010).

The household premium structure creates variation in the per-person price subsidized at the threshold. The annual premium of NPR 3,500 is shared across household members, so a single-person household faces NPR 3,500 per person while a five-member household faces NPR 700 per person. At age 70, each individual's price drops to zero regardless of household size. The pooled sufficient statistics ΔQ and MC_{marginal} apply to the full population near the cutoff. In principle, each household-size group has its own demand curve and may have a different coverage response and marginal cost; however, estimating group-specific sufficient statistics is not feasible because enrolled household size is endogenous at the threshold (Appendix D). As an illustrative decomposition, I evaluate the welfare formulas at each point of the institutional price schedule, holding ΔQ and MC at their pooled values and varying only P. Table 4 presents these calculations. The net welfare effect is positive when $P > 2 \times MC$—satisfied for small households—but turns negative for large households where the per-person price was already below MC. The qualitative pattern is robust to this approximation: the sign of net welfare depends on the ratio P/MC, not on the level of ΔQ, so group-specific enrollment responses would change the magnitudes but not the direction of the welfare effects.

4 — Regression Discontinuity Design

The unit of analysis is the enrollment spell: each observation i represents one individual's insurance period, with claims aggregated over the spell's duration. I exploit the sharp change in premium price at age 70 to estimate the causal effect of free insurance on claims outcomes using the following specification:

$$Y_i = \alpha + \tau D_i + f(A_i) + D_i \cdot f(A_i) + X_i'\beta + \varepsilon_i \tag{6}$$

where Y_i is the outcome of interest (e.g., total amount claimed, number of claims, or an indicator for any claim), $A_i = \text{Age}_i - 70$ is the running variable measured in quarters and centered at the cutoff, $D_i = \mathbf{1}[A_i \geq 0]$ is the treatment indicator, $f(\cdot)$ is a linear function of the running variable, and $D_i \cdot f(A_i)$ allows the slope to differ on each side of the cutoff. X_i is a vector of pre-determined covariates including gender and household head status. The parameter of interest is τ, the discontinuous change in the outcome at age 70. Standard errors are clustered at the household level to account for within-household correlation.

4.1. Covariate Balance at the Threshold

The regression discontinuity design requires that individuals just above and just below age 70 are comparable on average in all characteristics other than the insurance subsidy. I test this assumption using an independent data source: the 2021 Nepal Census, which covers the entire population regardless of insurance enrollment.

A practical challenge is age heaping: respondents in Nepal disproportionately report ages at multiples of five, creating artificial spikes at ages 65, 70, and 75. Because age 70 is both the policy threshold and a heaping point, naive estimation would confound the heaping artifact with a genuine discontinuity. I address this using stochastic redistribution (Heitjan and Rubin 1991): I fit a smooth Poisson model to unweighted population counts excluding heaped ages, estimate the excess count at each multiple of five, and randomly reassign excess individuals to neighboring ages proportional to the smooth density. I repeat this procedure $M = 50$ times. Within each draw, I run the full set of balance regressions on the redistributed ages, then combine estimates across draws using Rubin's combination rules (Rubin 1987): the point estimate is $\bar{\theta} = M^{-1} \sum_m \hat{\theta}_m$, and the total variance is $V = \bar{W} + (1 + M^{-1})B$, where $\bar{W}$ is the average within-draw variance and B is the between-draw variance. This accounts for both sampling uncertainty and the additional uncertainty from the stochastic age correction. All regressions are estimated by OLS with standard errors clustered at the household level.

Table 2 reports the results. I test nine covariates spanning demographics (sex, caste, religion, ever-married status, disability, household size) and economic characteristics (economic inactivity, literacy, wealth). None of the demographic covariates shows a significant discontinuity at the threshold—caste, religion, and ever-married status are ascribed or near-universal among the elderly and cannot change at age 70. "Economically inactive (aged)"—which uses the census's explicit reason-for-inactivity field—is insignificant, indicating no excess retirement at the threshold. Literacy, household size, and wealth quintile are all insignificant. Appendix E presents the age profiles of each covariate, confirming visual continuity at the threshold.

5 — Results

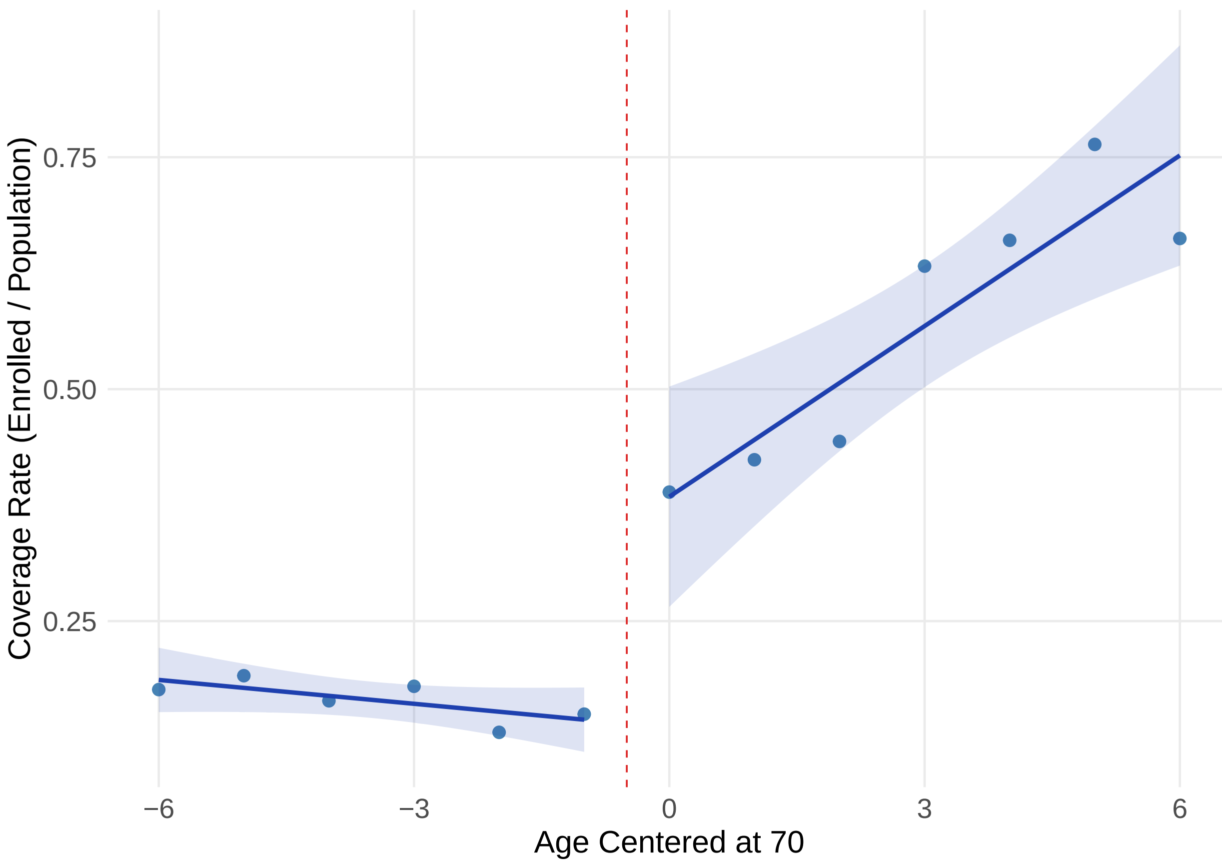
Figure 3 presents the first-stage evidence. The coverage rate—defined as the share of the age-specific population enrolled in NHIP—is flat at approximately 22% below age 70, then jumps sharply to about 49% at the cutoff. This confirms that the free premium at age 70 generates a large enrollment response, more than doubling the coverage rate at the threshold.

