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Leveraging Probability Distortion to Target Prevention: A Cardiovascular Screening Experiment in the Philippines

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We test whether a conditional cash lottery targets prevention on those doing too little because of inverse-S probability distortion that also causes overvaluation of a lottery. Consistent with theory, Filipinos perceiving their cardiovascular disease (CVD) risk in a wide intermediate interval $(10\%, 85\%]$ are 3 percentage points (60%) less likely to have a check-up before baseline if they exhibit inverse-S distortion. A random lottery offer conditional on going for a check-up (CVD screening) increases the probability by 47 points overall. Estimates of compliance and lottery-induced CVD preventive care are larger (not significantly) for inverse-S (but also S) types perceiving intermediate risk.

JEL: D91, I12

Keywords: Prospect Theory | Probability Weighting | Behavioral Incentive | Lottery | Self-selection

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Psychological biases underlie unhealthy behaviors that contribute to the large burden of noncommunicable disease (Li et al., 2025). Direct intervention on heterogeneous and unobservable biases is infeasible. Targeting through self-selection on a bias could alleviate this information constraint. We test this by offering a cash-prize lottery conditional on going for a medical check-up and observing whether it particularly incentivizes those who would underinvest in prevention due to probability distortion otherwise.

Inverse-S probability distortion is the muted behavioral response to change in intermediate probabilities (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). This *likelihood insensitivity* (Tversky and Wakker, 1995) causes inverse-S types – who often predominate (Wakker, 2010; Fehr-Duda and Epper, 2012; l'Haridon and Vieider, 2019) – to undervalue gains from preventive efforts to reduce loss probabilities in a wide interval (Baillon et al., 2022*a*). Since these types overvalue a small-chance lottery (Kahneman and Tversky, 1979), a conditional cash lottery (CCL) may correct their tendency toward sub-optimal prevention.

We offered randomly selected older adults in the Philippines the opportunity to enter lotteries – each giving a chance of winning the equivalent of three-weeks minimum-wage earnings – if they were to go for a check-up at a clinic tasked with screening for cardiovascular disease (CVD) risk. We elicited probability distortion and risk tolerance (with incentives) as well as perceived CVD risk, i.e. probability of having a heart attack/stroke within ten years. Among those perceiving risk between 10% and 85% – the approximate interval where likelihood insensitivity is predicted to cause sub-optimal prevention (Baillon et al., 2022*a*) – we test whether inverse-S types do less prevention at baseline and have higher lottery compliance. To examine whether gains from lottery-induced check-ups vary with probability distortion, we use the lottery offer to instrument a clinic visit and estimate effects on receipt of preventive care, health behavior and biomarker-predicted CVD risk that are potentially heterogeneous by risk attitudes and perceptions.[1]

As predicted, at perceived CVD risks of 10-85%, inverse-S types are less likely – by about 3 percentage points (pp) (60%) – to have gone for a check-up before baseline than those who, consistent with expected utility theory (EUT), weight probabilities linearly (*non-distorters*). Health behaviors and biomarkers also indicate that inverse-S types initially do less prevention.

The lottery offer increases the probability of visiting a clinic by 47 pp overall (Capuno, Kraft

[1] Capuno, Kraft and O'Donnell (2021) estimate these effects without exploring heterogeneity.

and O'Donnell, 2021). While the point estimate of compliance is higher for inverse-S types than non-distorters, particularly at perceived risks of 10-85%, it is also higher for S types (expected to undervalue a lottery), and neither difference is statistically significant. In the sample, inverse-S distortion is more prevalent among compliers than among always-takers and never-takers, particularly in the 10-85% risk interval and when excluding those making dominated elicitation-task choices.

Despite inverse-S types doing less baseline prevention of perceived risks from 10% to 85%, evidence that they gain more from a lottery-induced clinic visit is not strong. The point estimate of the effect on preventive care receipt is larger for those types than for non-distorters within the 10-85% risk interval, but the difference is not statistically significant and the estimate is also larger for S types. However, the only group in which a clinic visit leads to healthier behavior comprises inverse-S types perceiving intermediate risk.

EUT is ambiguous regarding the effect of risk attitude on self-protection – the probability-reducing variant of preventive behavior (Ehrlich and Becker, 1972; Dionne and Eeckhoudt, 1985). Prospect theory predicts that, within a wide interval of intermediate probabilities, inverse-S probability distortion pulls self-protection below the EU maximizing optimum (Baillon et al., 2022*a*). We conduct the first test of this prediction.

We also test whether a CCL can correct the sub-optimality by indirectly targeting those whose underprevention leaves them with most to gain from doing more. Prior evidence of advantageous (risk) selection into prevention (Jones, Molitor and Reif, 2019; Einav et al., 2020; Oster, 2020; Kowalski, 2023; Iizuka, Kawamura and Shigeoka, 2025) and reverse selection on healthcare gains (Einav et al., 2013; Iizuka, Kawamura and Shigeoka, 2025) could result from moral hazard encouraging lower-risks to use low-value care (Pauly, 1968; Zeckhauser, 1970), while costs, ordeals or psychological biases discourage higher-risks from using high-value care (Baicker, Mullainathan and Schwartzstein, 2015; Brot-Goldberg et al., 2017). While observables can be used to improve targeting on gains or risks (Inoue, Athey and Tsugawa, 2023; Iizuka, Kawamura and Shigeoka, 2025), impact will be limited if selection is primarily through unobservables, such as biases. We aim to use a behavioral incentive with anticipated heterogeneous responses related to a bias to correct self-selection out of care caused by the same bias.[2]

[2] Provision of information and assistance are found to raise take-up – likely held down by psychological biases – but worsen targeting of U.S. food stamps (Finkelstein and Notowidigdo, 2019). In India, financial incentives combined with personalized information are found to raise take-up and improve targeting of mental healthcare (Breza et al., 2026), which is found to increase willingness to pay for prevention (Angelucci and Bennett, 2026).

Lotteries have been used to increase take-up of screening (Vital Statistics, 1957), health risk assessment (Haisley et al., 2012), vaccination (Yokley and Glenwick, 1984; Stitzer et al., 2010; Barber and West, 2022) and weight-loss programs (Volpp et al., 2008). We evaluate a CCL not for its effect on prevention overall but for targeting. Björkman Nyqvist et al. (2018) find that a lottery offer conditional on testing negative for sexually transmitted infections reduced HIV incidence by one fifth in Lesotho, with this large effect entirely attributable to compliance of (externality-generating) risk seekers.[3] Consistent with *asymmetric paternalism* (Camerer et al., 2003; Thaler and Sunstein, 2003; Loewenstein, Brennan and Volpp, 2007), we test using a CCL to target prevention of a noncommunicable disease on an internality: probability distortion.

Cost-effective primary prevention could reduce premature CVD deaths in low- and middle-income countries (LMIC) that account for four fifths of the global total (World Health Organization, 2016, 2017, 2020; GBD Collaborative Network, 2026). Mostly, it is high-risk but asymptomatic individuals without prior CVD events who die prematurely from the disease (World Health Organization, 2007). Targeting high-risk groups is more efficient than population screening (World Health Organization, 2010). This could be achieved through self-selection of those with most to gain from opportunistic screening at clinics – a core CVD strategy (World Health Organization, 2016, 2020).

I. Theoretical framework

We use a restricted case from Baillon et al. (2022*a*) to show inverse-S probability distortion causes underprevention relative to the EU benchmark.

Exertion of effort, $e \in [0, \bar{e}]$, reduces the probability, $p(e)$, of a negative health event – a heart attack, let's say – and a separable component of utility, $u(e)$, with $p(e)$ convex and $u(e)$ concave. Fixing utility from health with and without a heart attack at -1 and 0, respectively, EU maximization solves $\max_e u(e) - p(e)$ to give optimal effort at $u'(e^*) = p'(e^*)$.[4]

In prospect theory (PT) (Tversky and Kahneman, 1992), a prospect is evaluated by weighting outcome deviations from a reference point by (marginal) transformed cumulative probabilities. An inverse-S probability weighting function (PWF), $w(p)$, crosses the diagonal ($w(p) = p$) once from above (it is *regressive*) and is concave at lower p, then convex (Wakker, 2010). For such PWFs,

[3] There is mixed evidence of CCL effectiveness in preventing communicable disease in other low-income settings (Thirumurthy et al., 2016; Gorgens et al., 2022; Bosman et al., 2024).

[4] We assume an interior solution. At a corner, probability distortion could move prevention in only one direction. The second order condition is satisfied by the assumed convexity of $p(e)$ and concavity of $u(e)$.

$w'(p) < 1 \, \forall p \in (p_1, p_2)$, a *likelihood insensitivity interval* (Baillon et al., 2022*a*). Under PT with an optimistic reference point of no effort and no heart attack, effort is chosen to maximize $u(e) - w(p(e))$ at $u'(e^\circ) = w'(p(e^\circ))p'(e^\circ)$. If e^* would result in a probability in the insensitivity interval, then $w'(p(e^*)) < 1$ and, at the EU optimum, the marginal benefit of prevention would be undervalued by an inverse-S type. Their chosen effort would be sub-optimal: $e^\circ < e^*$.

The prediction that inverse-S distortion causes underprevention is robust to allowing a) utility from consumption as well as health and effort, and not imposing separability, b) a monetary cost of effort, c) mortality risk, d) alternative reference points, and e) ambiguity (Baillon et al., 2022*a*).[5] Evidence on PWFs, including from LMIC (l'Haridon and Vieider, 2019), suggests a wide insensitivity interval of approximately 10–85% (Baillon et al., 2022*a*), which includes the probability someone in middle age with elevated risk factors has a heart attack/stroke within ten years (Ueda et al., 2017).

The regressivity of an inverse-S PWF inflates demand for a small-chance ($\leq 1/3$ or so) lottery (Kahneman and Tversky, 1979). Hence, likelihood insensitivity simultaneously reduces prevention over a wide risk interval and magnifies the appeal of a lottery. Conditioning lottery entry on a preventive action, like CVD risk screening, potentially leverages a bias to target those led by the same bias to do too little prevention.

An S-shaped PWF reduces the appeal of a small-chance lottery but also induces overprevention of risks roughly between 10% and 85% (Baillon et al., 2022*a*), and so there is no internality-correction argument for incentivizing S types to increase prevention of those risks.[6]

II. Study Design

A. Setting

CVD causes almost one third of deaths in the Philippines, where the CVD death rate is above the regional average (GBD Collaborative Network, 2026). CVD risk factors are not more prevalent than in neighboring countries (ibid.), pointing to prevention deficiencies (World Health Organization, 2012). Around 37% of older hypertensives remain undiagnosed (Kraft et al., 2024). On current trends, a targeted one-third reduction in premature CVD mortality will not be reached until 2050

[5] With a pessimistic reference – heart attack despite maximum effort – both outcomes are gains. Underprevention by inverse-S types is still predicted. The result survives dispensing with a reference point and modeling with rank-dependent utility (Quiggin, 1982), which, for a binary prospect (Luce, 1991), encompasses most non-expected utility theories (Wakker, 2010).

[6] Incentivizing those types to prevent risks below 10% and above 85%, where their $w'(p) < 1$, could be justified.

(NCD Countdown 2030 Collaborators, 2018), although implementation of low-cost interventions (World Health Organization, 2020) would be sufficient to meet the 2030 deadline (Bertram et al., 2018). One such intervention requires public clinics to screen all patients aged 40+ for CVD risk and to refer, medicate and counsel accordingly (Department of Heath, 2012*a*,*b*).

We conducted a field experiment in Nueva Ecija, a largely rural (83%) province, with a population of over 2 million, a poverty rate of around 30% and higher than average prevalence of CVD risk factors (FNRI-DOST, 2015).

B. Sampling

We stratified all 849 barangays (smallest administrative unit) in the province by rural/urban and randomly selected 222 rural and 82 urban. We randomly assigned 137 to a CCL treatment group, 137 to a control group and 30 to an information treatment that is not analyzed here.

Within each barangay, we randomly sampled ≈12 households.[7] From each household, we randomly selected one individual a) aged 40–70, b) without reported diagnosis of heart disease or diabetes and no prior heart attack or stroke, and c) not on hypertension medication.[8] We excluded those with CVD history to focus on primary prevention (Capuno, Kraft and O'Donnell, 2021). Age limits were chosen to ensure all participants were eligible for CVD risk screening at clinics (Department of Heath, 2012*b*) and for consistency with the algorithm used to predict CVD risk (Ueda et al., 2017).

Baseline data were collected in January–May 2018. Endline data were collected about seven months later (mean: 32 weeks).

C. Lottery treatment

At baseline, each participant in the CCL treatment group received a voucher exchangeable for a lottery ticket (Supplemental Appendix A) if they attended a designated clinic within about six weeks (mean: 44 days). Participants were told entering the lottery gave them a chance of winning 5,000 pesos (≈US$100) and there would be one winner in their barangay. They were instructed to ask for a medical assessment at the clinic. Clinic staff were told to verify vouchers against a

[7] The sample is powered to detect minimum (average) effects of a check-up on primary outcomes (Capuno, Kraft and O'Donnell, 2021), Appendix E.

[8] If criteria were not met, we resampled another 40–70 year-old from the same household, or from another (random) household, if necessary.

claimant list and IDs, issue tickets and conduct or refer for any assessment deemed appropriate (Supplemental Appendix A, Figure A3). One week after voucher expiry, the winning ticket in each barangay was drawn. The chance of winning averaged 14%. Winners were notified by text message and paid via a remittance company.

D. Data

At baseline, we a) asked about healthcare use, health, behavior and sociodemographics, b) elicited risk attitudes and CVD risk perceptions, and c) measured blood pressure (BP), height and weight. At endline, we repeated questions and measurements used to construct outcomes. Variables are defined in Supplemental Appendix B, Table A1.

Prevention.—Our main baseline prevention measure is a reported check-up in the last 30 days, $\textit{CHECK-UP}_i \in \{0,1\}$, where i indexes an individual. This is the behavior the CCL aimed to encourage after baseline. In supplementary analysis, we use a *preventive effort index* that is a weighted average of standardized measures of *not* having baseline CVD risk factors indicated by biomarkers (high BP, overweight and central obesity) and reported behaviors (smoking, heavy episodic drinking, unhealthy diet and lack of exercise) (Supplemental Appendix C).

CCL compliance is estimated by the treatment–control mean difference in an indicator of any reported visit to a public clinic between baseline and endline, $VISIT_i \in \{0,1\}$. Like Capuno, Kraft and O'Donnell (2021), we use this indicator to estimate clinic visit effects on receipt of preventive care, health behavior and predicted CVD risk. A *preventive care index* averages standardized indicators of having CVD risk factors measured, diagnosed and medicated, and receiving related lifestyle advice between baseline and endline (Supplemental Appendix B, Table A2).[9] A *health behavior index* is constructed from endline reports of no heavy episodic drinking, healthy diet and exercise, with smoking excluded since it enters the final outcome. *Predicted CVD risk* is an algorithm-generated probability of having a heart attack or stroke within ten years based on sex, age, systolic BP, body mass index and smoking (Ueda et al., 2017).

Risk attitudes.—We elicited probability distortion and risk tolerance with an instrument designed for low-education populations and previously fielded in the Philippines (Baillon et al., 2022*b*). In each of two incentivized money-gain choice sets, the participant chooses between two pouches con-

[9]Indicators are standardized relative to control means, with less-correlated indicators receiving greater weight (Anderson, 2008).

taining colored balls. The color of the ball drawn determines the payoff.

In Set 1, we elicit the certain gain x_i that leaves the participant indifferent compared with a 50% chance of winning 400 pesos (≈US$8) or nothing: $x_i \sim 400_{0.5}0$. In Set 2, we elicit z_i leaving indifference between a 50% chance of winning that amount and a 25% chance of 400 pesos: $z_{i0.5}0 \sim 400_{0.25}0$. Each of x_i and z_i is obtained by bisection (Supplemental Appendix D). Each participant has a 1/5 chance that one randomly selected choice (in Set 1 or 2) is played for real (Harrison, Lau and Rutström, 2007; Aydogan, Berger and Théroude, 2024; Berlin et al., 2026).

EU maximizers have $x_i = z_i$, with $x_i < 200$ indicating risk aversion. Others exhibiting the *common ratio effect* (Allais, 1953) have $x_i \neq z_i$, revealing probability distortion. If the PWF is inverse-S, overweighting $p = 0.25$ and underweighting $p = 0.5$, the 25% lottery in Set 2 is relatively more attractive and the 50% lotteries less attractive, leading to $z_i > x_i$.[10] Conversely, with an S-shaped PWF, $p = 0.25$ is underweighted and $p = 0.5$ overweighted, giving $z_i < x_i$.

We measure probability distortion and risk tolerance by $x_i - z_i$ and $(x_i + z_i)/2$, respectively (Baillon et al., 2022*b*). These capture distinct components of the data.[11] Under prospect theory, the difference measure captures shape of the PWF, while the average measure captures its elevation, reflecting optimism/pessimism (Wakker, 2010), and utility curvature.

We categorize the probability distortion of participants as $INVERSE\text{-}S_i = \mathbb{1}(x_i - z_i < 0)$, $LINEAR_i = \mathbb{1}(x_i - z_i = 0)$ or $S_i = \mathbb{1}(x_i - z_i > 0)$ and test robustness to alternative thresholds that allow small deviations between x_i and z_i arising from error.[12] For risk tolerance, we categorize as risk $AVERSE_i = \mathbb{1}\big(\frac{x_i+z_i}{2} \leq 180\big)$, $NEUTRAL_i = \mathbb{1}\big(180 < \frac{x_i+z_i}{2} < 220\big)$ or $SEEKING_i = \mathbb{1}\big(\frac{x_i+z_i}{2} \geq 220\big)$.[13]

Risk perceptions.—The PWF is defined over subjective probabilities (Tversky and Fox, 1995), which we elicit at baseline by asking: "What is the chance you will have a heart attack or stroke in the next 10 years?" This is the subjective analogue of risk-factor-predicted CVD risk used in

[10] Fixing $u_i(0) = 0 \ \forall i$, from the indifference points: $\frac{u_i(z_i)}{u_i(x_i)} = \frac{w_i(0.25)}{w_i(0.5)^2}$. Hence, $z_i > x_i \ iff \ w_i(0.25) > w_i(0.5)^2$, which holds for any inverse-S PWF crossing the diagonal between 0.25 and 0.5. Prelec's (1998) single-parameter function is one such case (Supplemental Appendix E).