Table 2 — Covariate Balance at Age 70: 2021 Nepal Census

Covariate	Mean Pre-70	RD Estimate	SE
Female	0.508	0.007	(0.009)
High Caste	0.477	−0.009	(0.009)
Hindu	0.810	0.004	(0.007)
Ever married	0.989	0.000	(0.002)
Has disability	0.064	−0.002	(0.004)
Household size	5.203	0.121	(0.134)
Economically inactive (aged)	0.374	−0.001	(0.009)
Literate	0.328	−0.009	(0.008)
Wealth quintile	2.855	−0.024	(0.027)
Bandwidth (years)	3.41		
Observations	110,292		
Estimator	Local linear (OLS)		

Notes: Each row reports the OLS estimate from a local linear regression with a uniform kernel. The MSE-optimal bandwidth ($h = 3.41$) is selected by `rdrobust`. Standard errors clustered at the household level in parentheses. Estimates are pooled across 50 Monte Carlo draws of stochastic age redistribution using Rubin's combination rules; standard errors account for both sampling and imputation uncertainty. Mean Pre-70 is the weighted mean within the bandwidth below the cutoff. Signif. codes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Figure 3 — Insurance coverage jumps discontinuously at age 70



Note: Each point is the coverage rate (NHIP enrollees divided by census population) for a one-year age bin. Age is centered at 70. The solid line is a local linear fit estimated separately on each side of the cutoff; shaded areas show 95% confidence intervals. Population counts are from the 2021 Nepal Census.

5.1. Main Effects: Claims Fall at Age 70

Table 3 reports the main RDD estimates. The share of enrollees with at least one claim decreases by 12.2 percentage points, the number of claims decreases by 0.86 (33%), total amount claimed decreases by NPR 1,604 (31%), and mean claim amount decreases by NPR 227.8. All estimates are statistically significant at the 1% level.

This pattern is initially puzzling—why would free insurance lead to fewer claims? The mechanism is adverse selection: when insurance requires a contribution, individuals with higher expected healthcare needs are more likely to enroll. Once the contribution is waived at 70, lower-risk individuals who previously opted out now find enrollment worthwhile. This influx of healthier enrollees dilutes the risk pool, reducing average claims per enrollee.

Table 3 — RD estimates for Claims

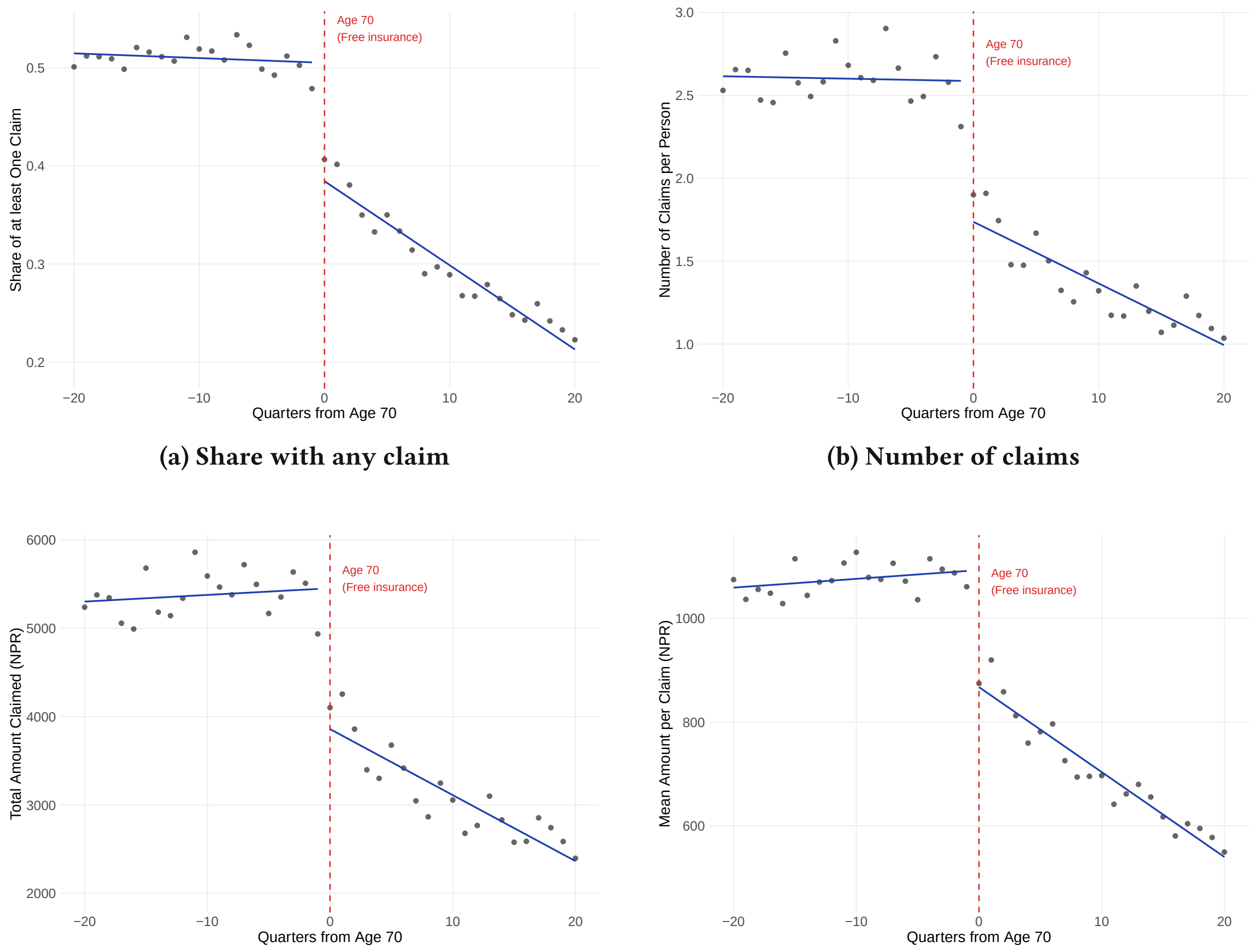
	Atleast One Claim	Number of Claims	Total Amount Claimed	Mean Claim Amount
	(1)	(2)	(3)	(4)
RD Estimate	-0.1226***	-0.8564***	-1,604.6***	-227.8***
	(0.0030)	(0.0243)	(65.46)	(13.71)
Observations	570,904	570,904	570,904	570,904
Mean, left of cutoff	0.5100	2.560	5,173.0	1,043.3
Controls	No	No	No	No
Weighting scheme	Uniform	Uniform	Uniform	Uniform
Bandwidth	±20 q	±20 q	±20 q	±20 q
Degree of polynomial	1	1	1	1

Note: Sample includes each individual's first full insurance period observed between May 2023 and May 2025.

Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 4 presents the graphical evidence. All four outcomes exhibit a sharp discontinuous decline at age 70, confirming the regression estimates.

Figure 4 — Claims outcomes decrease discontinuously at age 70



(a) Share with any claim **(b) Number of claims**

(c) Total amount claimed **(d) Mean claim amount**

Note: Each panel shows binned averages by age in quarters. The vertical dashed line indicates the age 70 cutoff. Sample includes each individual's first full insurance period observed between May 2023 and May 2025.

5.2. Mechanism: Adverse Selection

The classic test for adverse selection is the positive correlation test of Chiappori and Salanié (2000), which examines whether individuals with more coverage have higher risk. However, this test requires variation in coverage levels. In Nepal's NHIP, all enrollees receive identical coverage—there is no choice of deductibles, coinsurance, or benefit levels. This uniformity precludes the standard positive correlation test.

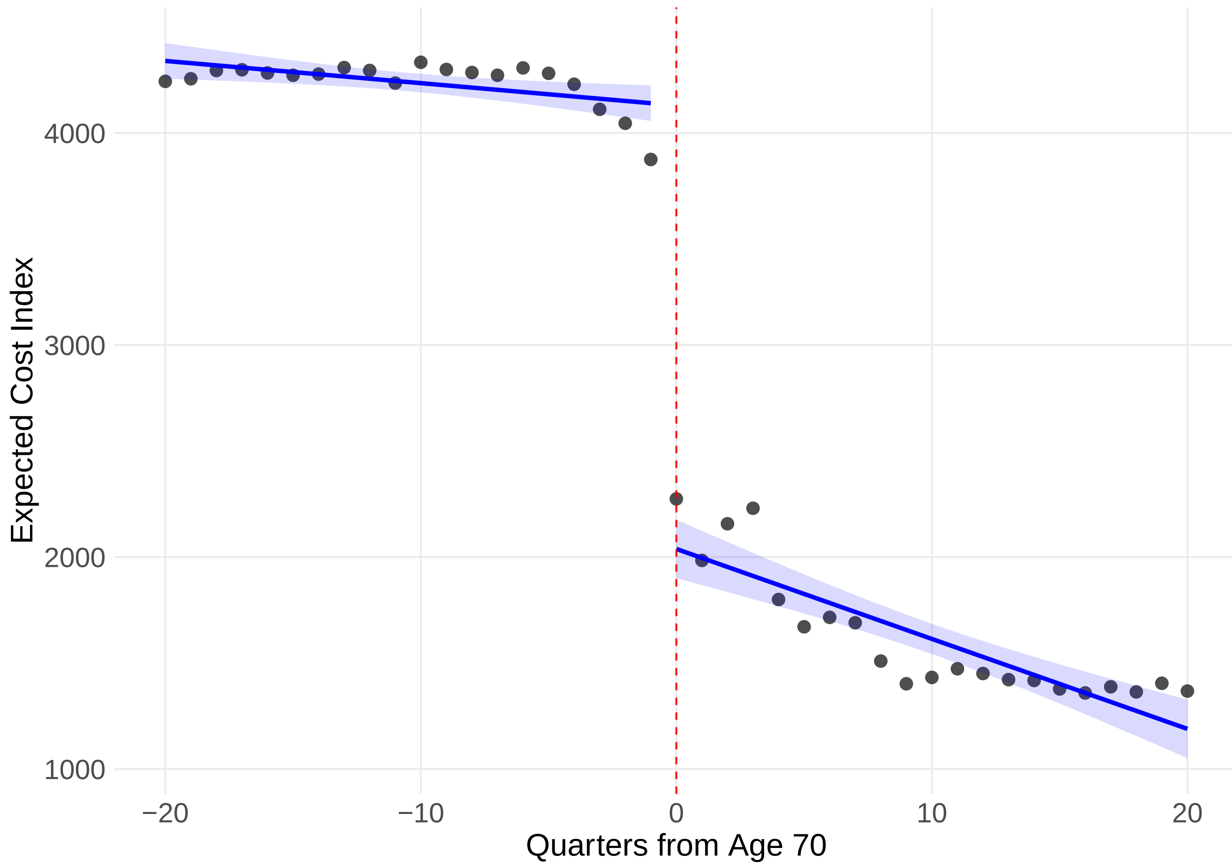
I therefore adopt an alternative approach following Einav and Finkelstein (2011) and Fischer, Frölich, and Landmann (2023): constructing an expected cost index from strictly exogenous enrollment-time characteristics. If adverse selection is present, individuals with higher expected costs should be concentrated among those who pay for insurance (below age 70), while the pool of enrollees above 70—who face zero price—should include more low-risk individuals.

I construct the expected cost index by predicting total claimed amounts using only demographics and geography observable at the time of enrollment: gender, household head status, ethnicity, education, profession, district, and registration category. Crucially, the index excludes age and any prior claims history, so it is well-defined for both new and renewed enrollees. I estimate the prediction model on a training sample of individuals aged 50–60—well below the policy threshold—and generate predicted costs for all individuals in the study sample.

Figure 5 plots the mean expected cost index by age in quarters. There is a clear discontinuous drop at age 70: the average enrollee just above 70 has a lower predicted cost than the average enrollee just below 70. This is direct evidence of adverse selection—when insurance requires payment, high-risk individuals are more likely to enroll, but when it becomes free, lower-risk individuals join, diluting the risk pool.