[11] Let x and z be column vectors of x_i and z_i, respectively. Risk tolerance is the inner product of $\begin{bmatrix} x & z \end{bmatrix}$ with $\begin{bmatrix} \frac{1}{2} & \frac{1}{2} \end{bmatrix}'$, and probability distortion the product with $\begin{bmatrix} 1 & -1 \end{bmatrix}'$. Since these vectors are orthogonal, $\begin{bmatrix} \frac{1}{2} & \frac{1}{2} \end{bmatrix} \times \begin{bmatrix} 1 & -1 \end{bmatrix}' = 0$, the two measures partition the variance of the data. The correlation between the measures is -0.0311 (p-value = 0.0808), and -0.0014 (p-value = 0.9488) when respondents making dominated choices are excluded.

[12] Alternatives are $x_i - z_i < -25$, $-25 \leq x_i - z_i \leq 25$, and $x_i - z_i > 25$ for *INVERSE-S*, *LINEAR* and *S*, respectively. A 25-point difference can occur if participants are forced to choose between options with equal expected value, or if random error causes one inconsistent choice. In either case, midpoint approximation (Supplemental Appendix D) yields $|x_i - z_i| = 25$.

[13] The bounds reflect partial identification (Supplemental Appendix D) and allow for small errors: with linear utility and no distortion (and no error), choices imply $x_i = z_i = 187.5$ or 212.5.

screening and treatment protocols (World Health Organization, 2020). Participants could answer on a 0–100 scale either using a slider or verbally (Delavande, 2014), and were first given a tutorial with practice questions (Supplemental Appendix F).

We distinguish subjective probabilities inside the $(10\%, 85\%]$ insensitivity interval, where underprevention by inverse-S types is predicted (Baillon et al., 2022*a*), from other probabilities. We label $(10\%, 85\%]$ risks *intermediate* to emphasize exclusion of the extremities, although risks $> 20\%$ are considered *high* for clinical purposes (World Health Organization, 2020). We test robustness to shifting the interval to $(5\%, 80\%]$, where inverse-S distortion could cause underprevention if preventive effort were costlier in poorer health (Baillon et al., 2022*a*).

Covariates.—Baseline covariates are age, sex, marital status, employment, education, wealth index (Filmer and Pritchett, 2001), diagnosed illness or angina symptoms, health-related quality of life (HRQoL) (Stewart et al., 1988), inpatient admission, family CVD history and health insurance. All regressions condition on urban/rural strata.

E. Sample Characteristics

Sample selection.—We interviewed 3,796 participants at baseline. We exclude the information treatment group ($n = 375$), attrition cases ($n = 262$) and item non-response cases ($n = 12$), leaving 3,147 that constitute 92% of the baseline CCL treatment and control groups (Supplemental Appendix G, Table A3). Sample selection is unrelated to CCL assignment (Table A3).

Most participants are female (67%), rural (74%), working (58%) and 68% report having health insurance (Table A4). The mean age is 52 years and 42% have no more than elementary schooling.

Risk attitudes.—The medians and means of x_i and z_i are all within the risk neutral interval of $(180, 220)$ (Table A5). We categorize around 43% as (risk) *AVERSE*, 17% as *NEUTRAL* and 40% as *SEEKING* (Table A5). While the medians of x_i and z_i are equal, mean $x_i - z_i$ is positive and significantly different from zero ($p = 0.0027$). We categorize around 33% as *INVERSE-S*, 29% as *LINEAR* and 38% as *S* (Table A5).[14]

[14] Allowing x_i to deviate slightly from z_i due to error and imprecision rather than probability distortion (see fn. 12) increases the *LINEAR* category by 7–9 pp, with the other two falling in equal measure (Table A6). Also in the Philippines and using essentially the same instrument, although in the loss domain without incentives, Baillon et al. (2022*b*) find lower prevalence of S types. Our finding that inverse-S distortion does not predominate is contrary to most evidence from student samples (Bruhin, Fehr-Duda and Epper, 2010; Fehr-Duda and Epper, 2012; Rieger, Wang and Hens, 2017; l'Haridon and Vieider, 2019) and to some LMIC lab-in-field experiments (Tanaka, Camerer and Nguyen, 2010; Liu, 2013; Vieider et al., 2018, 2019) but not all of them (Humphrey and Verschoor, 2004*a*,*b*; Harrison, Humphrey and Verschoor, 2010; Verschoor and D'Exelle, 2022). All the LMIC studies that find inverse-S predominance impose a homogeneous PWF. Not all laboratory experiments find inverse-S predominance (Blavatskyy, 2010; van de Kuilen and Wakker, 2011; Wilcox, 2023).

One third of participants make at least one dominated choice by taking an extreme option offering a lower chance of the same payoff (Table A3).[15] Dominated choices are common (Von Gaudecker, Van Soest and Wengstrom, 2011; Charness, Gneezy and Imas, 2013; Björkman Nyqvist et al., 2018), potentially reflecting extreme attitudes or misunderstanding. We check robustness to their exclusion, which has little impact on the probability distortion categorization but increases the shares categorized as risk $AVERSE$ and $NEUTRAL$ (Table A5).[16]

Risk perceptions.—The median and mean reported chance of a heart attack or stroke within ten years are 10% and 22%, respectively (Table A5 and Figure A8). About 46% of participants report a risk in the $(10\%, 85\%]$ interval. The reported risk is $\leq 10\%$ for about 52% and $> 85\%$ for only 2%.

Balance.—Treatment and control groups are well balanced (Table A8). Equal means is rejected (p-value< 0.05) for only 1 of 24 comparisons. All normalized differences are well below the 0.25 threshold (Imbens and Rubin, 2015).

III. Results

A. Prevention by risk attitudes and perceptions

We assess whether baseline prevention is associated with probability distortion by regressing $CHECK\text{-}UP_i$ on indicators of probability distortion interacted with (rescaled) perceived CVD risk (p_i) inside the intermediate interval, $I_{1i} = \mathbb{1}_{\{p_i \in (0.1, 0.85]\}}$, or outside it, $I_{2i} = 1 - I_{1i}$, risk tolerance and covariates $\mathbf{X_i}$:

$$
\begin{aligned}
CHECK\text{-}UP_i = \alpha_1 + \sum_{k=1}^{2} \left(\beta_{1k} INVERSE\text{-}S_i + \beta_{2k} S_i \right) I_{ki} \\
+ \rho_1 I_{2i} + \vartheta_1 AVERSE_i + \vartheta_2 SEEKING_i + \mathbf{X}_i \boldsymbol{\psi}_1 + \varepsilon_{1i}.
\end{aligned}
\tag{1}
$$

Table 1 reports estimates from three specifications of this linear probability model (LPM) (Table A9 for full estimates). Consistent with the prediction that inverse-S types perceiving (intermediate) CVD risks between 10% and 85% do less prevention than the expected utility benchmark, all estimates of β_{11} are negative, with p-values < 0.05. Using the parsimonious specification (column 1:

[15] We code these choices as 0 or 400 when the safest option or riskiest option is taken at the respective extreme (Supplemental Appendix D). The proportion does not differ by treatment exposure (Table A3).

[16] Details of elicited x_i and z_i in Table A7 and Supplemental Appendix H, Figure A7.

Table 1—: Check-up probability differences by risk attitudes and perceptions

	(1)	(2)	(3)
Probability distortion (ref. LINEAR)			
INVERSE-S $\times$ Intermediate CVD risk	-0.0275	-0.0297	-0.0412
	(0.0139)	(0.0139)	(0.0185)
INVERSE-S $\times$ Low/High CVD risk	0.0064	0.0058	0.0061
	(0.0124)	(0.0126)	(0.0160)
S $\times$ Intermediate CVD risk	-0.0097	-0.0087	-0.0166
	(0.0150)	(0.0150)	(0.0199)
S $\times$ Low/High CVD risk	0.0018	0.0012	-0.0149
	(0.0134)	(0.0140)	(0.0166)
Risk tolerance (ref. NEUTRAL)			
AVERSE	-0.0012	-0.0013	-0.0048
	(0.0134)	(0.0138)	(0.0155)
SEEKING	-0.0154	-0.0139	-0.0226
	(0.0121)	(0.0122)	(0.0147)
Additional controls	No	Yes	Yes
Dominated excluded	No	No	Yes
Mean	0.0499	0.0499	0.0497
R^2	0.0106	0.0234	0.0281
Observations	3147	3147	2113

Note: Estimates of linear probability model of check-up (30 days) before baseline, eq.(1). For probability distortion, each row gives estimates of the conditional difference in the check-up probability between the respective distortion category and no distortion (LINEAR), with perceived CVD risk either Intermediate ($p \in (0.1, 0.85]$) or Low/High ($p \notin (0.1, 0.85]$); estimates of parameters $\beta_{jk}, j, k \in \{1, 2\}$ in eq.(1). For risk tolerance, each cell gives the estimated conditional check-up probability difference between the respective category (risk AVERSE or SEEKING) and risk NEUTRAL; estimates of ϑ_k. Column (1) controls are sex-specific 5-year age groups and urban. Columns (2) and (3) additionally control for marital status, employment, educational attainment, wealth quintile, disease indicators, HRQoL, inpatient admission in last year, family CVD history and health insurance (Supplemental Appendix B, Table A1 for definitions). Column (3) excludes participants making dominated choices in risk attitude elicitation tasks. Cluster (barangay) adjusted standard errors in parentheses. Table A9 gives full estimates of model (2). Table A10 gives robustness checks.

age-sex and urban controls), inverse-S types are estimated to be 2.75 pp less likely to go for a check-up than those with no distortion who also perceive intermediate risk. This difference is large relative to a check-up prevalence of 5%. It is robust to more controls (column 2) and gets even larger when dominated-choice participants are excluded (column 3). It is also robust to estimating with probit, stratifying by perceived CVD risk interval, lowering the intermediate interval to $p_i \in (0.05, 0.8]$ and using an alternative categorization of probability distortion (Table A10), as well as controlling for risk tolerance with (power) utility curvature instead of the non-parametric measure (Table A11).

The same pattern holds with broader prevention measures. The conditional mean of the preventive effort index is significantly lower (≈ 0.1 of a standard deviation) for inverse-S compared with no distortion at intermediate risk (Table A12). This association strengthens when the index is restricted to include only biomarkers (Table A13).

Theory also predicts underprevention by S types perceiving risk outside the intermediate interval (Baillon et al., 2022*a*). For such Low/High risks, the point estimate of the check-up probability difference between S and no distortion types (β_{22} in eq. (1)) is consistent with the prediction only when dominated choices are excluded. Even then, p-value > 0.1.[17]

Baseline check-up propensity does not vary significantly with risk tolerance, although point estimates indicate risk seekers in the sample are somewhat less likely to have gone for a check-up than risk neutrals, particularly when dominated choices are excluded.

B. *Lottery compliance by risk attitudes and perceptions*

To examine whether lottery compliance differs by risk attitude and perception, we test for heterogeneous effects of the lottery offer on the probability of visiting a clinic and we characterize compliers non-parametrically (Marbach and Hangartner, 2020).

Compliance heterogeneity.—We estimate LPMs for any public clinic visit between baseline and endline. The most general model is,

[17]Further inconsistency is a significantly lower preventive effort index for S types perceiving intermediate risk (Table A12).

(2)

$$VISIT_i = \alpha_2 + LOTTERY_i \left[\delta_0 + \sum_{k=1}^{2} \left(\delta_{1k} INVERSE\text{-}S_i + \delta_{2k} S_i \right) I_{ki} + \delta_3 I_{2i} + \delta_4 AVERSE_i + \delta_5 SEEKING_i \right]$$
$$+ \sum_{k=1}^{2} \left(\xi_{1k} INVERSE\text{-}S_i + \xi_{2k} S_i \right) I_{ki} + \rho_2 I_{2i} + \lambda_1 AVERSE_i + \lambda_2 SEEKING_i + \tau \; VISIT_{0i} + \mathbf{X}_i \boldsymbol{\psi}_2 + \varepsilon_{2i} \,,$$

where $LOTTERY_i = \mathbb{1}_{\{i \in \text{CCL Treatment Group}\}}$, $VISIT_{0i}$ indicates a pre-baseline clinic visit and $\mathbf{X}_i$ are baseline covariates.[18]

Table 2 shows estimates of the *LOTTERY* effect. Those in columns (1) and (2) are from restricted versions of eq.(2) that exclude interactions and controls for risk attitudes and perceptions. These estimates indicate that the lottery offer raises the probability of visiting a clinic by 47 pp – more than a threefold increase on the control mean (Capuno, Kraft and O'Donnell, 2021). Column (3) gives estimates with potential heterogeneity by risk attitude but not risk perception. Point estimates are larger for *INVERSE-S* and *S* types than for no probability distortion (*LINEAR*) and for risk *SEEKING* compared with risk *NEUTRAL* types, although no difference is statistically significant.

Column (4) shows estimates from eq.(2). Though imprecise (p-value$= 0.137$), the point estimate hints at higher compliance (by 8.9 pp) of *INVERSE-S* types compared with no distortion within the intermediate risk interval. The estimate is robust to using probit, excluding dominated choices (with slightly reduced magnitude) and controlling for (power) utility curvature rather than risk tolerance indicators (Tables A16) and A17). It increases in magnitude and becomes significant using an alternative categorization of probability distortion (Table A16). Outside the intermediate risk interval (predominantly, $p_i < 0.1$), we estimate that *INVERSE-S* types have 14.2 pp lower compliance (p-value$= 0.080$, Table 2). Among those displaying no distortion, we estimate 16.2 pp higher compliance if they perceive low/high risk, not intermediate risk (p-value< 0.01).

Characterizing compliers.—Since risk attitudes are independent (in expectation) of the random lottery offer, their means among *always-takers* and *never-takers* are identified from the control group mean over those who visit a clinic between baseline and endline and the treatment group mean over those who do not, respectively (Marbach and Hangartner, 2020).[19] Assuming no *defiers*, we use these means and the overall mean to identify the mean of each risk attitude indicator among

[18] Supplemental Appendix I explains deviations from the pre-analysis plan specification.

[19] There is a near-significant (p-value $= 0.0695$) treatment-control difference in the mean of the probability distortion measure $(x_i - z_i)$, but the normalized difference is negligible (0.0267) (Table A8).

Table 2—: Effects of lottery offer on probability of visiting health clinic

	(1)	(2)	(3)	(4)
LOTTERY	0.4695	0.4708	0.4363	0.3500
	(0.0225)	(0.0218)	(0.0483)	(0.0591)
LOTTERY × INVERSE-S			0.0153	
			(0.0392)	
× Intermediate CVD risk				0.0885
				(0.0593)
× Low/High CVD risk				-0.1417
				(0.0808)
LOTTERY × S			0.0557	
			(0.0370)	
× Intermediate CVD risk				0.0762
				(0.0585)
× Low/High CVD risk				-0.0396
				(0.0764)
LOTTERY × AVERSE			-0.0121	-0.0111
			(0.0419)	(0.0418)
LOTTERY × SEEKING			0.0313	0.0342
			(0.0416)	(0.0410)
LOTTERY × Low/High CVD risk				0.1621
				(0.0603)
Controls				
Sociodemographics & health	No	Yes	Yes	Yes
Risk attitudes	No	No	Yes	Yes
Risk perceptions	No	No	No	Yes
Control mean	0.1414	0.1414	0.1414	0.1414
R^2	0.2370	0.2641	0.2661	0.2714
Observations	3147	3147	3147	3147

Note: Linear probability model estimates of conditional cash lottery ($LOTTERY_i$) effect on probability of public clinic visit between baseline and endline. Column (4) specified as eq.(2). Columns (1) and (2) exclude all interactions with $LOTTERY_i$, with controls for urban/rural sample strata only in (1) and all covariates except risk attitudes in (2). Covariates in Table A1, with age and sex entered as sex-specific age groups. Column (3) extends specification (2) with controls for risk attitude categories and their interactions with $LOTTERY_i$. Top row shows estimated effect, on average in columns (1) and (2), and in the respective reference group in columns (3) and (4). Reference group is risk NEUTRAL with LINEAR probability weighting (no distortion) in (3) and the subset of this group with perceived Intermediate CVD risk ($p_i \in (0.1, 0.85]$) in (4). Other rows give differential effects by risk attitude categories in column (3) and also by probability distortion and perceived CVD risk categories in (4). For example, in (4), 0.0885 and -0.1417 are the estimates of δ_{11} and δ_{12} in (2), respectively. Cluster (barangay) adjusted standard errors in parentheses. Table A15 gives full estimates of model (4) and Tables A16 and A17 give robustness checks.

the unobserved compliers (Supplemental Appendix J). Confidence intervals are bootstrapped.

We estimate 47% compliers, 39% never-takers and 14% always-takers. For each of these principal strata, Figure 1 shows estimated proportions in each probability distortion category. Using the full analysis sample (Panel A), *INVERSE-S* types are estimated to be about one third of compliers and never-takers, and 31% of always-takers, with no significant difference (Supplemental Appendix G, Table A18). Excluding dominated-choice participants (Panel B), *INVERSE-S* prevalence among compliers is estimated to be 3.8 pp and 6.8 pp higher than among never-takers and always-takers, respectively, with neither difference significant (Table A19). We estimate that compliers have the lowest mean perceived CVD risk (20.3% vs. ≈23.6%) and are least likely to perceive risk in the intermediate interval (≈40% vs. 52% for never-takers and 50% for always-takers) (Figure A10 and Table A18). Within that interval, *INVERSE-S* are most prevalent among compliers (Figure 1, Panel C). Outside of the interval, they are least prevalent in that stratum (Panel D). While neither difference is significant (Table A20), the pattern of point estimates is consistent with over-representation of *INVERSE-S* distortion among compliers only within the risk interval where theory predicts, and baseline measures show, those types underprevent.