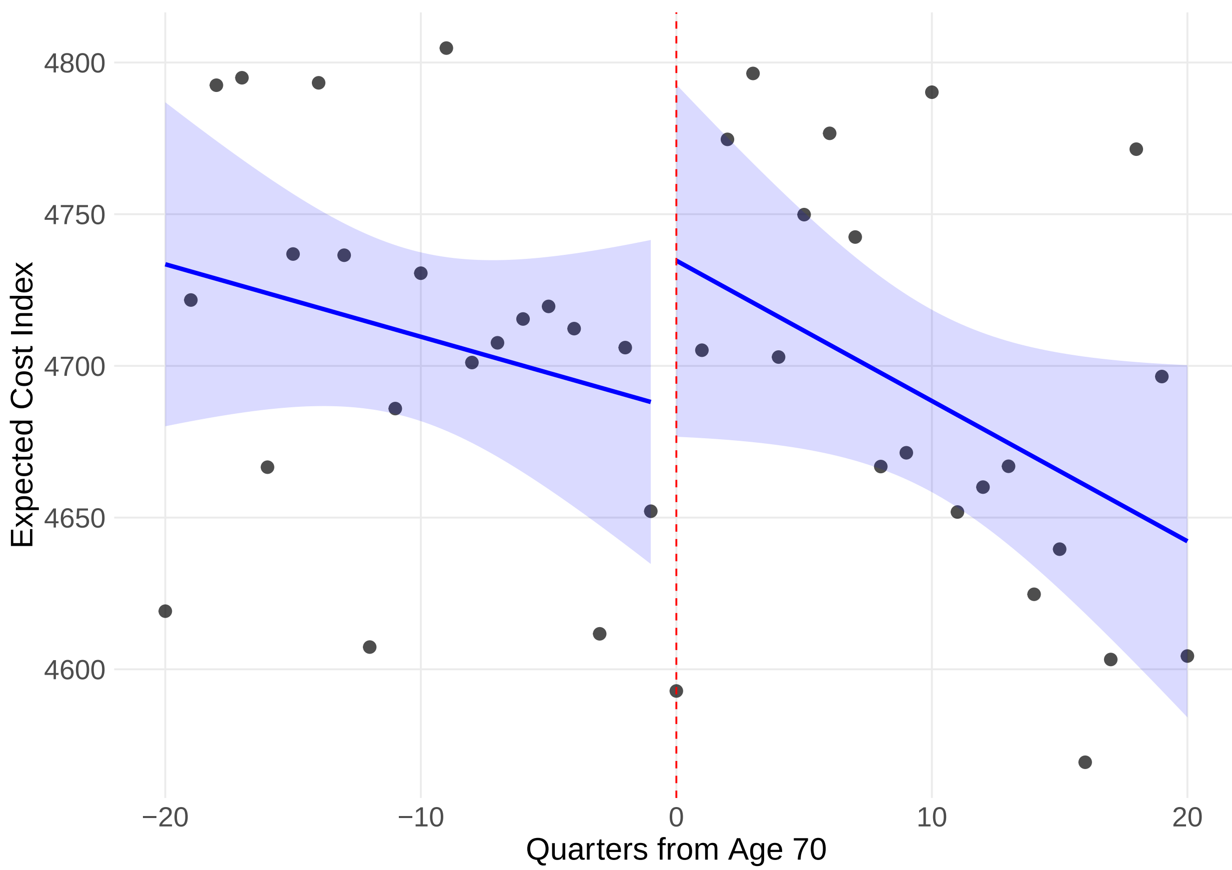
Critically, this discontinuity did not exist before the policy. Figure 6 shows the same expected cost index for enrollees before April 2019, when the age-70 subsidy was introduced. There is no jump at age 70, confirming that the compositional shift is a consequence of the free-premium policy rather than some underlying feature of the age distribution.

Figure 5 — Expected cost index drops discontinuously at age 70



Note: Each point is the mean predicted total claimed amount (NPR) for enrollees in a one-quarter age bin. Predictions are from a model trained on ages 50–60 using strictly exogenous enrollment-time characteristics (gender, ethnicity, education, profession, district, household head status, registration category). The discontinuous drop at age 70 indicates that healthier individuals enroll when insurance is free.

Figure 6 — No discontinuity in expected cost index before the free-premium policy



Note: Placebo test applying the same 2024-trained model to pre-policy enrollees (before April 2019). The absence of a discontinuity confirms that the post-policy compositional shift reflects the free-premium policy, not an inherent feature of the age distribution.

Consistent with the selection evidence from the expected cost index, the same discontinuous decline in actual claims outcomes appears among renewed enrollees (Appendix A).

5.3. Welfare Analysis

Applying the sufficient statistics framework from Equation 2–Equation 4, I compute the welfare consequences of the age-70 subsidy. Table 4 reports the inputs and results. The coverage rate jumps from $Q_{\text{below}} = 0.22$ to $Q_{\text{above}} = 0.49$ at the cutoff, adding 33,828 marginal enrollees from a population of 126,994 at age 70. The marginal cost of these new enrollees is NPR 821—far below the average predicted cost of enrollees above 70 (NPR 2,233), confirming that the marginal enrollees drawn in by free insurance are substantially healthier than the average. This is a direct cost-side confirmation of the adverse selection documented in the expected cost index analysis.

The welfare implications depend on the per-person price P being subsidized. As discussed in the framework section, the household-size decomposition holds ΔQ and MC at their pooled values and varies only P across the institutional price schedule; the magnitudes are therefore illustrative, though the sign of net welfare at each price point depends only on the ratio P/MC. Because the household premium of NPR 3,500 is shared across members, single-person households face NPR 3,500 per person while five-member households face only NPR 700. For small households ($N \leq 2$), $P > 2 \times MC$ and the subsidy generates positive net welfare: the welfare gain from correcting underinsurance exceeds the overinsurance cost. For large households ($N \geq 3$), the per-person price was already near or below MC, and the subsidy creates pure overinsurance. At the enrolled average price ($\bar{P} = 988$, dominated by large households), the net welfare effect is negative (NPR -11.1 million) and the MVPF is 0.60—marginal enrollees value the subsidy at 60 paisa per rupee of fiscal cost.

These results suggest that the blanket free-at-70 policy is welfare-improving for single-person and two-person households facing genuine underinsurance, but generates overinsurance for larger households whose per-person price was already low (Appendix D presents the full heterogeneity analysis by household size). A more targeted subsidy—reducing premiums for small households below age 70 rather than eliminating them entirely at age 70—could capture the welfare gains while avoiding the overinsurance losses.

6 — Robustness

A potential concern for the regression discontinuity design is that individuals might strategically time their enrollment to exploit the free premium at age 70. Specifically, if individuals allow their insurance to lapse just before turning 70 and re-enroll afterward to avoid paying the premium, this manipulation could bias the estimates. I investigate this concern using the complete enrollment history of all individuals.

6.1. Enrollment Gaps Are Not Unique to Age 70

Nepal's NHIP operates on a quarterly enrollment cycle: insurance spells begin in February, May, August, or November, and renewals open one quarter before the current spell expires. Consistent

Table 4 — Welfare Analysis of the Age-70 Subsidy

Panel A: Sufficient Statistics	
Q_{below} (coverage rate below 70)	0.2221
Q_{above} (coverage rate above 70)	0.4885
ΔQ (coverage jump)	0.2664
Population at age 70	126,994
ΔE (marginal enrollees)	33,828
$\bar{AC}_{\text{below}}$ (avg. predicted cost, NPR)	3,928
$\bar{AC}_{\text{above}}$ (avg. predicted cost, NPR)	2,233
MC_{marginal} (cost of new enrollees, NPR)	821

Panel B: Welfare Effects by Per-Person Price

	P/person (NPR)	Welfare Gain (NPR)	Overinsurance Cost (NPR)	Net Welfare (NPR)	MVPF
HH size = 1	3,500	34,689,011	3,255,540	31,433,471	2.13
HH size = 2	1,750	8,345,354	6,511,080	1,834,274	1.07
HH size = 3	1,167	1,737,343	9,763,830	-8,026,487	0.71
HH size = 4	875	56,835	13,022,160	-12,965,325	0.53
HH size = 5+	700	0	15,925,244	-15,925,244	0.43
Enrolled avg. (below 70)	988	476,692	11,537,310	-11,060,618	0.60
Behavioral avg. (pooled)	2,091	13,055,436	5,448,472	7,606,964	1.27

Notes: With linear demand from P to 0: when $P \geq MC$, welfare gain $= (P - MC)^2/(2P) \times \Delta Q \times$ Pop and overinsurance cost $= MC^2/(2P) \times \Delta Q \times$ Pop. When $P < MC$, welfare gain $= 0$ and overinsurance cost $= (MC - P/2) \times \Delta Q \times$ Pop. Net welfare $= (P/2 - MC) \times \Delta Q \times$ Pop, positive iff $P > 2MC$. MVPF (marginal) $= P/(2 \times MC)$: the value per rupee of fiscal cost for marginal enrollees (Hendren and Sprung-Keyser 2020). $MC_{\text{marginal}} = (\bar{AC}_{\text{above}} Q_{\text{above}} - \bar{AC}_{\text{below}} Q_{\text{below}})/\Delta Q$. $\bar{AC}$ is the mean predicted cost from a risk index trained on ages 50–60. Q = coverage rate (enrolled / UN population). P = per-person premium: NPR 3,500/N for $N \leq 5$; NPR 700 for $N > 5$. "Enrolled avg." uses $\bar{P}$ of enrollees below 70 (uncontaminated by the subsidy). "Behavioral avg." pools enrollees on both sides (reflects endogenous enrollment response). Panel B holds ΔQ and MC at pooled values and varies only P; see text for discussion.

with this institutional feature, virtually all enrollment gaps are multiples of one quarter—sub-quarter gaps are essentially nonexistent from 2020 onward.

Table B1 in Appendix B reports the distribution of gap lengths by age at renewal, using data from 2020 onward. Two patterns emerge. First, among individuals renewing below age 70, the gap rate is remarkably stable: approximately 76% renew without any gap, 11% have a one-quarter gap, and 7% have gaps exceeding one year. These rates are nearly identical across every single year of age from 60 to 69. Second, the gap rate *falls* at the threshold. At age 70, 78.8% of renewals are continuous—a modest increase from 76.9% at age 69—but by age 71 the rate jumps to 91.5%, and by ages 72 and above it exceeds 95%. The transitional pattern at age 70 reflects the fact that some individuals turning 70 during their spell had enrolled while still paying; by age 71, the full effect of the free premium is realized.

If individuals were strategically allowing their insurance to lapse around their 70th birthday to re-enroll for free, we would observe *higher* gap rates at age 70 relative to adjacent ages. The opposite is true: the free premium reduces gaps, consistent with the premium itself being the primary barrier to continuous coverage. The flat gap rate below 70 further confirms that gaps are a structural feature of the program—driven by the cost of premiums—rather than a response to the age-70 threshold.

Even among individuals who do take gaps around age 70, their behavior is inconsistent with strategic manipulation. Comparing pre-70 claims across transition types reveals a clear gradient: continuous enrollees averaged NPR 20,925 in total claims before age 70, while those with gaps exceeding two quarters averaged only NPR 7,750 (Table B2). Individuals whose gap spans their 70th birthday—the group most likely to be "strategic"—had mean pre-70 claims of NPR 8,757, less than half the NPR 19,354 average for other individuals. If individuals were strategically timing their enrollment to exploit free insurance, we would expect gap-spanners to have *higher* pre-70 utilization. Instead, they are healthier and use less care, consistent with price sensitivity among low-risk individuals rather than strategic manipulation.

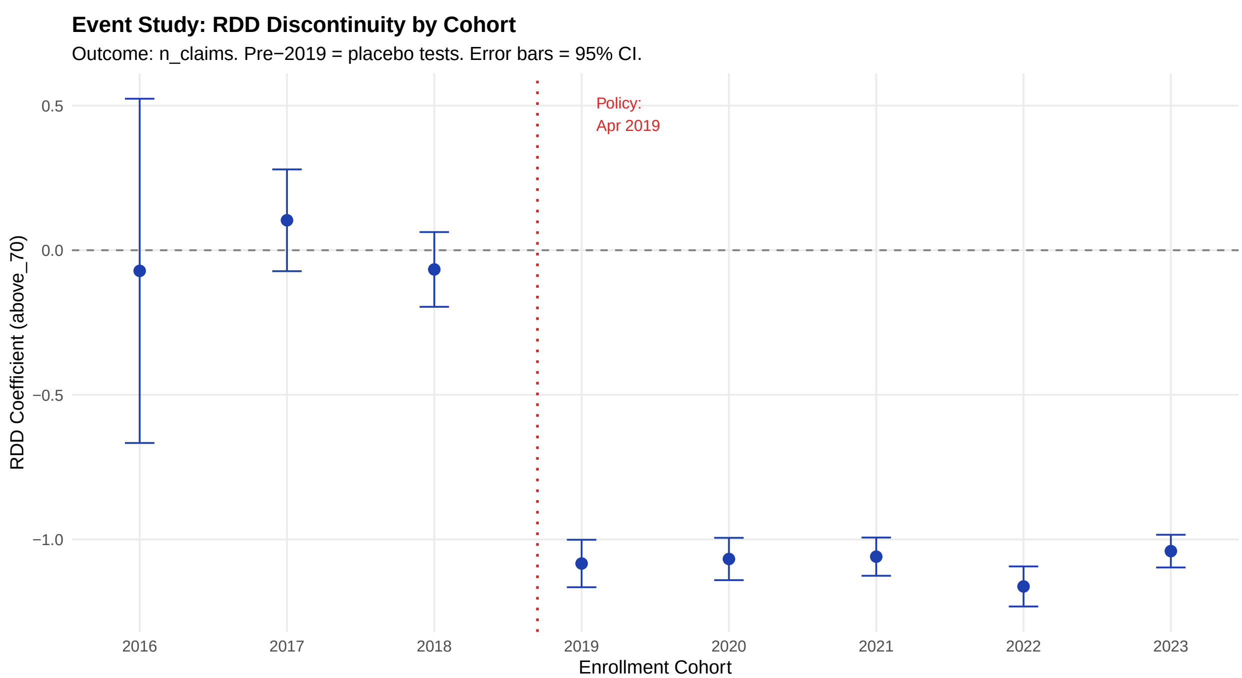
The treatment effect is also robust to geographic access. If the decline in claims at age 70 reflected reduced mobility rather than selection, we would expect larger effects among enrollees living farther from healthcare facilities. Table C1 in Appendix C shows that the treatment effect is remarkably uniform across distance bins, ranging from NPR $-1{,}056$ to $-1{,}378$, ruling out distance as a confound.

6.2. Event Study: The Discontinuity Coincides with the Policy

The free-at-70 policy was introduced in April 2019. If the claims discontinuity at age 70 reflects the policy rather than some pre-existing feature of the age distribution, it should appear only after 2019. Figure 7 tests this by estimating the RDD specification separately for each enrollment cohort year from 2016 to 2023.