Contrary to expectations, *S* types are most prevalent among compliers (not significant). Unlike for *INVERSE-S*, this point-estimate difference is driven by those perceiving Low/High CVD risk (Figure 1, Panel D).

Point estimates show that sample compliers are least likely to be risk *AVERSE*, most likely to be risk *SEEKING* and have the greatest mean risk tolerance, $(x + z)/2$ (Figure A11 and Table A18). Sample compliers are more likely than never-takers to be female (Table A21), suggesting the CCL widens the sex disparity in the probability of going for a check-up (Table A9). Compliers are more likely (than never-takers) to be among the poorest 40% (Table A21), possibly because the poor value the $100 prize more and are more willing to visit a *public* clinic. Health indicators do not differ systematically between compliers and other strata (Table A21).

C. *Clinic visit effects by risk attitudes and perceptions*

At baseline, *INVERSE-S* types perceiving intermediate CVD risk are less likely to have been for a check-up and their health behaviors and biomarkers also suggest they do less prevention than non-distorters. This leaves greater scope for a lottery-induced clinic visit to increase this type's receipt of

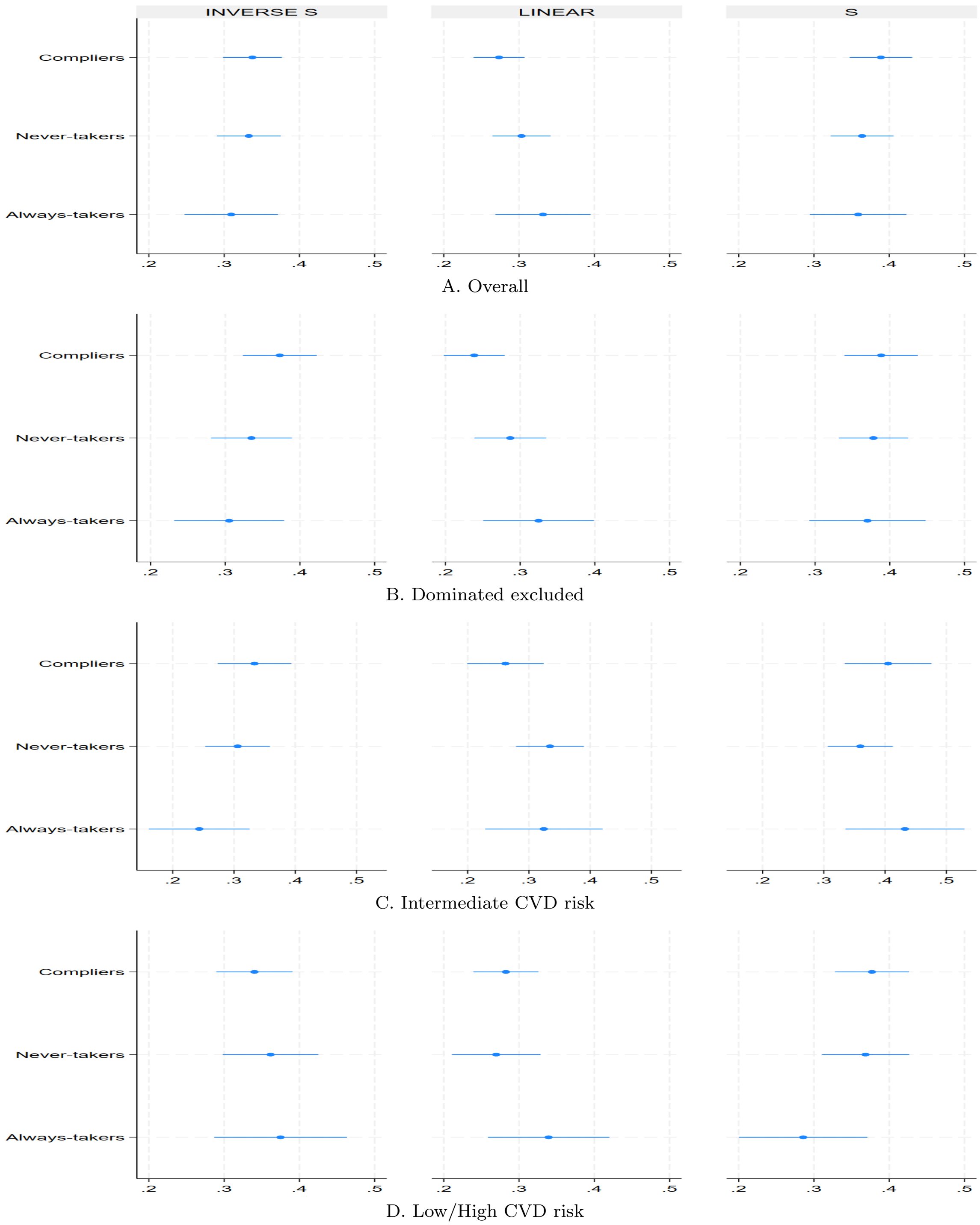

Figure 1. : Probability distortion category proportions by CCL principal strata

Note: Estimated proportions in each probability distortion category among conditional cash lottery (CCL) compliers, never-takers and always-takers. Supplemental Appendix J for identification and estimation. Interval lines show bootstrapped 95% confidence intervals that account for sample clustering and stratification (percentile method, 1000 repetitions). Panels give estimates: A) from full analysis sample (N = 3,147), B) excluding those taking dominated options in risk attitude elicitation tasks (N = 2,113), and those perceiving CVD risk as C) Intermediate, $p_i \in (0.1, 0.85]$ (N = 1,447), or D) Low/High, $p_i \notin (0.1, 0.85]$ (N = 1,700). Supplemental Appendix G, Table A18 gives numerical estimates. Supplemental Appendix H Figure A9 gives respective means of the probability distortion measure, $x_i - z_i$.

preventive care, modify their health behavior in response to medical advice and, ultimately, reduce their CVD risk. We test this by estimating effects of a clinic visit on prevention-related outcomes, allowing for heterogeneity by risk attitudes and perceptions. The most general model is

(3)
$$y_i = \alpha_3 + VISIT_i\left[\gamma_0 + \sum_{k=1}^{2}\left(\gamma_{1k} INVERSE\text{-}S_i + \gamma_{2k} S_i\right) I_{ki} + \gamma_3 I_{2i} + \gamma_4 AVERSE_i + \gamma_5 SEEKING_i\right]$$
$$+ \sum_{k=1}^{2}\left(\zeta_{1k} INVERSE\text{-}S_i + \zeta_{2k} S_i\right) I_{ki} + \rho_3 I_{2i} + \theta_1 AVERSE_i + \theta_2 SEEKING_i + \omega y_{0i} + \mathbf{X}_i \boldsymbol{\psi}_3 + \varepsilon_{3i}\,,$$

where y_i is the preventive care index, health behavior index or predicted CVD risk at endline (Supplemental Appendices C and B, Table A2) and y_{0i} is the baseline value of the respective outcome. We estimate by two-stage least squares (2SLS), with $VISIT_i$ and its interactions instrumented by $LOTTERY_i$ and its interactions with the same indicators.

Table 3 reports effects on the preventive care index. Columns (1)-(3) give estimates from restricted versions of eq.(3), while column (4) gives that model. Robust tests (Montiel Olea and Pflueger, 2013; Lewis and Mertens, 2025) reject the null of weak instruments.[20] Even using weak-instrument-robust inference (Anderson and Rubin, 1949), we still reject the null of no impact of a clinic visit on receipt of preventive care. Without allowing heterogeneity (columns 1-2), a visit is estimated increase the preventive care index by 0.15 standard deviation (SD).[21]

Column (3) allows heterogeneity by risk attitudes. The top row estimate is that a visit increases preventive care for risk neutrals with no distortion by 0.23 SD (p-value$=0.070$). The point estimates suggest larger effects for *INVERSE-S* and *S* types, but neither difference is statistically significant.[22]

Column (4) also allows for heterogeneity by risk perceptions. The top row estimate indicates no effect for risk neutrals without probability distortion who perceive intermediate risk. Consistent with *INVERSE-S* types who perceive this risk having more to gain because they are less likely to go for a check-up without the lottery incentive, the point estimate is that these types receive substantially

[20] Testing this null is infeasible for the most general model even with a test allowing multiple endogenous regressors (Lewis and Mertens, 2025). However, testing the null for each endogenous regressor separately (Sanderson and Windmeijer, 2016) gives test statistics well above Stock and Yogo (2005) critical values (Supplemental Appendix G, Table A22), although this procedure does not allow for non-iid errors.

[21] This is only slightly different from estimates in Capuno, Kraft and O'Donnell (2021) (Tables 4 and G2) obtained with a slightly different sample and covariate specification. Capuno, Kraft and O'Donnell (2021) demonstrate robustness to using probit for the first stage and correcting for multiple testing. They show the effect is mainly through increased BP measurement and receipt of lifestyle advice.

[22] The null of no effect is more strongly rejected for both *INVERSE-S* and *S*, with p-values of 0.018 and 0.022, respectively.

Table 3—: Effect of a clinic visit on receipt of preventive care

	(1)	(2)	(3)	(4)
VISIT	0.1615	0.1540	0.2293	-0.0766
	(0.0534)	(0.0512)	(0.1265)	(0.1901)
VISIT × INVERSE-S			0.0403	
			(0.1012)	
× Intermediate CVD risk				0.2826
				(0.1957)
× Low/High CVD risk				-0.1042
				(0.1171)
VISIT × S			0.0450	
			(0.0973)	
× Intermediate CVD risk				0.4145
				(0.1873)
× Low/High CVD risk				-0.1899
				(0.1155)
VISIT × AVERSE			-0.1367	-0.1261
			(0.1165)	(0.1167)
VISIT × SEEKING			-0.1218	-0.1113
			(0.1211)	(0.1206)
VISIT × Low/High CVD risk				0.4797
				(0.1904)
Controls				
Sociodemographics & health	No	Yes	Yes	Yes
Risk attitudes	No	No	Yes	Yes
Risk perceptions	No	No	No	Yes
Weak IV test	435.62	465.16	102.43	N/A
critical value ($\alpha = 0.05, \tau = 0.1$)	[14.19]	[14.19]	[57.41]	
AR test $\sim \chi^2(1)$	8.84	8.72	10.55	23.62
p-value	[0.0029]	[0.0031]	[0.0610]	[0.0026]
AR confidence set	[0.0579, 0.2650]	[0.0547, 0.2534]		
Observations	3147	3147	3147	3147

Note: 2SLS estimates of effect of a public health clinic visit on an index of preventive care receipt. See Supplemental Appendices C and B, Table A2 for index construction. Units are standard deviations from control group mean. Column (4) gives estimates from model eq.(3). Columns (3), (2) and (1) are from restricted models with cumulative exclusion of risk perceptions (& interactions), risk attitudes and covariates, respectively. Columns (1) controls for urban/rural sample strata. Covariates listed in Supplemental Appendix B, Table A1, plus outcome at baseline. Age and sex entered as sex-specific 5-year age groups. Top row gives the estimated effect on average in columns (1) and (2) and in the respective reference group in columns (3) and (4). Reference group is risk neutral with linear probability weighting in (3). In (4), it is the subset of this group perceiving CVD risk in the intermediate interval, $p \in (0.1, 0.85]$. Other rows give differential effects of a clinic visit by risk attitude and risk perception categories. In (4), for example, 0.2826 and -0.1042 are the estimates of γ_{11} and γ_{12}, respectively, in eq.(3). Cluster (barangay) adjusted standard errors in parentheses. Weak IV test is the (robust) Effective F-statistic (Montiel Olea and Pflueger, 2013) in columns (1) & (2) and an extension for multiple endogenous variables (Lewis and Mertens, 2025) in column (3). Critical values (all columns) from Lewis and Mertens (2025) for bias tolerance (τ) at 10% of worst-case benchmark using 5% significance (α). In column (4), there are too many endogenous variables to compute this test (see fn.[20]). For $VISIT_i$ (not its interactions), first-stage estimates in Table 2, except the model used there does not include baseline outcome. AR test is the (weak IV robust) Anderson and Rubin (1949) test of no effect(s) of the endogenous variable(s) in the reduced form. AR confidence set is the 95% confidence interval for the effect of the endogenous variable derived from this test.

more preventive care from a clinic visit. However, the estimate is not statistically significant and, contrary to expectation, the estimated differential effect is even larger, and significant, for S types perceiving risk in the intermediate interval. Outside of this interval, both types of distortion are associated with a smaller effect.

We do not reject hypotheses of no average or differential effects of a clinic visit on health behavior or predicted CVD risk (Supplemental Appendix G, Tables A23 and A24). However, *INVERSE-S* types perceiving intermediate risk – those the CCL is expected to target – is the only group in which a visit significantly improves health behavior (0.32 SD, p-value= 0.042).

IV. Conclusion

Consistent with a previously untested prediction that likelihood insensitivity causes underprevention of risks in a wide interval (10%, 85%] (Baillon et al., 2022*a*), we show that older Filipinos perceiving cardiovascular disease (CVD) risk in that interval are substantially less likely to go for a check-up if they exhibit the cognitive bias. This finding is robust to measuring prevention with other health behaviors and biomarkers, extensive control for covariates and alternative categorizations of probability distortion and CVD risk. Nonetheless, it is only correlational evidence. A limitation is common to all analyses of out-of-lab behavior in relation to elicited preferences (and biases) (Jaeger et al., 2010; Dohmen et al., 2011; Falk et al., 2018).

We do not find robust evidence that inverse-S types are more responsive to a conditional cash lottery (CCL) that incentivizes a check-up. The point estimate of lottery compliance is larger for those types and they are more prevalent among sample compliers, particularly at intermediate perceived CVD risk, but differences are not statistically significant and, unexpectedly, differences for S-shaped distortion are often as large. Similarly, there is not strong evidence that inverse-S types perceiving intermediate risk gain more from a lottery-induced clinic visit.

Lack of statistical significance may reflect low power. The experiment was designed to estimate the average effect of a clinic visit (Capuno, Kraft and O'Donnell, 2021), not to test for effect or compliance heterogeneity. Even if the estimated heterogeneity were statistically significant, it would not amount to causal evidence that probability distortion impacts compliance and gains from induced prevention. However, association of inverse-S distortion with higher compliance would be sufficient to indirectly target underprevention through its association with the bias. The study did not aim to evaluate the cost-effectiveness of encouraging prevention through a CCL versus a conditional cash transfer of equal expected value. That comparison is distinct from examination of CCL response by probability distortion.

We chose to elicit risk attitudes over monetary gains even though preventive effort can be viewed, as in section I, as a certain loss incurred to reduce the probability of a larger (health-related) loss. In a field experiment with low-educated participants, incentivized elicitation would be difficult (Etchart-Vincent and l'Haridon, 2011), although not impossible (Verschoor and D'Exelle, 2022), for monetary losses and infeasible in the health domain. Only two studies elicited probability weighting for monetary gains and losses from low-income, rural samples. One (in Vietnam) finds similar inverse-S distortion across the frames (Vieider et al., 2019), while the other (in Uganda) finds such distortion only for losses (Verschoor and D'Exelle, 2022). There is some evidence that likelihood insensitivity is particularly pronounced for choices over health (Bleichrodt and Pinto, 2000) and other outcomes that are affect-rich (Rottenstreich and Hsee, 2001) or less fungible (than money) (Abdellaoui and Kemel, 2013; Krawczyk, 2015).[23] However, risk attitudes do tend to be correlated across domains (Dohmen et al., 2011; Einav et al., 2012; Warshawsky-Livne et al., 2012; Vieider et al., 2015).

Björkman Nyqvist et al. (2018) also elicit risk attitudes over monetary gains and find risk seeking to be positively associated with both risky health behavior and compliance with a CCL targeting that behavior. Our point estimates for behavior and compliance associations with risk seeking are somewhat consistent with those findings. Targeting risk seekers is uncontentious when they impose a negative externality, such as HIV infection spread through risky sex (ibid.), but more contentious if there is no externality and risk seeking is considered a preference. With our measure of risk tolerance, risk seeking can reflect optimism (Wakker, 2010), and targeting it may be justified to correct that bias.

While this study does not provide unambiguous evidence of leveraging probability distortion to target prevention, we hope it may encourage others to design and test interventions that aim to turn a bias against itself.

[23] Differences in probability weighting functions for gains versus losses (Abdellaoui, 2000; Booij, Van Praag and Van De Kuilen, 2010) and by domain (Krawczyk, 2015) tend to be in function elevation (optimism/pessimism) rather than shape.

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SUPPLEMENTAL APPENDIX

Leveraging Probability Distortion to Target Prevention: A Cardiovascular Screening Experiment in the Philippines

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March 17, 2026

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A. Details of conditional cash lottery treatment

Notification of winners.—Each conditional cash lottery (CCL) treatment group participant who presented at the designated public health clinic with a lottery voucher completed a form at the clinic to register receipt of a lottery ticket. The study team collected these forms and randomly drew one winner from all the lottery tickets issued in each barangay. Winners were notified by cellphone text. Cellphone numbers were recorded at the end of the baseline interview and updated on presentation on the clinic. A small number of participants (n=13) who received a lottery ticket but did not provide a cellphone number were entered into the lottery draw. None of them won. Winners were paid by electronic money transfer or courier.

The Nueva Ecija Cardiovascular Health Study (NECHS)

UPecon's Copy

COUPON

Pangalan ng kalahok

COUPON No.

Recipient's Copy

UPECON FOUNDATION, INC. | www.upecon.org.ph/NECHS
THE NUEVA ECIJA CARDIOVASCULAR HEALTH STUDY (NECHS)

COUPON No.

KAYAMANAN ANG KALUSUGAN

*Baka ikaw na ang maswerteng manalo ng **5,000 pesos** sa inyong barangay!*

Ang coupon na ito ay patunay na si

Pangalan

ay maaaring makalahok sa NECHS raffle

This coupon is non-transferable and valid until

PAANO MAKASALI SA RAFFLE

1. Dalhin itong coupon at isang valid ID na may litrato sa RHU ____________ hanggang
2. Humiling ng medical assessment sa RHU.
3. Pagkatapos ng assessment, humingi ng raffle ticket.
4. Basahin ang instruction sa raffle ticket para makasali sa raffle.