Before the policy (2016–2018), the RDD coefficient is indistinguishable from zero—there is no discontinuity in claims at age 70. Immediately after the policy takes effect in 2019, the coefficient drops to approximately -1.1 and remains stable through 2023. The sharp onset and persistence of the effect are consistent with a policy-induced change rather than a gradual demographic trend.

Figure 7 — The claims discontinuity at age 70 appears only after the 2019 policy



Note: Each point reports the RDD coefficient on the above-70 indicator estimated separately by enrollment cohort year. The outcome is number of claims. The dashed red line marks the introduction of the free-at-70 policy in April 2019. Error bars show 95% confidence intervals. Pre-2019 estimates serve as placebo tests.

7 — Conclusion

This paper shows that making health insurance free at Nepal's age-70 threshold reduces claims per enrollee—not because utilization falls, but because healthier individuals enter the risk pool. An expected cost index constructed from enrollment-time characteristics confirms the compositional shift, and both a pre-policy placebo and an event study establish that the pattern is policy-induced. The resulting marginal value of public funds for new enrollees is 0.60, with the subsidy correcting underinsurance for small households but generating overinsurance for larger ones.

These findings speak to a specific design challenge in subsidized health insurance. Nepal's NHIP incorporates household-level bundling and restricted enrollment windows—two features widely recommended to combat adverse selection. Yet selection persists because the relevant margin is not within an enrollment period but across a predictable eligibility threshold. When individuals can anticipate free coverage, they time their enrollment accordingly, and standard design fixes do not eliminate this margin. Threshold-based subsidies, while administratively simple, create new selection channels that policymakers should anticipate.

Several limitations warrant discussion. First, the analysis captures selection on the demand side only; supply-side responses—such as providers adjusting referral patterns or claim amounts for free enrollees—are not observed in these data. Second, the welfare framework assumes static demand and cost curves, and cannot account for dynamic effects such as improved health from earlier enrollment or changes in provider behavior over time. Third, the age-70 threshold identifies a local average treatment effect for individuals near the cutoff, and the selection dynamics may differ at other margins—for example, means-tested subsidies for younger populations. Fourth, the expected cost index relies on enrollment-time characteristics available in administrative data; richer health measures would sharpen the decomposition of selection and moral hazard. Finally, the welfare framework interprets low enrollment below 70 as low willingness to pay. If some individuals do not enroll because they cannot afford the lump-sum annual premium rather than because their valuation falls below P, the revealed demand curve understates true willingness to pay and the welfare gain from subsidization is a lower bound.

Despite these caveats, the core finding—that adverse selection operates even with institutional safeguards specifically designed to prevent it—carries a broader lesson. As voluntary health insurance programs expand across low- and middle-income countries, predictable eligibility thresholds will create selection margins that bundling and enrollment restrictions alone cannot close. Complementary interventions—whether mandatory enrollment, continuous coverage incentives, or risk adjustment—deserve consideration alongside premium subsidies.

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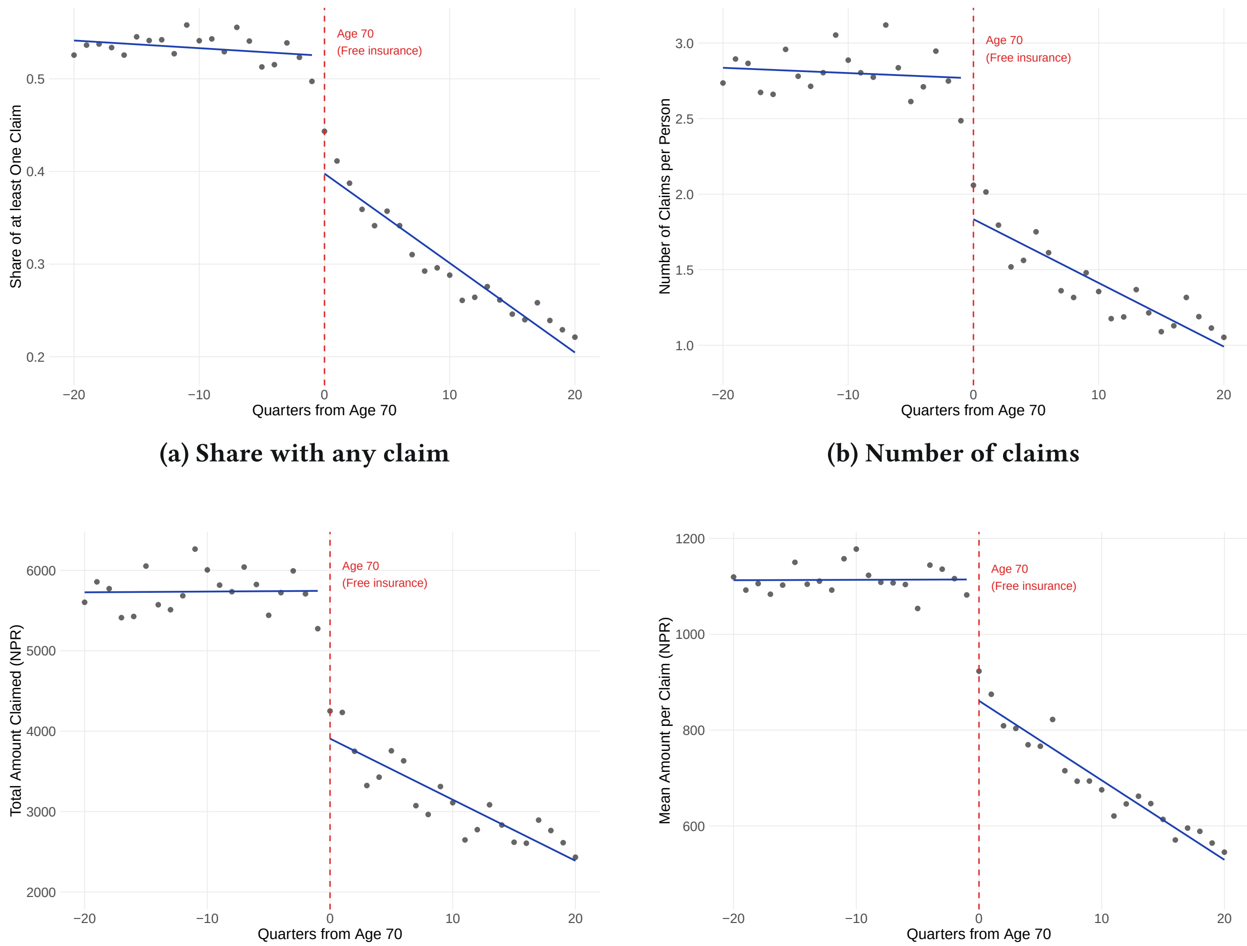
A — Claims Outcomes for Renewed Enrollees

Figure A1 — Claims outcomes for renewed enrollees



(a) Share with any claim **(b) Number of claims**

(c) Total amount claimed **(d) Mean claim amount**

Note: Sample restricted to individuals who renewed their insurance. Each panel shows binned averages by age in quarters. The vertical dashed line indicates the age 70 cutoff.