Kung may mga katanungan, tumawag sa:

NECHS Research Team
UP Campus, Diliman, Quezon City
Hotline Nos. :
0929-424-5515 (Smart)
0915-527-8801 (Globe)
Website: www.upecon.org.ph/NECHS

Verified by:

RHU Point Person   Date

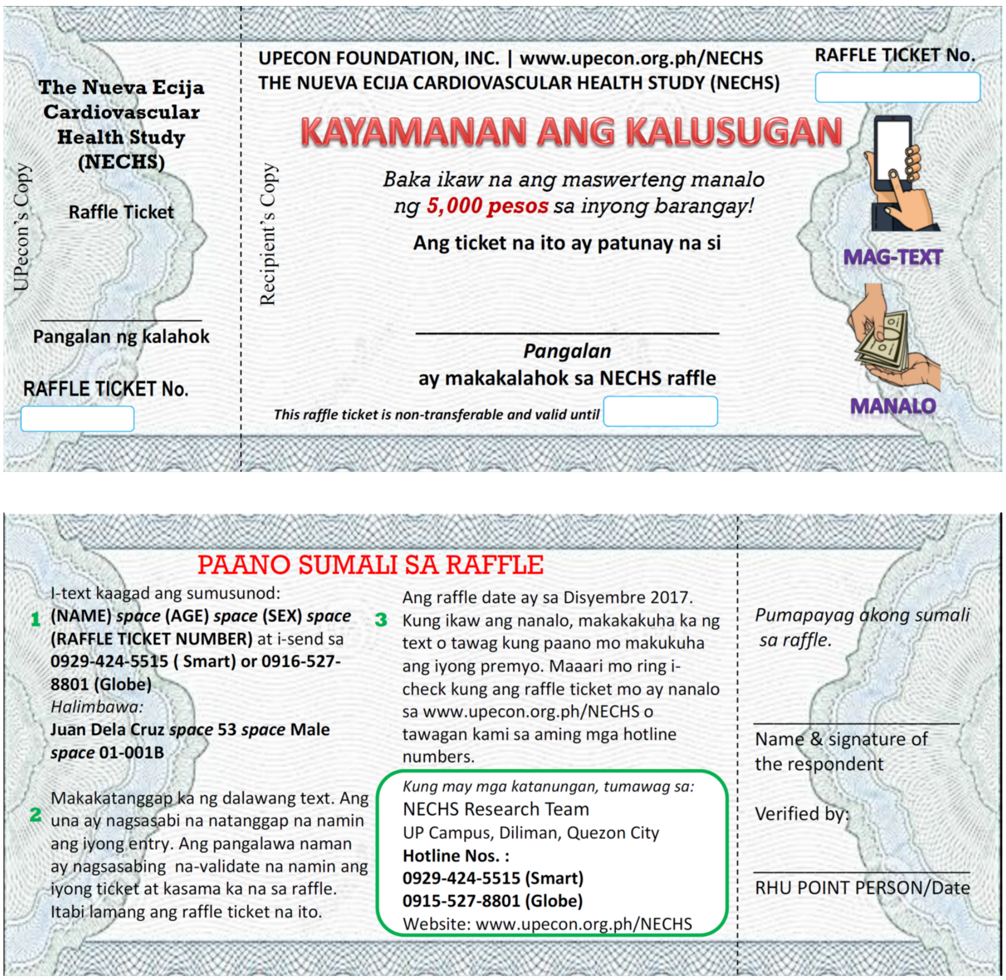
(1) Pumapayag akong sumali sa raffle.
(2) Pinapayagan ko ang UPecon na ibigay ang aking pangalan at tirahan sa RHU

Name & signature of the respondent

Verified by:

Enumerator/Date

Figure A1. : Voucher for lottery ticket (front and back side)



UPecon's Copy

The Nueva Ecija Cardiovascular Health Study (NECHS)

Raffle Ticket

Pangalan ng kalahok

RAFFLE TICKET No.

Recipient's Copy

UPECON FOUNDATION, INC. | www.upecon.org.ph/NECHS
THE NUEVA ECIJA CARDIOVASCULAR HEALTH STUDY (NECHS)

RAFFLE TICKET No.

KAYAMANAN ANG KALUSUGAN

*Baka ikaw na ang maswerteng manalo ng **5,000 pesos** sa inyong barangay!*

Ang ticket na ito ay patunay na si

Pangalan

ay makakalahok sa NECHS raffle

This raffle ticket is non-transferable and valid until

MAG-TEXT

MANALO

PAANO SUMALI SA RAFFLE

1 I-text kaagad ang sumusunod:
(NAME) ***space*** **(AGE)** ***space*** **(SEX)** ***space*** **(RAFFLE TICKET NUMBER)** at i-send sa **0929-424-5515 (Smart) or 0916-527-8801 (Globe)**
Halimbawa:
Juan Dela Cruz ***space*** **53** ***space*** **Male** ***space*** **01-001B**

2 Makakatanggap ka ng dalawang text. Ang una ay nagsasabi na natanggap na namin ang iyong entry. Ang pangalawa naman ay nagsasabing na-validate na namin ang iyong ticket at kasama ka na sa raffle. Itabi lamang ang raffle ticket na ito.

3 Ang raffle date ay sa Disyembre 2017. Kung ikaw ang nanalo, makakakuha ka ng text o tawag kung paano mo makukuha ang iyong premyo. Maaari mo ring i-check kung ang raffle ticket mo ay nanalo sa www.upecon.org.ph/NECHS o tawagan kami sa aming mga hotline numbers.

Kung may mga katanungan, tumawag sa:
NECHS Research Team
UP Campus, Diliman, Quezon City
Hotline Nos. :
0929-424-5515 (Smart)
0915-527-8801 (Globe)
Website: www.upecon.org.ph/NECHS

Pumapayag akong sumali sa raffle.

Name & signature of the respondent

Verified by:

RHU POINT PERSON/Date

Figure A2. : Lottery ticket (front and back side)

MANUAL OF TASKS OF THE
RURAL HEALTH UNIT POINT PERSON

Nueva Ecija Cardiovascular Health Study (NECHS)
UPecon Foundation, Inc.
Encarnacion Hall, U.P. Campus, Diliman, Quezon City

Table of Contents

Figure A3. : Instructions manual for study clinics

Note: Table of contents of the manual given to the public health clinic in each CCL treatment group barangay. The manual instructs clinic staff on how to respond to patients presented with a lottery voucher. The full manual is available from the authors on request.

B. Variables

Table A1—: Variable definitions

Variable	Definition
Panel A. Prevention	
CHECK-UP	1 if report visiting doctor or health facility for check-up in 30 days before baseline, 0 otherwise
VISIT	1 if report visiting public health clinic since baseline (/in last 6 months, at baseline), 0 otherwise
Preventive effort index	Weighted average of heathy behaviors & biomarkers (Appendix C)
Preventive care index	See Table A2
Health behavior index	See Table A2
Predicted CVD risk	See Table A2
Panel B. Risk attitudes	
Probability distortion	$x - z$, where $x \sim 400_{0.5}0, z_{0.5}0 \sim 400_{0.25}0$
INVERSE-S	$\mathbb{1}(x - z < 0)$
LINEAR	$\mathbb{1}(x - z = 0)$
S	$\mathbb{1}(x - z > 0)$
Risk tolerance	$(x + z)/2$
AVERSE	$\mathbb{1}(\frac{x+z}{2} \leq 180)$
NEUTRAL	$\mathbb{1}(180 < \frac{x+z}{2} < 220)$
SEEKING	$\mathbb{1}(\frac{x+z}{2} \geq 220)$
Panel C. Risk perceptions	
Perceived CVD risk, p	Reported % chance of having heart attack or stroke within 10 years /100
Intermediate	$p \in (0.1, 0.85]$
Low/High	$p \notin (0.1, 0.85]$
Panel D. Covariates	
Age	Age in years
Female	1 if female, 0 otherwise
Urban	1 if urban location, 0 otherwise
Married	1 if married or cohabiting, 0 otherwise
Working	1 if currently working, 0 otherwise
Education, ref. College graduate	
< Elementary	1 if not completed elementary school, 0 otherwise
Elementary	1 if no more than elementary school, 0 otherwise
Middle	1 if no more than middle school, 0 otherwise
High school	1 if no more than high school, 0 otherwise
Wealth index quintile group, ref. Richest	
Poorest	1 if poorest 20%, 0 otherwise
2nd poorest	1 if second poorest 20%, 0 otherwise
Middle	1 if middle 20%, 0 otherwise
2nd richest	1 if second richest 20%, 0 otherwise
Health	
Musculoskeletal	1 if report diagnosis of arthritis, rheumatism, osteoporosis or other bone disease, 0 otherwise
Chronic disease	1 if angina symptoms or report diagnosis of cancer, lung, neurological or psychiatric disease, 0 otherwise
SF-20 HRQoL	Mean score (0-100) on 6 components of SF-20 health-related quality of life
Family CVD risk	1 if report parent or sibling diagnosed with hypertension, cholesterol or diabetes, 0 otherwise
Health insurance	1 if report covered by public health insurance (PhilHealth), 0 otherwise
Inpatient	1 if reported inpatient admission in last 12 months, 0 otherwise

Note: Control for age and sex is via sex-specific 5-year age-group dummies. Wealth quintile groups formed from first principal component of house ownership, materials, size, amenities and state of repair, water source, sanitation, household durables, e.g. television, car, etc., ownership of assets (houses, land, agricultural, business, financial), receipt of remittances and conditional cash transfer (Filmer and Pritchett, 2001). Angina symptoms are identified from the Rose Questionnaire (Rose, 1962). SF-20 is constructed following Stewart et al. (1988). A public health clinic is a rural health unit, city health center or barangay health post.

Table A2—: Indicators used to construct outcomes for estimation of clinic visit effects on prevention

	Indicator	Definition
Panel A. Preventive care index		
Measurement		
a	Blood pressure (BP) measured	Had BP measured by medic since baseline
b	Blood sugar (BS)/ cholesterol (Chol) measured	Had BS or Chol measured by medic since baseline
Diagnosis		
c	Hypertension (HTN) diagnosis	Ever told by medic have HTN/high BP
d	Other CVD-related diagnosis	Ever told by medic have diabetes (DM), dyslipidaemia (DLP) or heart disease
Medication		
e	Anti-hypertensives	Taken prescribed medication for HTN since baseline
f	Anti-diabetic/statin	Taken prescribed medication for DM or DLP since baseline
Medical advice		
g	Quit smoking	Medic advised to quit smoking since baseline
h	Drink less	Medic advised to drink less alcohol since baseline
i	Reduce salt/fat	Medic advised to eat less salty and fatty foods since baseline
j	Eat fruit & veg.	Medic advised to eat more fruit, vegetables & pulses since baseline
k	Lose weight	Medic advised to lose weight since baseline
l	Exercise more	Medic advised to do more physical exercise since baseline
Panel B. Health behavior index		
m	Not heavy drinker	1 if no heavy episodic drinking – at least 4 (female)/5 (male) units of alcohol on single occasion – in the last 30 days, 0 otherwise.
n	No salt	1 if never add salt or salty sauce to food, 0 otherwise.
o	Fruit & Veg.	[# days in typical week eat fruit + # days in typical week eat vegetables]/2.
p	Exercise days	In last 7 days, max(# days walked $\geq$ 10 minutes continuously, # days did sports, fitness or leisure activities causing moderate-large increase in breathing/heart rate $\geq$ 10 minutes continuously).
Panel C. Predicted CVD risk		
q	Female	1 if female, 0 otherwise
r	Age	Age in years at endline
s	systolic BP	systolic BP measured at endline
t	Body mass index (BMI)	BMI calculated from weight and height measured at endline
u	Smoker	1 if report being a current smoker at endline, 0 otherwise

Note: Table is based on Table 1 in Capuno, Kraft and O'Donnell (2021). All indicators were *self-reported* at endline, except s and t that were *measured* at endline. *Medic* refers to a doctor or health worker. A preventive care index is constructed by standardizing each indicator in Panel A and then taking a participant-specific weighted average of the standardized values, with more weight given to indicators that correlate less with the others in order to maximize the information content of the index (Anderson, 2008). We standardize each indicator by subtracting the respective control-group mean at endline and dividing that deviation by the standard deviation of the indicator in the control group. We follow the same general procedure to construct a health behavior index from the indicators in Panel B. Smoking is excluded from these indicators because it is used to predict CVD risk. Predicted CVD risk is the percent chance of heart attack or stroke within 10 years estimated from the indicators in Panel C using the office-based Globorisk algorithm (Ueda et al., 2017).

C. Prevention measures

Baseline preventive effort index

To estimate associations between prevention and risk attitudes at baseline (sub-section III.A), we create an index of prevention effort from data on measured blood pressure (BP), weight (kg), height (m) and waist circumference (cm), and reported behaviors that potentially have consequences for health, particularly the risk of cardiovascular disease. The index is an aggregate over a number of indicators, all of which are defined such that a higher value is consistent with the result of more prevention effort. We do not presume that that effort is the only determinant of each indicator. For example, blood pressure is determined by genes and environmental exposures, not only lifestyle and medication.

An indicator of not having high BP is 1 if measured systolic BP $<$ 140 mm Hg and diastolic BP $<$ 90 mm Hg, and is 0 otherwise. BP is measured by standard procedure three times, with one-minute intervals. We use the mean of the last two measurements, as is recommended.

An indicator of not being overweight is 1 if body mass index (BMI) $<$ 25 and is 0 otherwise, with BMI calculated from measured weight and height. An indicator of not being centrally obese is 1 if measured waist circumference $<$ 80 cm if female and $<$ 90 cm if male, and is 0 otherwise.

Indicators of reported health behaviors are:

1)	Not smoker	1 if not currently smoker, 0 otherwise.
2)	Not heavy drinker	1 if no heavy episodic drinking in the last 30 days, 0 otherwise.
3)	No salt	1 if never add salt or salty sauce to food, 0 otherwise.
4)	Fruit & Veg.	[# days eat fruit + # days eat vegetables]/2.
5)	Exercise days	Number in last 7 days

Note. Heavy episodic drinking is at least 4 (female)/5 (male) units of alcohol on single occasion. Fruit & Veg. refers to number (#) of days in a typical week. Exercise days is: max(# days walked $\geq$ 10 minutes continuously, # days did sports, fitness or leisure activities causing moderate-large increase in breathing/heart rate $\geq$ 10 minutes continuously).

These are all standard indicators constructed from questions based on the World Health Organization's STEPwise approach to non-communicable disease risk factor surveillance (STEPS) instrument.

We standardize each indicator by subtracting the respective sample mean and dividing the result by the sample standard deviation. The preventive effort index is the participant-specific weighted average of the resulting z-scores, with more weight given to indicators that correlate less with the others in order to maximize the information content of the index (Anderson, 2008). Using the same method we create an index from the three biomarkers (not high BP, not overweight and not centrally obese) and another from the five reported behaviors, 1)-5).

Endline outcomes

To estimate effects of a clinic visit on receipt of preventive care, health behavior and CVD risk predicted from risk-factor exposure at endline (sub-section III.C), we construct three respective outcomes.

A preventive care index is generated from indicators of risk-factor measurements, diagnoses, medications and medical advice related to CVD prevention the participant reports receiving between baseline and endline (see Appendix B, Table A2). We standardize each indicator by subtracting the respective control-group mean at endline and dividing that difference by the standard deviation of the indicator in the control group. Then, we take a participant-specific weighted average of the standardized values, again with more weight on indicators that correlate less with the others (Anderson, 2008).

We follow the same general procedure to construct a health behavior index from endline values of the indicators 2)-5) listed above (see also Table A2). Smoking is excluded from this index since it is used to construct the final outcome – predicted CVD risk. This is the percent chance of having a heart attack or stroke within 10 years estimated from sex, age (years), systolic BP, BMI and smoking using the office-based Globorisk algorithm (Ueda et al., 2017). We estimate the effect of a clinic visit on predicted CVD risk rather than the summary index of biomarker risk factors used to examine associations of prevention effort with risk attitudes at baseline because the former is a pre-specified outcome, while the latter is not.

In regression analyses used to estimate the effect of a clinic visit on each of the three outcomes, we control for the baseline value of the respective outcome, which is calculated following the same general procedures.

D. Elicitation of risk attitudes

Elicitation.—The instrument is similar to one developed to elicit probability distortion and risk tolerance in a previous field survey in the Philippines with a sample of relatively low educational attainment (Baillon et al., 2022*b*). Each participant makes a sequence of choices in two sets. The choices are incentivized with a double (between- and within-subject) random incentive system (Aydogan, Berger and Théroude, 2024) that has been demonstrated to give similar risk attitudes as those elicited with within-subject random incentives (Harrison, Lau and Rutström, 2007; Aydogan, Berger and Théroude, 2024; Berlin et al., 2026).

In Set 1, we elicit the sure-thing money amount x that leaves the participant indifferent compared with a lottery offering a 50% chance of paying 400 pesos.

$$\text{Set 1: } x \sim 400_{0.5}0$$

In Set 2, we elicit a money amount z paid with a 50% probability that leaves the participant indifferent compared with another lottery paying 400 pesos with a 25% probability.

$$\text{Set 2: } z_{0.5}0 \sim 400_{0.25}0$$

In each case, elicitation is by bisection. The participant makes a sequence of choices between a more risky option (1) – $400_{0.5}0$ in Set 1 and $400_{0.25}0$ in Set 2 – and a less risky option (2) – $x_1 0$ in Set 1 and $z_{0.5}0$ in Set 2. We start by offering a choice between options with the same expected value. That is, in Set 1, we start with: (1) $400_{0.5}0$ vs (2) $200_1 0$. In Set 2, we start with: (1) $400_{0.25}0$ vs (2) $200_{0.5}0$. Depending on the option taken in this initial choice, we either increase or decrease the expected value of option (2) while keeping option (1) constant until the participant switches from one option to the other. For example, in Set 1, if the participant initially takes the sure-thing option (2), we reduce the value of x until they switch to the risky option (1). If they initially take the risky option (1), we increase x until they switch to the sure-thing option (2). The procedure ends after a switch or after offering five choices with no switch. Figure A4 shows the sequence in each choice set.