B — Enrollment Gap Analysis

Table B1 — Enrollment gap patterns by age at renewal (%)

Age	No gap	1 quarter	2–3 quarters	4+ quarters
60	75.5	11.0	5.7	7.8
61	75.4	11.1	5.7	7.8
62	75.6	11.0	5.7	7.6
63	76.0	10.8	5.6	7.6
64	75.9	10.9	5.6	7.6
65	76.1	10.8	5.5	7.6
66	75.9	11.0	5.6	7.4
67	76.2	10.8	5.6	7.4
68	76.6	10.7	5.3	7.4
69	76.9	10.7	5.3	7.1
70	**78.8**	**9.5**	**5.1**	**6.7**
71	**91.5**	**3.7**	**2.0**	**2.8**
72	94.6	2.2	1.3	1.9
73	95.9	1.7	1.0	1.5
74	96.5	1.4	0.8	1.3
75	96.9	1.3	0.7	1.1
76	97.0	1.2	0.7	1.1
77	97.1	1.2	0.6	1.1
78	97.2	1.1	0.6	1.1
79	97.2	1.1	0.6	1.1

Note: Sample includes all renewal spells (spell number > 1) from 2020 onward. Age is measured at the start of the new insurance spell. Columns report the percentage of renewals in each gap-length category. Rows sum to approximately 100%.

Table B2 — Pre-70 claims by enrollment transition type

Transition type	N	Mean total claimed (NPR)	Mean no. of claims	% with any claim
Panel A: By gap length				
Continuous (no gap)	88,036	20,925	10.5	68.5
Short gap (< 1 quarter)	7,920	17,669	8.6	72.3
Medium gap (1–2 quarters)	7,973	14,529	7.1	67.8
Long gap (> 2 quarters)	25,344	7,750	3.7	54.1
Panel B: Gap spans 70th birthday				
No	109,682	19,354	—	67.6
Yes	19,591	8,757	—	56.4

Note: Sample restricted to individuals with insurance spells both before and after age 70. Pre-70 claims are summed over all insured quarters before age 70. Panel A categorizes individuals by the length of their gap between the last pre-70 spell and the first post-70 spell. Panel B compares individuals whose gap spans their 70th birthday against all others.

C — Distance Heterogeneity

A potential concern is that the decline in claims at age 70 reflects reduced geographic access to healthcare rather than a change in the composition of enrollees. If mobility declines sharply at age 70, individuals living farther from health facilities may reduce utilization mechanically, irrespective of insurance incentives.

To investigate, I estimate the main RDD specification separately by distance to the enrollee's registered first point of contact (FPOC). Distance is measured as the Haversine distance from the ward centroid to the registered FPOC. I partition the sample into four bins: 0–5 km, 5–10 km, 10–15 km, and 15+ km.

Table C1 reports the results. The treatment effect is remarkably stable across all distance bins: NPR $-1{,}294$ for the nearest group, NPR $-1{,}378$ and $-1{,}372$ for the middle groups, and NPR $-1{,}056$ for the most remote group. The pooled estimate is NPR $-1{,}384$. None of these estimates are statistically distinguishable from one another.

If the claims decline were driven by mobility constraints, we would expect a monotonically increasing treatment effect with distance—individuals far from facilities should show a larger drop. The uniformity across distance bins is inconsistent with this explanation and supports the interpretation that the effect operates through the composition of enrollees, not through access barriers.

Table C1— RDD: Total Claimed by Distance to FPOC (2023-2024 Cohort)

	total_claimed				
	0-5 km	5-10 km	10-15 km	15+ km	Pooled
	(1)	(2)	(3)	(4)	(5)
above_70	-1,294.0***	-1,378.0***	-1,371.6***	-1,055.5***	-1,383.8***
	(94.0)	(119.7)	(165.7)	(154.5)	(62.8)
quarters_from_70 × above_70	-51.6***	-52.7***	-31.1**	-40.7***	-54.9***
	(7.7)	(9.6)	(13.5)	(12.4)	(5.1)
Observations	267,433	148,447	75,936	81,248	573,064

Outcome: total amount claimed (NPR) during enrollment spell. Distance: Haversine km from ward centroid to registered FPOC. Bandwidth +/-20 quarters. Clustered SE by household.

D — Heterogeneous Effects by Household Size

The age-70 threshold creates variation in both the price and coverage of insurance, and both vary systematically with household size. The per-person price reduction is ΔPrice $= -$Premium$/N$, where N is household size: $-3{,}500$ for a solo enrollee and -700 for a household of five. Conversely, the coverage expansion is ΔCoverage $= 100{,}000 - 100{,}000/N$: zero for solo enrollees and NPR 80,000 for households of five. These two sources of variation move in opposite directions:

Household Size	ΔPrice (NPR)	ΔCoverage (NPR)
1	$-3{,}500$	0
2	$-1{,}750$	50,000
3	$-1{,}167$	66,667
5	-700	80,000

Because both are deterministic functions of household size, they are perfectly collinear and cannot be separately identified in the same regression. I argue that the price mechanism dominates, based on the observation that coverage ceilings are almost never binding. Even among individuals who file at least one claim, the median is NPR 5,622 (treated) and NPR 2,744 (control)—far below the minimum pre-70 effective coverage of NPR 20,000 (for households of five). The 75th percentile conditional on claiming is NPR 14,163, still below the most restrictive ceiling. This implies that the coverage expansion is unlikely to affect behavior: the operative margin is price, not coverage.

I estimate a price-interaction model:

$$Y_i = \alpha + \tau D_i + \gamma_1(\Delta\text{Price}_i) + \gamma_2(D_i \times \Delta\text{Price}_i) + f(\text{Age}_i) + X_i'\beta + \varepsilon_i$$

where $\Delta\text{Price}_i = -\text{Premium}_i/N_i$. The key coefficient is γ_2, which captures how the treatment effect varies with the magnitude of the price reduction:

Coefficient	Estimate (SE)
Treatment (τ)	$-2{,}253.8^{***}$ (115.3)
Treatment $\times$ ΔPrice (γ_2)	-0.731^{***} (0.083)

The coefficient $\gamma_2 = -0.731$ implies that for each additional NPR 1 reduction in price, claims increase by NPR 0.73. A solo enrollee (ΔPrice $= -3{,}500$) experiences a price-induced utilization increase of NPR 2,559, while a five-member household (ΔPrice $= -700$) sees only NPR 512. This differential response is consistent with a downward-sloping demand curve for healthcare.

An important caveat applies to the household size variation. Enrolled household size is endogenous at the age-70 cutoff: when insurance becomes free, individuals can enroll alone rather than through a household policy, so the average enrolled household size drops sharply above the threshold. The per-person price reduction ΔPrice_i therefore reflects both the institutional price schedule and this behavioral enrollment response. The results above should be interpreted as descriptive evidence of a price-utilization gradient rather than as cleanly identified causal effects by household size. The welfare analysis in Table 4 addresses this by evaluating the pooled ΔQ and MC_{marginal} at each point of the exogenous institutional price schedule, rather than relying on household-size-specific RDD estimates.