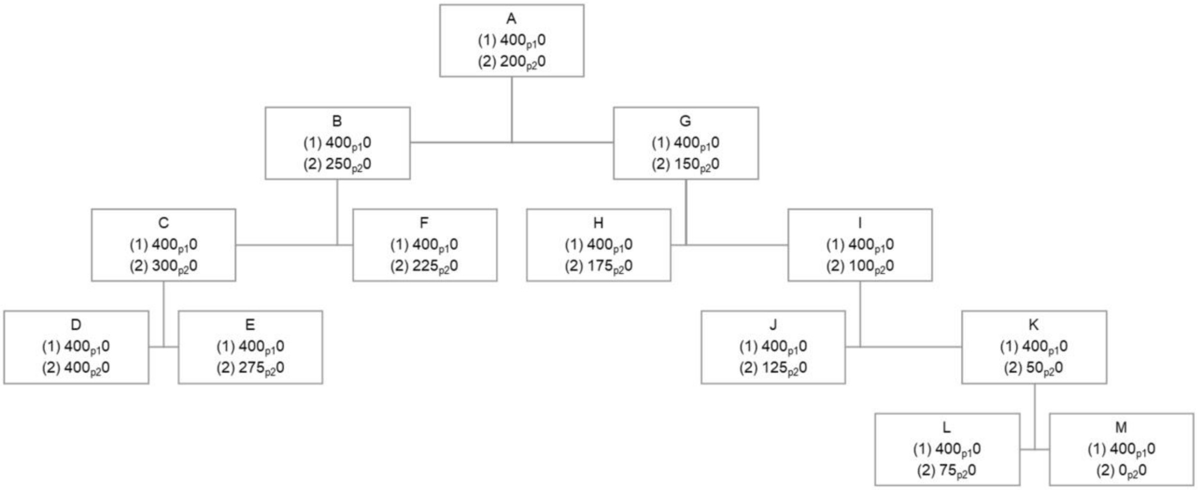


Figure A4. : Sequence of choices used to elicit risk attitudes

Note: Sequence of choices in the two sets used to elicit bounds on indifference point amounts x and z. In each set, each choice is between options (1) and (2). The first choice, A, is between: (1) a lottery paying 400 pesos with probability $p1$ and 0 with probability of $1-p1$, and (2) a lottery paying 200 or 0 with probabilities of $p2$ and $1-p2$, respectively. In choice set 1, $p1 = 0.5$ and $p2 = 1$. In choice set 2, $p1 = 0.25$ and $p2 = 0.5$. If option (1) is chosen, the next choice offered is to the left, e.g., (1) at $A \to B$. If option (2) is chosen, the next choice is to the right, e.g., (2) at $A \to C$.

From the switching point of each choice set, we deduce bounds on the participant's point of indifference. We use the midpoint of these bounds to approximate the indifference point. We assume an indifference point of 400 for those who always choose the riskier option (1) (up to D) and 0 for those who always choose the less risky (zero risk) option (2) (up to M).

Each participant is told that they have a 1 in 5 chance that one of their choices (from Set 1 or 2) will be played for real. Previous studies show risk attitudes elicited with this incentive system are similar to those obtained with random selection of one choice of each participant to play for real (Harrison, Lau and Rutström, 2007; Aydogan, Berger and Théroude, 2024; Berlin et al., 2026). If, through the roll of dice, they are selected to play for real, then the toss of a coin determines whether they play the first choice made in Set 1 or in Set 2. If it is Set 1, they are paid 200 pesos if they chose the sure-thing option and otherwise they take the lucky dip to determine whether they are paid 400 pesos (with 50% chance) or nothing. If it is Set 2, they take whichever lucky dip they selected in the first choice, $200_{0.5}0$ or $400_{0.25}0$, and are paid accordingly. The maximum potential earned amount is 400 pesos.

Instructions.—All interviews were conducted in Tagalog. Below we provide an English translation of the instructions read to participants.

I am going to ask you to make some more choices. Now, depending on what you choose and your luck, you may actually earn some money that you can keep. Every choice is between two options. You must choose one or the other. First, I will ask you to choose between receiving an amount of money for sure and taking a lucky dip for a chance to win a bigger cash prize. I will ask you to make a number of choices like this. Then, I will ask you to choose between two lucky dips that differ in the prize offered and the chance of winning. Again, I will ask you to make a number of choices like this.

Before I ask you to make these choices, let me explain how you can earn money. After you have made all the choices, you will roll this ten-sided dice. If the dice shows 0 or 1, then one of the choices you have made will be implemented. If you have chosen the lucky dip, then you will take it. If you win the cash prize, you will be paid for it. If you have chosen the amount of money for sure, then you will be paid for it. If the dice does not show 0 or 1, then no choice will be implemented and you will not have receive anything. So, there is a 1 in 5 chance that one of your choices will be implemented and you may receive money.

If the dice shows 0 or 1, then you will toss a coin to decide which choice you have made will be implemented. If the coin shows heads, then the first choice you make between the lucky dip and the sure amount of money will be implemented. If the coin shows tails, then the first choice you make between the two lucky dips will be implemented. If you win, then I will pay you in cash immediately. The payment will be a gift. You will not have to pay it back later.

This is not a test. There is not a right and a wrong choice for each question. I want to know how you would choose. That is why we give you the chance to win money based on your choices.

Next, I will explain the choices you have to make. At this point, do you have any questions?

First question of choice set 1 (Q13.4.A):

I am going to ask you to choose between taking a lucky dip for 400 pesos and receiving another amount for sure. I will ask you to make this type of choice a number of times. If you get lucky on the roll of the dice (it shows 0 or 1) and then the coin shows heads, then your first choice will be implemented and you will not be allowed to change it. If you have chosen the lucky dip, then you will take it. If you have chosen to receive the amount of money sure, then you will be paid it. You *must choose between these two options:*

- Option 1: Take a lucky dip in which you win 400 pesos or nothing with an equal (fifty-fifty) chance of each;

- Option 2: Receive 200 pesos for sure

If you take the lucky dip, then you will draw one ball from this pouch containing 4 balls – 2 black and 2 white. If you draw a black ball, then you will win 400 pesos. If you draw a white ball, then you will win nothing. So, there is an equal (fifty-fifty) chance of winning 400 pesos and getting nothing. If you do not take the lucky dip, then you will be paid 200 pesos. Which one do you choose?

First question of choice set 2 (Q13.5.A):

Now I am going to ask you to choose between two lucky dips that offer different cash prizes but also different chances of winning. I will ask you to make this type of choice a number of times. If you get lucky on the roll of the dice (it shows 0 or 1) and then the coin shows tails, then your first choice will be implemented and you will not be allowed to change it. Whichever lucky dip you have chosen, you will take it. If you win, you will be paid.

You must choose between taking a lucky dip from pouch 1 or pouch 2. Pouch 1 contains 4 balls, 1 black and 3 white. If you choose this pouch, you will draw one ball from it. If you draw a black ball, you will win 400 pesos. If you draw a white ball, then you will get nothing. This means there is a chance of 1 out of 4 (25%) of winning 400 pesos and 3 out of 4 (75%) chance of getting nothing.

Pouch 2 also contains 4 balls: 2 black and 2 white. If you choose this pouch, you will draw one ball from it. If you draw an black ball, you will win 200 pesos. If you draw a white ball, you will get nothing. This means there is an equal (50%) chance of winning 200 pesos and getting nothing. From which pouch do you choose to take a lucky dip?

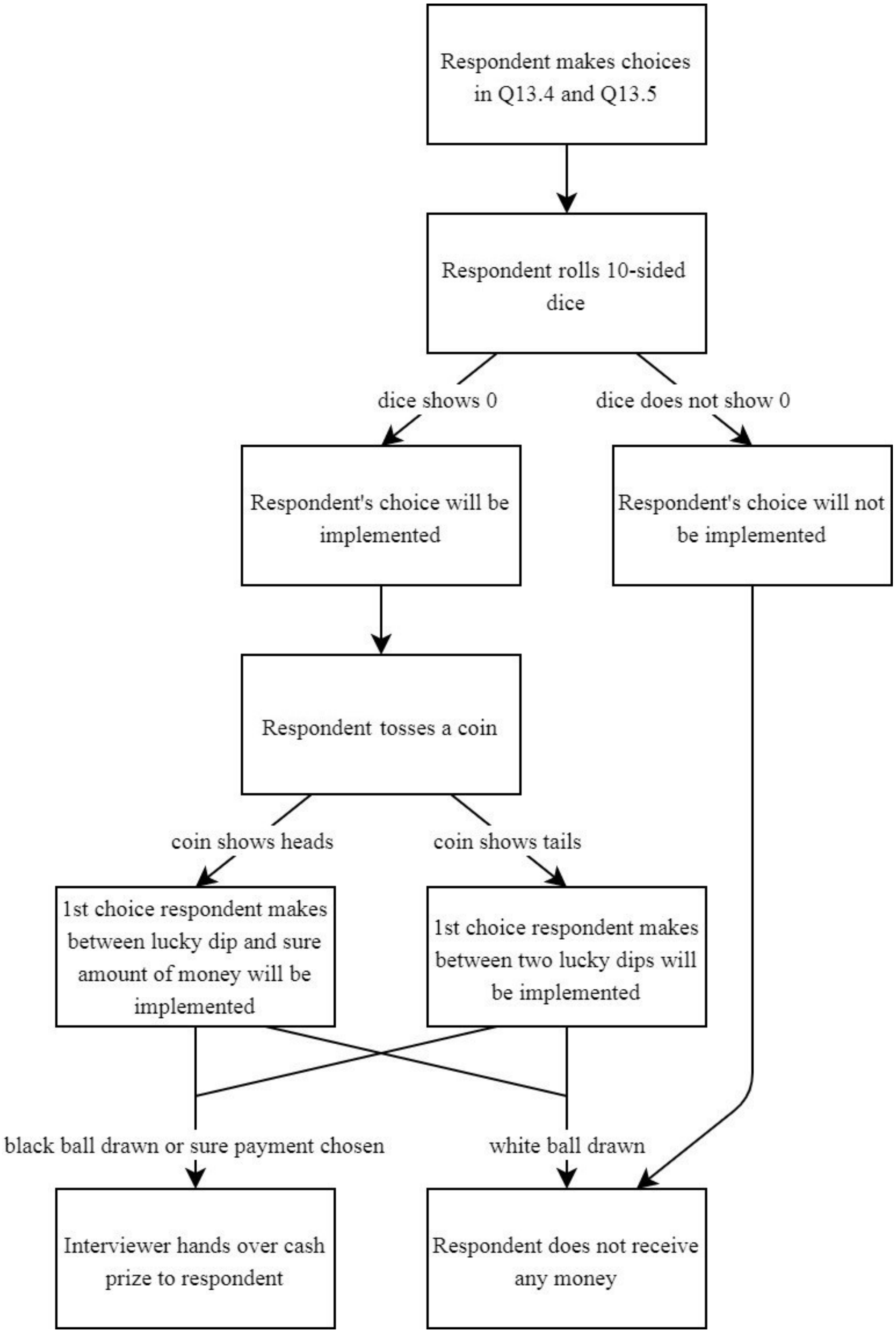


Figure A5. : Flow chart for risk attitude elicitation

E. Identification of risk attitude parameters

In this appendix, we first show that comparison of the magnitudes of the two indifference points elicited with the risk attitudes task identifies whether Prelec's (1998) probability distortion parameter α lies in the *INVERSE-S*, *LINEAR* or *S* interval. Then, we derive the value of this parameter and the utility curvature parameter for a power utility function (CRRA).

Under prospect theory, $u(0) = 0$, and the value of utility can be fixed at another point. Fixing $u(400) = 1$, the points of indifference in the two choice sets, $x \sim 400_{0.5}0$ and $z_{0.5}0 \sim 400_{0.25}0$, give[1]

$$u(x) = w(0.5),$$
$$u(z) = \frac{w(0.25)}{w(0.5)}.$$

If $x > z$, then $u(x) > u(z)$, which implies $w(0.25) < (w(0.5))^2$.

Prelec's (1998) widely-used single-parameter probability distortion function is

$$w(p) = exp(-(-lnp)^{\alpha}).$$

The parameter captures likelihood insensitivity, such that $\alpha < 1$ and $\alpha > 1$ corresponds to inverse S-shaped and S-shaped probability distortion, respectively. With $\alpha = 1$, the function is linear (decision weights are untransformed probabilities), as with expected utility.

[1] We drop the i subscripts indicating individual-specific values here to avoid clutter.

If $x > z$, then $\alpha > 1$:

$$u(x) > u(z)$$
$$(exp(-(-ln(0.5))^{\alpha}))^2 > exp(-(-ln(0.25))^{\alpha})$$
$$(-ln(0.25))^{\alpha} > 2(-ln(0.5))^{\alpha}$$
$$\left(\frac{ln(0.25)}{ln(0.5)}\right)^{\alpha} > 2$$
$$2^{\alpha} > 2$$
$$\alpha > 1$$

Analogously, $x < z \Rightarrow \alpha < 1$, $x = z \Rightarrow \alpha = 1$.

We assume a power utility function, $u(x) = x^{\gamma}$, $\gamma > 0$, $x \geq 0$, $u(x = 0) = 0$ and u concave for $\gamma < 1$.

The indifference points (certainty equivalents) from the two choice sets give

$$x^{\gamma} = w(0.5)400^{\gamma} \Rightarrow (x/400)^{\gamma} = w(0.5)$$
$$w(0.5)z^{\gamma} = w(0.25)400^{\gamma} \Rightarrow (z/400)^{\gamma} = \frac{w(0.25)}{w(0.5)}$$

Using Prelec's function, these equations are:

(A1) $$(x/400)^{\gamma} = exp(-(-ln0.5)^{\alpha} \Rightarrow \gamma ln(x/400) = -(-ln0.5)^{\alpha},$$

and

(A2) $$(z/400)^{\gamma} = \frac{exp(-(-ln0.25)^{\alpha}}{exp(-(-ln0.5)^{\alpha}} \Rightarrow \gamma ln(z/400) = (-ln0.5)^{\alpha} - (-ln0.25)^{\alpha}.$$

Substituting (A1) in (A3), rearranging, then dividing (A1) by the result gives,

(A3) $$\frac{ln(x/400)}{ln(x/400) + ln(z/400)} = \frac{(-ln\,0.5)^{\alpha}}{(-ln\,0.25)^{\alpha}}.$$

Solving gives

$$\alpha = \frac{ln\left[\frac{ln(x/400)}{ln(x/400)+ln(z/400)}\right]}{ln\left[\frac{ln\,0.5}{ln\,0.25}\right]}. \tag{A4}$$

With this and eq. (A1), we obtain the utility curvature parameter,

$$\gamma = \frac{-(-ln\,0.5)^{\alpha}}{ln(x/400)}. \tag{A5}$$

F. Elicitation of CVD risk perceptions

A. Instructions read to participants *I am going to ask you some questions about the chance of certain things happening in the future. That is, how likely they are to happen. To answer these questions, we will use this slider with a scale from 0 to 100. I will ask you to move the slider to indicate what you think is the chance that some particular event will happen. Let me explain with an example.*

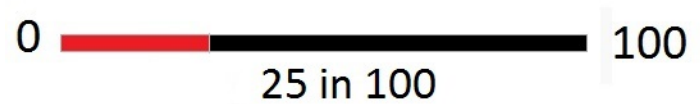


Figure A6. : Slider used to elicit CVD risk perceptions

There might be an earthquake that is strong enough to destroy buildings here in Nueva Ecija sometime during the next year. Then again, there might not be. You cannot know for sure whether there will be a destructive earthquake in Nueva Ecija in the next 12 months. But you might have an idea of the chance that this will happen. Try to think of what that chance is.

If you were absolutely sure that there will NOT be an earthquake sufficiently strong to destroy buildings in the next 12 months, that is, there is no chance of a destructive earthquake, point at 0 on the slider. If you believed that a destructive earthquake sometime during the next 12 months is very unlikely but not impossible, then you might point at 1 to indicate a 1 in 100 chance, point at 2 to indicate a 2 in 100 chance etc. The higher you think the chance of a destructive earthquake is, the further you move the slider to the right. If you believed that it is just as likely to happen as to not happen, then you would point at 50. Only if you were absolutely sure that there will be a destructive earthquake within the next 12 months would you move the slider to 100.

This is not a test. There is not a right or wrong answer to these questions, I just want to know what you think. OK, let's have a go.

B. Training Questions

Q10.1. *What do you think is the chance that there will be a destructive earthquake here in Nueva*

Ecija sometime during the next 12 months?

Q10.2. [Ask if Q10.1=50] *Do you really think the chance that there will be a destructive earthquake here in Nueva Ecija during the next 12 months is exactly the same as the chance that there will not be such an earthquake, or are you just not sure?*

Q10.3. *What do you think is the chance that there will be a destructive earthquake here in Nueva Ecija sometime during the next 10 years?*

Q10.4. [Ask if Q10.3=50] *Do you really think the chance that there will be a destructive earthquake here in Nueva Ecija sometime during the next 10 years is exactly the same as the chance that there will not be such an earthquake, or are you just not sure?*

[Read if Q10.1 > Q10.3] *You told me that you think that the chance that a destructive earthquake occurs in Nueva Ecija within the next 10 years is lower than the chance that this happens within the next 12 months. Remember, even if there is not an earthquake this year, there can be one next year, or the year after. Don't you think that there may be a higher chance of an earthquake happening as more time passes? Let me ask you again.*

Q10.5. [Ask if Q10.1 > Q10.3] [INTERVIEWER: Enter [Q10.1] on the slider and show this to the respondent while reading the question.] *You told me that you think there is a [Q10.1] in 100 chance that a destructive earthquake occurs in Nueva Ecija within the next 12 months. What do you think is the chance that this happens sometime during the next 10 years?*

C. Perceived Life Expectancy and CVD Risk Base Rate

[INTERVIEWER: If R2 is male [Q1.4=1], read 'man' in the questions that follow. If R2 is female [Q1.4=2], read 'woman'.]

READ: *Please consider an average Filipino man/woman your age. I am going to ask you about the chances of various things happening to such a person. Each time, I will refer only to a man/woman your age, but I would like you to think about the average Filipino man/woman your age. Please move the slider depending on what you think is the chance of these things happening.*

Q10.6. *What do you think is the chance that a man/women your age will have a heart attack or a stroke sometime during the next 10 years?*

NOTE TO FIELD INTERVIEWER: Please make sure that this instruction is read out directly after the question, i.e. before the respondent provides an answer.

READ: *One way to think about this is to consider 100 men/women your age. How many of them would you expect to have a heart attack or a stroke sometime during the next 10 years?*

Q10.7. *How confident are you in your answer to this last question?* [INTERVIEWER: Read all possible responses.]

Not at all confident.	1
Not particularly confident.	2
Slightly confident.	3
Reasonably confident.	4
Extremely confident.	5

Q10.8. *What do you think is the chance that a man/woman your age will live for at least 10 more years?*

READ: *Again you can think about 100 men/women your age. How many of them would you expect to live for at least 10 more years?*

Q10.9. *Now think about the unfortunate case in which a man/woman your age were to have a heart attack or a stroke. What do you think is the chance that he/she would live for at least 10 more years after having experienced a heart attack or a stroke?*

READ: *You may take into consideration that some people die immediately as a result of a heart attack or stroke, but others don't.*

E. Question on perceived personal CVD risk *Now, I am going to ask you some questions about yourself, not an average Filipino man/woman your age. I will ask you how likely you think it is that you will suffer a heart attack or stroke, and what are your chances of living for at least another 10 years. I very much hope that you will live a long and healthy life, and you do not suffer* *from severe illness. I am just interested in what you expect might happen to your health.*

Q10.10. *What do you think is the chance that you will have a heart attack or a stroke sometime during the next 10 years?*

Q10.11. *How confident are you in your answer to this last question?* [INTERVIEWER: Read all possible responses.]

Not at all confident.	1
Not particularly confident.	2
Slightly confident.	3
Reasonably confident.	4
Extremely confident.	5

Q10.12. *How worried are you about having a heart attack or a stroke?*

Not at all worried.	1
Not particularly worried.	2
Slightly worried.	3
Reasonably worried.	4
Extremely worried.	5

Q10.13. *What do you think is the chance that you will live for at least 10 more years?*

Q10.14. *Now please try to think about the unfortunate case in which you were to have a heart attack or a stroke. What do you think is the chance that you would live for at least 10 more years after having experienced a heart attack or a stroke?*

G. Additional tables

Table A3—: Sample selection

	Control (1)	Lottery treatment (2)	Information treatment (3)	Total (4)	H_0: (1) = (2) p-value (5)
Panel A. Baseline sample					
	1724	1697	375	3796	
Panel B. Excluded					
Information treatment	0	0	375	375	
Attrition	143	119		262	
Item non-response	4	8		12	
Total	*147*	*127*	*375*	*649*	
Total/Baseline	0.0853	0.0748	1	0.1699	0.2663
Panel C. Analysis sample					
	1577	1570	0	3147	
Dominated Choice					
No	1089	1024	N/A	2113	
Yes	488	546	N/A	1034	
Dominated/Analysis	0.3094	0.3478	N/A		0.1771
Panel D. Dominated excluded sample					
	1089	1024	0	2113	

Note: Panel A gives number of participants meeting the study inclusion criteria and interviewed at baseline. Each person who did not meet the inclusion criteria was dropped prior to full baseline interview and replaced by another randomly selected participant. Inclusion criteria are a)-c) in section II.B. Panel B gives numbers of participants excluded to reach the analysis sample. In 8/12 cases, item non-response was due to termination of the endline interview on measurement of extreme high blood pressure (BP) (systolic $>$ 180 mm Hg or diastolic $>$ 120 mm Hg), as stipulated in the study protocol. When this happened at baseline, the participant was dropped from the sample and replaced. Three of the other non-response cases are missing on (baseline) risk attitude measurements and one is missing on (baseline) CVD risk perceptions. The attrition/non-response exclusion rate from the control and lottery treatment groups combined is 0.0789. Dominated choice arises when always opting either for safety or risk and finally taking an option offering a lower chance of the same payoff (Appendix D). The p-values in column (5) are for tests of equal rates of exclusion due to attrition/non-response (Panel B) and dominated choices (Panel C) for the control and lottery treatment groups. Further details of the participant flow are given in Figure 1 in Capuno, Kraft and O'Donnell (2021).

Table A4—: Sample characteristics

	Mean	SD	Min	Max
Covariates				
Age	52.30	8.195	40	70.78
Female	0.669	0.471	0	1
Urban	0.264	0.441	0	1
Married	0.800	0.400	0	1
Working	0.576	0.494	0	1
Education, ref. college grad.				
< Elementary	0.133	0.340	0	1
Elementary	0.282	0.450	0	1
Middle	0.177	0.382	0	1
High school	0.283	0.450	0	1
Wealth quintile, ref. richest				
Poorest	0.204	0.403	0	1
2nd poorest	0.203	0.402	0	1
Middle	0.201	0.401	0	1
2nd richest	0.196	0.397	0	1
Musculoskeletal	0.176	0.381	0	1
Chronic disease	0.0864	0.281	0	1
SF-20 HRQoL	85.01	9.936	30.97	100
Family CVD risk	0.672	0.470	0	1
Health insurance	0.681	0.466	0	1
Inpatient	0.0178	0.132	0	1
Risk attitudes & perceptions				
Probability distortion	8.016	149.9	-400	400
Risk tolerance	197.5	112.0	0	400
CVD risk perception	22.06	23.87	0	100
Healthcare visits				
Check-up	0.0499	0.218	0	1
Clinic visit	0.0909	0.287	0	1
N participants	3147			
N clusters	274			

Note: Analysis sample baseline characteristics (Table A1 for definitions). Sample after attrition and item non-response (Table A3).

Table A5—: Risk attitudes and perceptions - summary statistics

		Dominated choices excluded					
		No			Yes		
		Mean	SD	Median	Mean	SD	Median
Panel A. Indifference points							
x		201.5	132.8	187.5	176.4	105.0	187.5
z		193.5	136.7	187.5	171.6	105.2	187.5
Panel B. Probability distortion							
$x - z$		8.0	149.9	0.0	4.7	122.7	0.0
INVERSE-S	$[x < z]$	33.2%			34.9%		
LINEAR	$[x = z]$	29.3%			26.9%		
S	$[x > z]$	37.5%			38.2%		
Panel C. Risk tolerance							
$(x + z)/2$		197.5	112.0	200.0	174.0	85.4	175.0
AVERSE	$[(x + z)/2 \leq 180]$	42.8%			50.8%		
NEUTRAL	$[180 < (x + z)/2 < 220]$	17.3%			20.8%		
SEEKING	$[(x + z)/2 \geq 220]$	39.9%			28.4%		
Panel D. Perceived CVD risk							
p		22.06	23.87	10	21.70	24.00	10
LOW	$[p \leq 0.1]$	51.8%			53.1%		
INTERMEDIATE	$[0.1 < p \leq 0.85]$	46.0%			44.7%		
HIGH	$[p > 0.85]$	2.2%			2.2%		
N		3,147	3,147	3,147	2,113	2,113	2,113

Note: Analysis sample at baseline. Dominated choice is taking an option that offers a smaller chance of winning a given payoff. t-tests of $H_0 : \bar{x} = \bar{z}$, where $\bar{v}$ is the mean of v, give p-values of 0.0027 and 0.0763 without and with exclusion of dominated choices, respectively. Perceived CVD risk is the reported subjective probability of having a heart attack or stroke within 10 years.

Table A6—: Alternative categorization of probability distortion

	Dominated choices excluded			
	NO		YES	
	Main	Alternative	Main	Alternative
Probability distortion				
Inverse S-shaped	33.2%	29.6%	34.9%	30.5%
Linear	29.3%	36.7%	26.9%	35.7%
S-shaped	37.5%	33.7%	38.2%	33.8%
N	3,147	3,147	2,113	2,113

Note: Main categorization of probability distortion used in analysis is: Inverse S-shaped = $\mathbb{1}(x - z < 0)$; Linear = $\mathbb{1}(x - z = 0)$; S-shaped = $\mathbb{1}(x - z > 0)$. *Alternative* categorization is: Inverse S-shaped = $\mathbb{1}(x - z < -25)$; Linear = $\mathbb{1}(-25 \leq x - z \leq 25)$; S-shaped = $\mathbb{1}(x - z > 25)$. Analysis sample at baseline. Dominated choices take an option that offers a smaller chance of winning a given payoff.

Table A7—: Frequencies of risk attitude task indifference points

	z															
x															Dominated excl.	
	0	25	62.5	87.5	112.5	137.5	162.5	187.5	212.5	237.5	262.5	287.5	350	400	NO	YES
0	129	21	3	1	0	1	2	5	3	3	2	0	3	7	180	0
25	26	179	10	34	4	15	7	28	18	4	7	6	28	30	396	340
62.5	4	8	1	8	1	2	2	2	3	0	1	0	2	3	37	30
87.5	5	25	7	102	6	32	15	26	13	9	8	9	54	43	354	306
112.5	2	6	0	5	1	5	4	8	0	1	1	3	1	4	41	35
137.5	9	13	3	38	7	29	13	44	12	8	2	6	18	18	220	193
162.5	5	7	2	11	3	8	15	12	7	5	2	3	5	8	93	80
187.5	10	27	5	33	7	32	9	80	23	18	15	18	42	56	375	309
212.5	16	28	3	14	6	24	13	30	19	11	10	9	9	17	209	176
237.5	5	5	0	7	1	8	4	14	11	10	8	6	12	6	97	86
262.5	7	18	0	16	1	11	4	19	8	9	10	7	18	16	144	121
287.5	2	7	1	7	4	12	14	34	4	9	7	19	17	19	156	135
350	11	37	4	23	1	23	11	45	10	12	10	22	104	36	349	302
400	38	30	3	22	4	22	8	49	15	9	6	9	56	225	496	0
Dominated excl.																
NO	269	411	42	321	46	224	121	396	146	108	89	117	369	488	3147	.
YES	0	360	36	298	42	201	111	342	128	96	81	108	310	0	.	2113

Note: Frequencies of $x \sim 400_{0.5}0$ and $z_{0.5}0 \sim 400_{0.25}0$ elicited from Choice Set 1 and Choice Set 2, respectively.

Table A8—: Balance checks

	Control		Treatment - Control			
	Mean	SD	Coeff. (b)	SE	p-value	Normalized b
Covariates						
Age	52.40	8.885	-0.198	0.313	0.527	-0.00711
Female	0.658	0.598	0.0228	0.0199	0.251	0.0143
Urban	0.270	1.517	-0.0128	0.0532	0.810	-0.00855
Married	0.810	0.414	-0.0206	0.0149	0.168	-0.0151
Working	0.570	0.750	0.0114	0.0243	0.640	0.00677
Education, ref. college grad.						
< Elementary	0.143	0.420	-0.0190	0.0149	0.204	-0.0164
Elementary	0.297	0.535	-0.0317	0.0195	0.105	-0.0207
Middle	0.187	0.478	-0.0195	0.0152	0.202	-0.0150
High school	0.261	0.557	0.0428	0.0200	0.0331	0.0280
Wealth quintile, ref. richest						
Poorest	0.215	0.598	-0.0221	0.0212	0.297	-0.0161
2nd poorest	0.206	0.485	-0.00782	0.0172	0.650	-0.00572
Middle	0.205	0.483	-0.00785	0.0174	0.652	-0.00576
2nd richest	0.197	0.507	-0.00272	0.0179	0.879	-0.00202
Musculoskeletal	0.183	0.540	-0.0141	0.0190	0.460	-0.0108
Chronic disease	0.0824	0.291	0.00785	0.0106	0.458	0.00821
SF-20 HRQoL	84.77	17.21	0.486	0.611	0.427	0.0144
Family CVD risk	0.676	0.621	-0.00737	0.0214	0.731	-0.00462
Health insurance	0.682	0.607	-0.00115	0.0213	0.957	-0.000725
Inpatient	0.0140	0.125	0.00771	0.00493	0.119	0.0172
Risk attitudes & perceptions						
Probability distortion	1.268	214.8	13.60	7.461	0.0695	0.0267
Risk tolerance	199.3	162.4	-3.554	6.221	0.568	-0.00933
CVD risk perception	21.22	38.85	1.671	1.367	0.223	0.0206
Healthcare visits						
Check-up	0.0507	0.258	-0.00157	0.00940	0.868	-0.00212
Clinic visit	0.0996	0.400	-0.0173	0.0131	0.188	-0.0177
N participants	1577	1577	3147	3147	3147	3147
N clusters	137	137	274	274	274	274
Joint significance		F-statistic =	1.150	p-value =	0.289	

Note: Balance of analysis sample on baseline characteristics by conditional cash lottery (CCL) treatment status. Sample after attrition and item non-response. There are 1570 participants and 137 clusters in the CCL treatment group. First two columns from left show control group means and standard deviations (SD). Other columns relate to Treatment (T) - Control (C) differences. Coefficient is from a regression of the respective variable on CCL treatment group indicator, with strata (urban) fixed effect. Standard errors (SE) clustered at barangay. p-value in each row for test: T - C = 0. Normalized difference in final column. Bottom panel gives the F-statistic and p-value for joint significance of all variables in explaining treatment status. In regression analysis, age and sex enter as sex-specific indicators of 5-year age intervals. See Table A1 for variable definitions.

Table A9—: Check-up probability differences by risk attitudes & perceptions and covariates

	Coefficient	(SE)
Probability distortion, ref. LINEAR		
INVERSE-S × Intermediate CVD risk	-0.0297	(0.0139)
INVERSE-S × Low/High CVD risk	0.0058	(0.0126)
S × Intermediate CVD risk	-0.0087	(0.0150)
S × Low/High CVD risk	0.0012	(0.0140)
Perceived CVD risk, ref. Intermediate $p \in (0.1, 0.85]$		
Low/High CVD risk, $p \notin (0.1, 0.85]$	-0.0042	(0.0141)
Risk tolerance, ref. NEUTRAL		
AVERSE	-0.0013	(0.0138)
SEEKING	-0.0139	(0.0122)
Covariates		
FEMALE AGED 45-49	-0.0150	(0.0159)
FEMALE AGED 50-54	-0.0036	(0.0174)
FEMALE AGED 55-59	-0.0156	(0.0157)
FEMALE AGED 60-70	-0.0173	(0.0174)
MALE AGED 40-44	-0.0452	(0.0156)
MALE AGED 45-49	-0.0403	(0.0171)
MALE AGED 50-54	-0.0527	(0.0157)
MALE AGED 55-59	-0.0206	(0.0214)
MALE AGED 60-70	-0.0431	(0.0160)
Urban	0.0083	(0.0113)
Married	-0.0039	(0.0099)
Working	-0.0070	(0.0097)
Education, ref. College		
< Elementary	0.0043	(0.0141)
Elementary	0.0098	(0.0137)
Middle	0.0186	(0.0146)
High school	0.0128	(0.0121)
Wealth quintile, ref. Richest		
Poorest	-0.0160	(0.0137)
2nd Poorest	0.0062	(0.0139)
Middle	0.0046	(0.0132)
2nd Richest	-0.0142	(0.0129)
Musculoskeletal	0.0249	(0.0124)
Chronic disease	0.0212	(0.0158)
SF-20 HRQoL	-0.0005	(0.0005)
Family CVD risk	0.0153	(0.0085)
Health insurance	0.0266	(0.0082)
Inpatient	0.0596	(0.0423)
Constant	0.0917	(0.0492)
mean	0.0499	
R^2	0.0234	
N	3147	

Note: Estimates of linear probability model of check-up in 30 days before baseline interview, eq.(1). Full estimates from model (2) in Table 1. Participants choosing dominated options in risk attitude elicitation tasks included. Variable definitions in Appendix B, Table A1. Cluster (barangay) adjusted standard errors in parentheses.

Table A10—: Check-up probability differences by risk attitudes & perceptions - robustness

	Baseline	Probit	Stratified by CVD risk	Alternative categorization of CVD risk	Alternative categorization of Prob. distortion
	(1)	(2)	(3)	(4)	(5)
Probability distortion (ref. LINEAR)					
INVERSE-S × Intermediate CVD risk	-0.0297	-0.0298	-0.0300	-0.0232	-0.0300
	(0.0139)	(0.0133)	(0.0140)	(0.0125)	(0.0125)
INVERSE-S × Low/High CVD risk	0.0058	0.0047	0.0039	0.0115	0.0071
	(0.0126)	(0.0127)	(0.0128)	(0.0152)	(0.0136)
S × Intermediate CVD risk	-0.0087	-0.0098	-0.0038	-0.0147	-0.0048
	(0.0150)	(0.0145)	(0.0147)	(0.0138)	(0.0139)
S × Low/High CVD risk	0.0012	-0.0000	-0.0021	0.0141	-0.0005
	(0.0140)	(0.0136)	(0.0143)	(0.0156)	(0.0141)
Risk tolerance (ref. Risk NEUTRAL)					
AVERSE	-0.0013	-0.0032		-0.0019	-0.0009
	(0.0138)	(0.0131)		(0.0137)	(0.0138)
& Intermediate CVD risk			-0.0025		
			(0.0178)		
& Low/High CVD risk			-0.0015		
			(0.0188)		
SEEKING	-0.0139	-0.0154		-0.0151	-0.0133
	(0.0122)	(0.0120)		(0.0123)	(0.0121)
& Intermediate CVD risk			-0.0170		
			(0.0163)		
& Low/High CVD risk			-0.0122		
			(0.0165)		
N	3147	3147	3147	3147	3147

Note: Robustness of estimates of conditional differences in probability of check-up in 30 days before baseline interview by risk attitudes & perceptions. Column (1) gives estimates of model eq.(1) from Table 1 column (2). This column and columns (3-5) are linear probability model estimates. Column (2) gives probit estimates. Column (3) stratified by perceived CVD risk categories: Intermediate, $p \in (0.1, 0.85]$; Low/High, $p \notin (0.1, 0.85]$. Other columns give pooled model estimates with interactions between these risk categories and probability distortion categories. Column (4) alternative categorization of CVD risk: Intermediate, $p \in (0.05, 0.8]$; LOW/High, $p \notin (0.05, 0.8]$. Column (5) alternative categorization of probability distortion: INVERSE-S if $x - z < -25$; LINEAR if $-25 \leq x - z \leq 25$; S if $x - z > 25$. Participants choosing dominated options in risk attitude elicitation tasks included. Controls are sex-specific 5-year age categories, urban, marital status, employment, educational attainment, wealth quintile, disease indicators, SF-20 HRQoL, inpatient admission in last year, family history of CVD risk factors and health insurance, see Appendix B, Table A1. Cluster (barangay) adjusted standard errors in parentheses.