Subject to this caveat, the results have two implications. First, the overall negative treatment effect is not offset by moral hazard from the price reduction—selection effects dominate even at the largest price drop. Second, within the treated group, larger price reductions do generate more utilization, consistent with standard demand theory. The selection and price effects work in opposite directions, but selection is quantitatively larger.

E — Covariate Balance: Robustness and Placebo

Figure E1 displays the age profiles of each covariate, with separate linear fits on each side of the threshold. The visual continuity at age 70 is consistent with the small point estimates in Table 2.

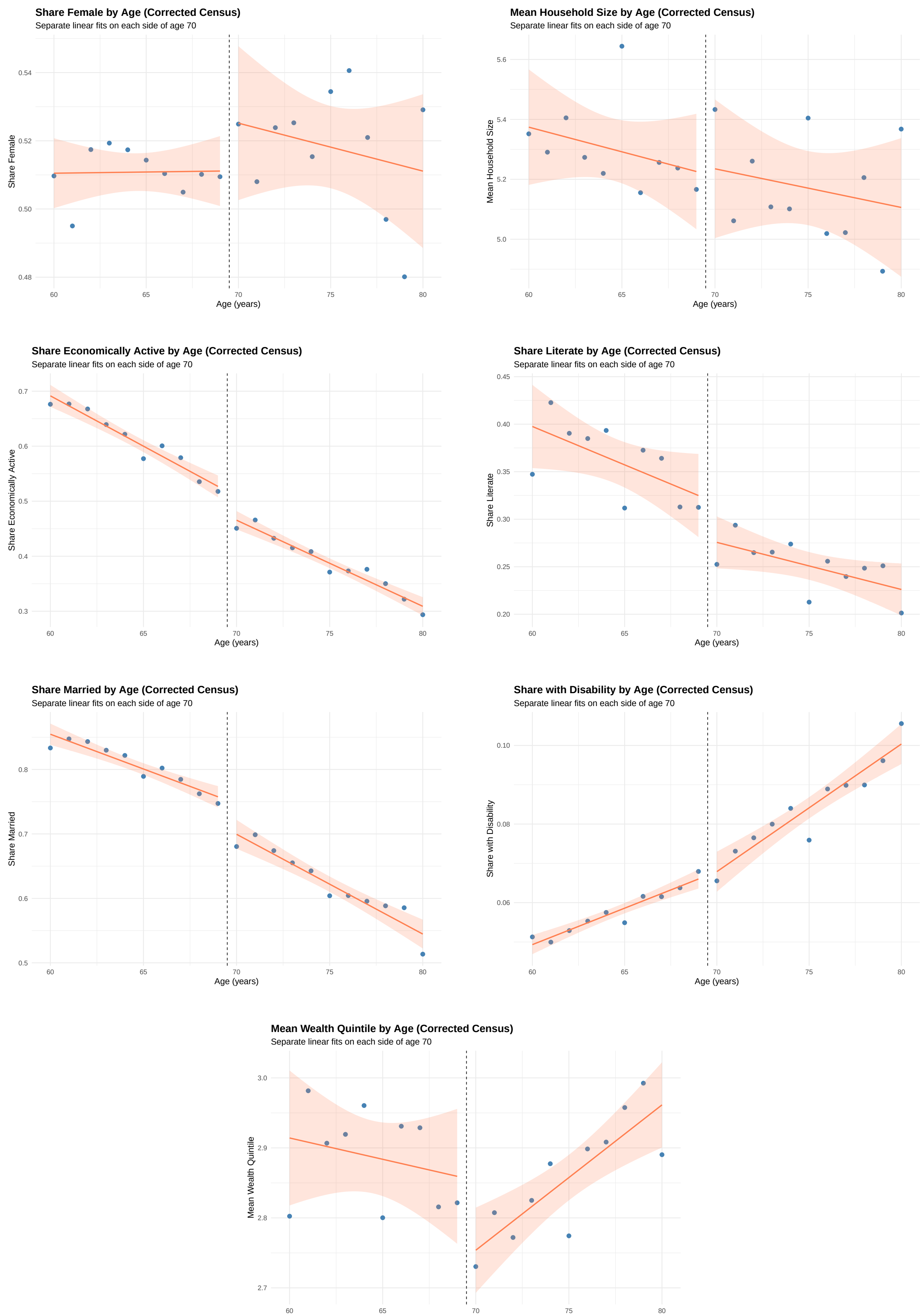


Figure E1— Covariate age profiles around the age-70 threshold (2021 Nepal Census). Each panel shows the weighted mean by age with separate linear fits on each side of the cutoff. Ages corrected for heaping via stochastic redistribution.

F — Additional Tables

Table F1 — DID-RDD: Causal Effect of Age-70 Free Premium Policy (April 2019)

	any_claim Any Claim (1)	n_claims No. Claims (2)	total_claimed Total Claimed (NPR) (3)	mean_claim Mean Claim (NPR) (4)
above_70	-0.011	0.097	-138.8	-37.8
	(0.018)	(0.154)	(580.1)	(92.1)
post2019	-0.016	0.341***	375.4	7.86
	(0.013)	(0.106)	(428.3)	(70.7)
above_70 × post2019	-0.040*	-0.882***	-1,113.6*	-91.6
	(0.022)	(0.178)	(605.7)	(103.6)
Observations	35,985	35,985	35,985	35,985

Post: start_date = 2019-05-15 (first start date after policy). Pre: same iid's most recent spell with start_date < 2019-04-14. above_70 (beta2): pre-existing discontinuity − should be approx. 0. above_70:post2019 (beta4): causal effect of free premium policy. Bandwidth +/-20 quarters from age 70. Clustered SE by household.

Table F2 — Split-Sample RDD by Cohort: Number of Claims

	n_claims							
	2016 (1)	2017 (2)	2018 (3)	2019 (4)	2020 (5)	2021 (6)	2022 (7)	2023 (8)
above_70	-0.071	0.104	-0.066	-1.08***	-1.07***	-1.06***	-1.16***	-1.04***
	(0.304)	(0.090)	(0.066)	(0.042)	(0.037)	(0.034)	(0.035)	(0.029)
quarters_from_70 × above_70	0.037	-0.018**	-0.011*	-0.002	-0.019***	-0.029***	-0.047***	-0.045***
	(0.028)	(0.008)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Observations	1,822	32,002	71,157	226,347	292,368	425,213	477,285	549,583

Table F3 — Split-Sample RDD by Quarterly Cohort (Aug): Number of Claims

	n_claims						
	2017-Aug	2018-Aug	2019-Aug	2020-Aug	2021-Aug	2022-Aug	2023-Aug
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
above_70	-0.108	0.071	-0.554***	-0.660***	-0.707***	-0.778***	-0.702***
	(0.223)	(0.149)	(0.078)	(0.080)	(0.088)	(0.087)	(0.073)
quarters_from_70 × above_70	-0.019	-0.015	0.075***	0.022**	-0.020*	-0.026**	-0.002
	(0.031)	(0.020)	(0.011)	(0.011)	(0.011)	(0.011)	(0.010)
Observations	5,279	12,606	77,077	78,581	78,995	77,803	91,617