Table A11—: Check-up probability differences by risk attitudes & perceptions - robustness to replacing risk tolerance indicators with (power) utility curvature

	Baseline excl. dominated	Utility curvature parameter included as: 3 categories	2 categories	Linear
	(1)	(2)	(3)	(4)
Probability distortion (ref. Linear)				
INVERSE-S × Intermediate CVD risk	-0.0412	-0.0427	-0.0417	-0.0452
	(0.0185)	(0.0183)	(0.0185)	(0.0184)
INVERSE-S × Low/High CVD risk	0.0061	0.0052	0.0055	0.0023
	(0.0160)	(0.0152)	(0.0157)	(0.0160)
S × Intermediate CVD risk	-0.0166	-0.0133	-0.0138	-0.0183
	(0.0199)	(0.0200)	(0.0201)	(0.0197)
S × Low/High CVD risk	-0.0149	-0.0111	-0.0116	-0.0160
	(0.0166)	(0.0163)	(0.0163)	(0.0165)
Risk tolerance (ref. NEUTRAL)				
AVERSE	-0.0048			
	(0.0155)			
SEEKING	-0.0226			
	(0.0147)			
Power utility curvature, $u(x) = x^\gamma$				
approx. CONCAVE, $\mathbb{1}(\gamma < 0.9)$		-0.0032		
		(0.0194)		
approx. CONVEX, $\mathbb{1}(\gamma > 1.1)$		-0.0234		
		(0.0186)		
CONVEX, $\mathbb{1}(\gamma > 1)$			-0.0161	
			(0.0099)	
CONTINUOUS, γ				-0.0053
				(0.0034)
N	2113	2113	2113	2113

Note: Robustness of estimates of conditional differences in probability of check-up in 30 days before baseline interview by risk attitudes & perceptions to replacing risk tolerance indicators with (categories of) participant-specific (power) utility curvature, $\hat{\gamma}$ in $u(x) = x^\gamma$. See Appendix E for estimation of this parameter. Column (1) gives the estimates of model eq.(1) from Table 1 column (3). Participants making dominated choices are excluded since their γ cannot be estimated. Other columns replace risk tolerance indicators with (categories of) $\hat{\gamma}$. Column (2) includes indicators of $\hat{\gamma} < 0.9$ (approx. CONCAVE) and $\hat{\gamma} > 1.1$ (approx. CONVEX), with the reference being approximately linear utility, $0.9 \leq \hat{\gamma} \leq 1.1$. Column (3) includes an indicator of $\hat{\gamma} > 1$ (CONVEX), with the reference $\hat{\gamma} \leq 1$. Column(4) includes $\hat{\gamma}$ in the regression linearly. Controls as Table 1. Cluster (barangay) adjusted standard errors in parentheses.

Table A12—: Preventive effort index differences by risk attitudes & perceptions

	(1)	(2)	(3)
Probability distortion (ref. LINEAR)			
INVERSE-S × Intermediate CVD risk	-0.0953	-0.0921	-0.0995
	(0.0231)	(0.0227)	(0.0261)
INVERSE-S × Low/High CVD risk	0.0061	0.0060	0.0259
	(0.0219)	(0.0217)	(0.0266)
S × Intermediate CVD risk	-0.0653	-0.0609	-0.0595
	(0.0231)	(0.0228)	(0.0254)
S × Low/High CVD risk	0.0034	-0.0038	0.0276
	(0.0213)	(0.0211)	(0.0261)
Risk tolerance (ref. NEUTRAL)			
AVERSE	-0.0201	-0.0243	-0.0321
	(0.0178)	(0.0180)	(0.0201)
SEEKING	0.0064	0.0063	0.0182
	(0.0183)	(0.0184)	(0.0211)
Additional controls	No	Yes	Yes
Dominated excluded	No	No	Yes
R^2	0.0317	0.0547	0.0731
N	3147	3147	2113

Note: OLS estimates of conditional differences in an index of prevention effort before baseline by risk attitudes and risk perception indicators from a model as eq.(1), except that the index replaces CHECK-UP as the dependent variable. The index is a weighted average of z-scores for a) not having high blood pressure, b) not being overweight, c) not being centrally obese, d) not smoking, e) not engaging in heavy episodic drinking of alcohol, f) not adding salt to food, g) number of days eat fruit or vegetables per week, and h) number of days in last 7 that exercised for at last 10 minutes by walking or doing sports (Appendix C). Greater weight is given to indicators that correlate less with the others. Mean of the index is zero by construction. Coefficients show differences in standard deviation units. For probability distortion, each row gives estimates of the difference in the conditional mean of the index between the respective distortion category and no distortion (LINEAR), with perceived CVD risk either Intermediate ($p \in (0.1, 0.85]$) or Low/High ($p \notin (0.1, 0.85]$); estimates of parameters β_k and δ_k, $k \in \{1, 2\}$ in eq.(1) (with the change of dependent variable). For risk tolerance, estimates are for differences between each of risk AVERSE and SEEKING and risk NEUTRAL. Column (1) controls are sex-specific 5-year age groups and urban. Columns (2) and (3) additionally control for marital status, employment, educational attainment, wealth quintile, disease indicators, SF-20 HRQoL, inpatient admission in last year, family history of CVD risk factors and health insurance (Appendix B, Table A1 for variable definitions). Column (3) excludes participants choosing dominated options in risk attitude elicitation tasks. Cluster (barangay) adjusted standard errors in parentheses.

Table A13—: Biomarker preventive effort index differences by risk attitudes & perceptions

	(1)	(2)	(3)
Probability distortion (ref. LINEAR)			
INVERSE-S × Intermediate CVD risk	-0.1375	-0.1330	-0.1583
	(0.0432)	(0.0430)	(0.0521)
INVERSE-S × Low/High CVD risk	-0.0165	-0.0197	-0.0087
	(0.0386)	(0.0383)	(0.0474)
S × Intermediate CVD risk	-0.0273	-0.0202	-0.0091
	(0.0436)	(0.0438)	(0.0534)
S × Low/High CVD risk	0.0099	0.0019	0.0521
	(0.0350)	(0.0347)	(0.0431)
Risk tolerance (ref. NEUTRAL)			
AVERSE	-0.0277	-0.0268	-0.0346
	(0.0325)	(0.0324)	(0.0364)
SEEKING	-0.0066	-0.0080	0.0323
	(0.0319)	(0.0324)	(0.0380)
Additional controls	No	Yes	Yes
Dominated excluded	No	No	Yes
R^2	0.1282	0.1497	0.1614
N	3147	3147	2113

Note: As Table A12 except here the preventive effort index is constructed only from measured biomarkers: a) not having high blood pressure, b) not being overweight, and c) not being centrally obese (Appendix C).

Table A14—: Behavioral preventive effort index differences by risk attitudes & perceptions

	(1)	(2)	(3)
Probability distortion (ref. LINEAR)			
INVERSE-S × Intermediate CVD risk	-0.0673	-0.0679	-0.0652
	(0.0306)	(0.0304)	(0.0357)
INVERSE-S × Low/High CVD risk	0.0196	0.0214	0.0545
	(0.0298)	(0.0292)	(0.0350)
S × Intermediate CVD risk	-0.0775	-0.0747	-0.0928
	(0.0292)	(0.0287)	(0.0330)
S × Low/High CVD risk	0.0028	-0.0068	0.0232
	(0.0290)	(0.0288)	(0.0354)
Risk tolerance (ref. NEUTRAL)			
AVERSE	-0.0194	-0.0292	-0.0312
	(0.0233)	(0.0230)	(0.0267)
SEEKING	-0.0028	-0.0021	-0.0075
	(0.0240)	(0.0230)	(0.0285)
Additional controls	No	Yes	Yes
Dominated excluded	No	No	Yes
R^2	0.1356	0.1641	0.1700
N	3147	3147	2113

Note: As Table A12 except here the preventive effort index is constructed only from reported health behaviors: d) not smoking, e) not engaging in heavy episodic drinking of alcohol, f) not adding salt to food, g) number of days eat fruit or vegetables per week, and h) number of days in last 7 that exercised for at last 10 minutes by walking or doing sports (Appendix C).

Table A15—: Linear probability model of health clinic visit between baseline and endline - full estimates

	Coefficient	(SE)
LOTTERY	0.3500	(0.0591)
LOTTERY × INVERSE-S × Intermediate CVD risk	0.0885	(0.0593)
LOTTERY × INVERSE-S × Low/High CVD risk	-0.0532	(0.0540)
LOTTERY × S × Intermediate CVD risk	0.0762	(0.0585)
LOTTERY × S × Low/High CVD risk	0.0367	(0.0481)
LOTTERY × Low/High CVD risk	0.1621	(0.0603)
LOTTERY × AVERSE	-0.0111	(0.0418)
LOTTERY × SEEKING	0.0342	(0.0410)
Probability distortion × Perceived CVD risk, ref. LINEAR × Intermediate		
INVERSE-S × Intermediate CVD risk	-0.0423	(0.0347)
INVERSE-S × Low/High CVD risk	-0.0328	(0.0267)
S × Intermediate CVD risk	0.0059	(0.0358)
S × Low/High CVD risk	-0.0576	(0.0268)
Low/High CVD risk	-0.0098	(0.0327)
Risk tolerance, ref. NEUTRAL		
AVERSE	0.0181	(0.0257)
SEEKING	-0.0146	(0.0241)
Covariates		
FEMALE AGED 45-49	-0.0078	(0.0262)
FEMALE AGED 50-54	0.0085	(0.0259)
FEMALE AGED 55-59	0.0265	(0.0298)
FEMALE AGED 60-70	0.0480	(0.0324)
MALE AGED 40-44	-0.0747	(0.0359)
MALE AGED 45-49	-0.1099	(0.0358)
MALE AGED 50-54	-0.0979	(0.0341)
MALE AGED 55-59	-0.0631	(0.0369)
MALE AGED 60-70	-0.0325	(0.0327)
Urban	-0.0362	(0.0248)
Married	0.0138	(0.0214)
Working	-0.0059	(0.0171)
Education, ref. College		
< Elementary	-0.0688	(0.0351)
Elementary	-0.0405	(0.0273)
Middle	0.0028	(0.0292)
High school	-0.0060	(0.0267)
Wealth quintile, ref. Richest		
Poorest	0.1082	(0.0267)
2nd poorest	0.0973	(0.0283)
Middle	0.0698	(0.0282)
2nd richest	0.0448	(0.0257)
Musculoskeletal	-0.0576	(0.0219)
Chronic disease	0.0207	(0.0265)
SF-20 HRQOL	-0.0014	(0.0008)
Family CVD risk	-0.0151	(0.0166)
Health insurance	0.0210	(0.0163)
Inpatient	0.1166	(0.0525)
VISIT before baseline	0.1266	(0.0283)
Constant	0.2554	(0.0901)
Mean	0.1414	
R^2	0.2714	
Observations	3147	

Note: Full estimates of linear probability model of public health clinic visit between baseline and endline, eq.(2). Table 2 column (4) gives estimates for LOTTERY effects only from this model. Variable definitions in Appendix B, Table A1. Cluster (barangay) adjusted standard errors in parentheses.

Table A16—: Effects of lottery offer on probability of visiting health clinic - robustness

	Baseline (1)	Probit (2)	Recategorize prob. distortion (3)	Dominated excluded (4)
LOTTERY	0.3500	0.3477	0.3451	0.3562
	(0.0591)	(0.0601)	(0.0538)	(0.0730)
LOTTERY × INVERSE-S				
× Intermediate CVD risk	0.0885	0.0841	0.1120	0.0683
	(0.0593)	(0.0527)	(0.0549)	(0.0764)
× Low/High CVD risk	-0.0532	-0.0623	-0.1097	0.0699
	(0.0540)	(0.0541)	(0.0510)	(0.0640)
LOTTERY × S				
× Intermediate CVD risk	0.0762	0.0742	0.1049	0.0540
	(0.0585)	(0.0524)	(0.0580)	(0.0679)
× Low/High CVD risk	0.0367	0.0321	-0.0096	0.1246
	(0.0481)	(0.0478)	(0.0451)	(0.0572)
LOTTERY × Low/High CVD risk	0.1621	0.1616	0.2046	0.0771
	(0.0603)	(0.0564)	(0.0531)	(0.0719)
LOTTERY × AVERSE	-0.0111	-0.0110	-0.0184	0.0098
	(0.0418)	(0.0414)	(0.0413)	(0.0485)
LOTTERY × SEEKING	0.0342	-0.0373	0.0293	0.0448
	(0.0410)	(0.0407)	(0.0404)	(0.0520)
Model	LPM	Probit	LPM	LPM
Probability distortion categories	Base	Base	Alternative	Base
Dominated excluded	NO	NO	NO	YES
Control mean	0.1414	0.1414	0.1414	0.1414
(pseudo-)R^2	0.2714	0.2240	0.2724	0.2805
Observations	3147	3147	3147	2113

Note:
Robustness of estimates of effects of conditional cash lottery (LOTTERY) on probability of visiting a public health clinic between baseline and endline, as specified in eq. (2) (for linear model). Column (1) estimates from Table 2 column (4). Top row gives estimated effect (ζ in eq.(2)) in the reference group: risk NEUTRAL, LINEAR (no) probability distortion and perceived Intermediate CVD risk ($p_i \in (0.1, 0.85]$). Other rows give differential effects by risk attitude and perceived CVD risk categories. Column (2) gives probit estimates. Other columns give linear probability model (LPM) estimates. Column (3) uses alternative categorization of probability distortion: INVERSE-S, $x - z < -25$; LINEAR, $-25 \leq x - z \leq 25$; S, $x - z > 25$. Base: INVERSE-S, $x - z < 0$; LINEAR, $x = z$; S, $x - z > 0$. Column (4) excludes participants choosing dominated options in risk attitude elicitation tasks. Controls as Table 2. Cluster (barangay) adjusted standard errors in parentheses.

Table A17—: Effects of lottery offer on probability of visiting health clinic - robustness to replacing risk tolerance indicators with (power) utility curvature

	Baseline excl. dominated	Utility curvature parameter included as: 3 categories	2 categories	Linear
	(1)	(2)	(3)	(4)
LOTTERY	0.3562	0.3862	0.3785	0.3687
	(0.0730)	(0.0718)	(0.0600)	(0.0623)
LOTTERY × INVERSE-S				
× Intermediate CVD risk	0.0683	0.0724	0.0691	0.0714
	(0.0764)	(0.0761)	(0.0760)	(0.0758)
× Low/High CVD risk	0.0699	0.0720	0.0703	0.0731
	(0.0640)	(0.0646)	(0.0641)	(0.0655)
LOTTERY × S				
× Intermediate CVD risk	0.0540	0.0537	0.0595	0.0573
	(0.0679)	(0.0673)	(0.0675)	(0.0678)
× Low/High CVD risk	0.1246	0.1216	0.1279	0.1249
	(0.0572)	(0.0579)	(0.0579)	(0.0571)
LOTTERY × Low/High CVD risk	0.0771	0.0778	0.0746	0.0758
	(0.0719)	(0.0722)	(0.0718)	(0.0720)
LOTTERY × AVERSE	0.0098			
	(0.0485)			
LOTTERY × SEEKING	0.0448			
	(0.0520)			
Power utility curvature, $u(x) = x^{\gamma}$				
LOTTERY $\times \mathbb{1}_{\{\hat{\gamma}<0.9\}}$		-0.0220		
		(0.0542)		
LOTTERY $\times \mathbb{1}_{\{\hat{\gamma}>1.1\}}$		-0.0047		
		(0.0550)		
LOTTERY $\times \mathbb{1}_{\{\hat{\gamma}>1\}}$			-0.0131	
			(0.0403)	
LOTTERY $\times \hat{\gamma}$				0.0035
				(0.0162)
Control mean	0.1414	0.1414	0.1414	0.1414
(pseudo-)R^2	0.2805	0.2812	0.2800	0.2801
Observations	2113	2113	2113	2113

Note:
Robustness of estimates of effects of lottery on probability of visiting a public health clinic between baseline and endline to replacing risk tolerance indicators with (categories of) participant-specific estimated power utility curvature, $\hat{\gamma}$ in $u(x) = x^{\gamma}$. See Appendix E for estimation of this parameter. Column (1) specified as eq.(2) except participants choosing dominated options in risk attitude elicitation are excluded (as in column (4) of Table A16) since γ cannot be estimated for these participants. Columns (2) and (3) replace risk tolerance indicators with 3 and 2 categories of $\hat{\gamma}$, respectively. The reference groups are approximately linear utility, $0.9 \leq \hat{\gamma} \leq 1.1$ in (2) and non-convex utility, $\hat{\gamma} \leq 1$, in (3). In column (4), $\hat{\gamma}$ enters linearly. Controls as Table 2. Cluster (barangay) adjusted standard errors in parentheses.

Table A18—: Risk attitudes and perceived CVD risk means (SE) by CCL principal strata

	All (1)	Compliers (2)	Never-takers (3)	Always-takers (4)	(2)=(3) (5)	(2)=(4) (6)
Panel A. Population proportion	1	0.4701	0.3885	0.1414		
		(0.0221)	(0.0195)	(0.0115)		
Panel B. Probability distortion						
$x - z$	8.0156	10.0177	5.3689	8.6323	0.6703	0.9191
	(3.8351)	(6.7401)	(7.1166)	(11.2018)		
INVERSE-S	0.3317	0.3376	0.3328	0.3094	0.8872	0.4755
	(0.0109)	(0.0200)	(0.0216)	(0.0317)		
LINEAR	0.2933	0.2734	0.3033	0.3318	0.3281	0.1361
	(0.0094)	(0.0173)	(0.0197)	(0.0323)		
S	0.3750	0.3890	0.3639	0.3587	0.4509	0.4535
	(0.0119)	(0.0212)	(0.0213)	(0.0327)		
Panel C. Risk tolerance						
(x+z)/2	197.4936	201.8680	195.5123	188.3969	0.4387	0.1622
	(3.1487)	(5.0669)	(5.7804)	(7.7719)		
AVERSE	0.4283	0.4160	0.4262	0.4753	0.7636	0.1672
	(0.0126)	(0.0212)	(0.0231)	(0.0358)		
NEUTRAL	0.1729	0.1715	0.1770	0.1659	0.8210	0.8660
	(0.0076)	(0.0144)	(0.0156)	(0.0266)		
SEEKING	0.3988	0.4126	0.3967	0.3587	0.6519	0.1662
	(0.0136)	(0.0225)	(0.0233)	(0.0322)		
Panel D. Perceived CVD risk, p						
$p \times 100$	22.0588	20.3265	23.5557	23.7040	0.0935	0.1105
	(0.6783)	(1.1289)	(1.2680)	(1.8729)		
Intermediate, $p \in (0.1, 0.85]$	0.4598	0.3989	0.5197	0.4978	0.0042	0.0228
	(0.0147)	(0.0246)	(0.0271)	(0.0398)		

Note:
Panel A gives estimates of population proportions in conditional cash lottery (CCL) principal strata: compliers (2) – who would visit a clinic only if offered the CCL incentive – never-takers (3) and always-takers (4). Other panels gives estimated means of risk attitudes and perceived CVD risk measures in the whole population (1) and by the CCL principal strata. In parentheses are bootstrap (1000 replications) standard errors adjusted for cluster sampling and sample stratification. Observations = 3147. Appendix J for identification and estimation. Columns (5) and (6) give p-values from tests of compliers' mean = never-takers' mean, and compliers' mean = always-takers mean, respectively.

Table A19—: Risk attitudes and perceived CVD risk means (SE) by CCL principal strata - dominated excluded

	All (1)	Compliers (2)	Never-takers (3)	Always-takers (4)	(2)=(3) (5)	(2)=(4) (6)
Panel A. Population proportion	1	0.4738	0.3848	0.1414		
		(0.0245)	(0.0220)	(0.0130)		
Panel B. Probability distortion						
$x - z$	4.7326	1.1661	9.5812	3.4903	0.3920	0.8619
	(3.5584)	(6.6702)	(5.6974)	(11.3193)		
INVERSE-S	0.3488	0.3730	0.3350	0.3052	0.3877	0.1550
	(0.0128)	(0.0252)	(0.0277)	(0.0376)		
LINEAR	0.2693	0.2385	0.2868	0.3247	0.1923	0.0590
	(0.0118)	(0.0208)	(0.0245)	(0.0378)		
S	0.3819	0.3885	0.3782	0.3701	0.7889	0.6985
	(0.0139)	(0.0251)	(0.0237)	(0.0397)		
Panel C. Risk tolerance						
$(x + z)/2$	174.0002	176.6255	172.6523	168.8718	0.6228	0.4239
	(2.3965)	(4.5240)	(5.1521)	(8.0010)		
AVERSE	0.5078	0.5027	0.5051	0.5325	0.9581	0.5746
	(0.0137)	(0.0257)	(0.0290)	(0.0438)		
NEUTRAL	0.2078	0.2012	0.2183	0.2013	0.6169	0.9975
	(0.0097)	(0.0196)	(0.0213)	(0.0362)		
SEEKING	0.2844	0.2962	0.2766	0.2662	0.6261	0.5248
	(0.0133)	(0.0243)	(0.0248)	(0.0392)		
Panel D. Perceived CVD risk, p						
$p \times 100$	21.6995	19.9028	23.9137	21.6948	0.1026	0.4823
	(0.7778)	(1.3104)	(1.6513)	(2.2683)		
Intermediate, $p \in (0.1, 0.85]$	0.4472	0.3798	0.5228	0.4675	0.0077	0.1059
	(0.0159)	(0.0276)	(0.0355)	(0.0491)		

Note:
As Table A18 but here estimates from sample that excludes participants choosing dominated options in risk attitude elicitation tasks. Observations = 2113.

Table A20—: Risk attitude means (SE) by CCL principal strata and perceived CVD risk

	All (1)	Compliers (2)	Never-takers (3)	Always-takers (4)	(2)=(3) (5)	(2)=(4) (6)
		Panel A. Intermediate CVD risk, $p \in (0.1, 0.85]$				
A1. Population proportion	1	0.4143	0.4290	0.1568		
		(0.0296)	(0.0258)	(0.0149)		
A2. Probability distortion						
$x - z$	15.5149	19.4901	7.0978	28.0405	0.3794	0.6672
	(4.9589)	(10.3636)	(7.7451)	(15.0077)		
INVERSE-S	0.3075	0.3335	0.3060	0.2432	0.5526	0.1194
	(0.0144)	(0.0307)	(0.0270)	(0.0419)		
LINEAR	0.3027	0.2617	0.3344	0.3243	0.1297	0.3422
	(0.0147)	(0.0319)	(0.0283)	(0.0489)		
S	0.3898	0.4048	0.3596	0.4324	0.3600	0.6809
	(0.0167)	(0.0361)	(0.0271)	(0.0496)		
A3. Risk tolerance						
$(x + z)/2$	198.6869	201.7397	197.8312	192.9617	0.7572	0.5418
	(4.6019)	(8.3337)	(7.7506)	(11.8522)		
AVERSE	0.4174	0.4028	0.4227	0.4414	0.6941	0.5414
	(0.0188)	(0.0341)	(0.0295)	0.0546		
NEUTRAL	0.1583	0.1572	0.1546	0.1712	0.9451	0.7768
	(0.0093)	(0.0237)	(0.0207)	(0.0354)		
SEEKING	0.4243	0.4400	0.4227	0.3874	0.7508	0.3843
	(0.0189)	(0.0345)	(0.0324)	(0.0517)		
		Panel B. Low/High CVD risk, $p \notin (0.1, 0.85]$				
B1. Population proportion	1	0.5185	0.3526	0.1289		
		(0.0269)	(0.0228)	(0.0136)		
B2. Probability distortion						
$x - z$	1.6324	3.4047	3.4983	-10.6027	0.9955	0.4669
	(4.8571)	(8.4407)	(11.2342)	(16.7052)		
INVERSE-S	0.3524	0.3403	0.3618	0.3750	0.6597	0.5109
	(0.0145)	(0.0258)	(0.0324)	(0.0450)		
LINEAR	0.2853	0.2825	0.2696	0.3393	0.7674	0.2416
	(0.0127)	(0.0221)	(0.0300)	(0.0412)		
S	0.3624	0.3772	0.3686	0.2857	0.8492	0.0760
	(0.0144)	(0.0251)	(0.0296)	(0.0436)		
B3. Risk tolerance						
$(x + z)/2$	196.4779	201.9736	193.0034	183.8728	0.3917	0.1331
	(3.5616)	(5.9294)	(7.3962)	(9.4533)		
AVERSE	0.4376	0.4251	0.4300	0.5089	0.9077	0.1391
	(0.0151)	(0.0249)	(0.0302)	(0.0456)		
NEUTRAL	0.1853	0.1805	0.2014	0.1607	0.5409	0.6719
	(0.0108)	(0.0194)	(0.0225)	(0.0390)		
SEEKING	0.3771	0.3944	0.3686	0.3304	0.5328	0.2196
	(0.0157)	(0.0257)	(0.0284)	(0.0421)		

Note:
As Table A18 but stratified by perceived CVD risk interval: Panel A, *Intermediate*, $p \in (0.1, 0.85]$ (N = 1447), and Panel B, *Low/High*, $p \notin (0.1, 0.85]$ (N = 1700).

Table A21—: Covariate means (SE) by CCL principal strata

	All (1)	Compliers (2)	Never-takers (3)	Always-takers (4)	(2)=(3) (5)	(2)=(4) (6)
Age	52.2972	52.2335	52.1136	53.0134	0.8255	0.2578
	(0.1619)	(0.3443)	(0.3132)	(0.5284)		
Female	0.6692	0.6916	0.6148	0.7444	0.0262	0.1850
	(0.0104)	(0.0201)	(0.0215)	(0.0317)		
Urban	0.2637	0.2403	0.2951	0.2556	0.3744	0.7523
	(0.0042)	(0.0269)	(0.0369)	(0.0421)		
Married	0.7998	0.8286	0.7738	0.7758	0.0568	0.1501
	(0.0072)	(0.0161)	(0.0176)	(0.0287)		
Working	0.5761	0.5867	0.5984	0.4798	0.7399	0.0211
	(0.0121)	(0.0214)	(0.0219)	(0.0407)		
Education < Elementary	0.1331	0.1330	0.1361	0.1256	0.9146	0.7855
	(0.0075)	(0.0141)	(0.0186)	(0.0225)		
Elementary	0.2819	0.3073	0.2590	0.2601	0.1016	0.2030
	(0.0097)	(0.0187)	(0.0179)	(0.0286)		
Middle	0.1773	0.1689	0.1639	0.2422	0.8473	0.0434
	(0.0073)	(0.0156)	(0.0147)	(0.0293)		
High school	0.2828	0.2795	0.2934	0.2646	0.6208	0.7019
	(0.0101)	(0.0182)	(0.0177)	(0.0320)		
College	0.1249	0.1113	0.1475	0.1076	0.1738	0.8971
	(0.0077)	(0.0140)	(0.0181)	(0.0219)		
Wealth quintile Poorest	0.2043	0.2169	0.1705	0.2556	0.0628	0.3020
	(0.0103)	(0.0165)	(0.0164)	(0.0329)		
2nd poorest	0.2027	0.2391	0.1623	0.1928	0.0028	0.1922
	(0.0086)	(0.0163)	(0.0160)	(0.0284)		
Middle	0.2008	0.1904	0.2000	0.2377	0.7415	0.1941
	(0.0086)	(0.0172)	(0.0183)	(0.0278)		
2nd richest	0.1957	0.1944	0.2033	0.1794	0.7431	0.6337
	(0.0090)	(0.0154)	(0.0180)	(0.0254)		
Richest	0.1964	0.1591	0.2639	0.1345	0.0019	0.4269
	(0.0110)	(0.0185)	(0.0229)	(0.0249)		
Musculoskeletal	0.1764	0.1370	0.2098	0.2152	0.0136	0.0125
	(0.0095)	(0.0161)	(0.0196)	(0.0275)		
Chronic disease	0.0864	0.0756	0.0885	0.1166	0.4338	0.1242
	(0.0053)	(0.0097)	(0.0109)	(0.0219)		
SF-20 HRQoL	85.0137	85.5488	85.3557	82.2952	0.7894	0.0004
	(0.3120)	(0.4888)	(0.5049)	(0.7778)		
Family CVD risk	0.6721	0.6745	0.6754	0.6547	0.9790	0.6287
	(0.0104)	(0.0199)	(0.0204)	(0.0336)		
Health insurance	0.6813	0.6739	0.6738	0.7265	0.9969	0.1897
	(0.0112)	(0.0184)	(0.0231)	(0.0354)		
Inpatient	0.0178	0.0257	0.0082	0.0179	0.0174	0.4978
	(0.0025)	(0.0053)	(0.0036)	(0.0089)		

Note: As Table A18 but here showing means for covariates used in regression analyses. Observations = 3,147. See Appendix B, Table A1 for variable definitions.

Table A22—: Tests of weak instruments for each endogenous variable

	Preventive care index (1)	Health behavior index (2)	Predicted CVD risk (3)
Panel A. Risk attitudes			
VISIT	202.69	201.90	202.96
VISIT×*INVERSE-S*	327.56	326.80	328.00
VISIT×*S*	346.32	345.90	344.51
VISIT×*AVERSE*	315.14	315.61	318.85
VISIT×*SEEKING*	334.76	334.29	333.50
Panel B. Risk attitudes & perceptions			
VISIT	141.70	142.70	142.84
VISIT×*INVERSE-S*×Intermediate CVD risk	134.68	134.56	134.74
VISIT×*INVERSE-S*×Low/High CVD risk	273.54	273.13	272.27
VISIT×*S*×Intermediate CVD risk	147.18	147.53	146.64
VISIT×*S*×Low/High CVD risk	305.46	303.52	304.95
VISIT×*AVERSE*	325.57	325.74	329.46
VISIT×*SEEKING*	336.14	336.09	335.67
VISIT×Low/High CVD risk	182.82	182.83	182.52

Note: Sanderson and Windmeijer (2016) test of the null of weak instruments for estimation of each endogenous variable in a model. Variable names as in Table 3. Intermediate CVD risk is $p_i \in (0.1, 0.85]$. Low/High CVD risk is $p_i \notin (0.1, 0.85]$. Instruments are $LOTTERY_i$ and its interactions with the risk attitude and perceptions indicators. Panel A is for a model given by eq.(3) excluding perceived CVD risk indicators (& interactions). Estimates for this model are in column (3) of Table 3. Panel B is for the model given by eq.(3), with estimates in column (4) of Table 3. Within each panel, each row gives the test statistic for the respective endogenous variable. Each test statistic is distributed $\chi^2(1)$ under the null. All p-values are < 0.001. Test statistics and p-values are made robust to general heteroskedasticity and correlated errors within sample clusters. If errors were iid, then each test statistic could be compared with Stock and Yogo (2005) critical value for one endogenous variable to test for weak instruments. However, these critical values are not valid with robust inference.

Table A23—: Effect of a clinic visit on health behavior

	(1)	(2)	(3)	(4)
VISIT	0.0409	0.0303	0.0496	0.0650
	(0.0684)	(0.0612)	(0.1214)	(0.1667)
VISIT × INVERSE-S			0.0761	
			(0.1100)	
× Intermediate CVD risk				0.2514
				(0.1741)
× Low/High CVD risk				-0.0560
				(0.1312)
VISIT × S			-0.0798	
			(0.0980)	
× Intermediate CVD risk				0.1261
				(0.1692)
× Low/High CVD risk				-0.2307
				(0.1215)
VISIT × AVERSE			-0.0647	-0.0444
			(0.1161)	(0.1197)
VISIT × SEEKING			0.0308	0.0282
			(0.1070)	(0.1102)
VISIT × Low/High CVD risk				-0.0327
				(0.1600)
Controls				
Sociodemographics & health	No	Yes	Yes	Yes
Risk attitudes	No	No	Yes	Yes
Risk perceptions	No	No	No	Yes
Weak IV test	435.61	465.55	102.31	N/A
critical value ($\alpha == 0.05, \tau = 0.1$)	[14.19]	[14.19]	[57.33]	
AR test $\sim \chi^2(1)$	0.3586	0.2461	4.000	18.324
p-value	[0.5493]	[0.6199]	[0.5494]	[0.0189]
AR confidence set	[-0.0919, 0.1737]	[-0.0883, 0.1489]		
Observations	3147	3147	3147	3147

Note: 2SLS estimates of effect of a public health clinic visit on an index of health behavior. See Appendix C and Appendix B, Table A2 for index construction. Units are standard deviations from control group mean. Column (4) gives estimates from model eq.(3). Columns (3), (2) and (1) are from restricted models with cumulative exclusion of risk perceptions (& interactions), risk attitudes and covariates, respectively. Columns (1) controls for urban/rural sample strata. Covariates are listed in Appendix B, Table A1, plus the baseline value of the outcome. Age and sex entered as sex-specific 5-year age groups. Top row gives the estimated effect on average in columns (1) and (2) and in the respective reference group in columns (3) and (4). Reference group is risk neutral with linear probability weighting in (3). In (4), it is the subset of this group perceiving CVD risk in the intermediate interval, $p \in (0.1, 0.85]$. Other rows give differential effects of a clinic visit by risk attitude and risk perception categories. In (4), for example, 0.2514 and -0.0560 are the estimates of γ_1 and γ_2, respectively. Cluster (barangay) adjusted standard errors in parentheses. Weak IV test is the (robust) Effective F-statistic (Montiel Olea and Pflueger, 2013) in columns (1) & (2) and an extension for multiple endogenous variables (Lewis and Mertens, 2025) in column (3). Critical values (all columns) from Lewis and Mertens (2025) for bias tolerance (τ) at 10% of worst-case benchmark using 5% significance (α). In column (4), there are too many endogenous variables to compute this test (see fn.[20]). For $VISIT_i$ (not its interactions), first-stage estimates in Table 2, except the model used there does not include baseline outcome. AR test is the (weak IV robust) Anderson and Rubin (1949) test of no effect(s) of the endogenous variable(s) in the reduced form. AR confidence set is the 95% confidence interval for the effect of the endogenous variable derived from this test.

Table A24—: Effect of a clinic visit on predicted CVD risk

		(1)	(2)	(3)	(4)
VISIT		-0.0840	0.0370	0.0756	1.0295
	(0.5584)	(0.2567)	(0.8233)	(1.1491)	
VISIT × INVERSE-S				0.1716	
				(0.6381)	
× Intermediate CVD risk					-0.2894
					(1.1957)
× Low/High CVD risk					0.4305
					(0.7632)
VISIT × S				-0.0034	
				(0.6730)	
× Intermediate CVD risk					-0.8533
					(1.2857)
× Low/High CVD risk					0.5148
					(0.7147)
VISIT × AVERSE				-0.2854	-0.3298
				(0.7879)	(0.7942)
VISIT × SEEKING				0.0226	-0.0417
				(0.7827)	(0.7830)
VISIT × Low/High CVD risk					-1.4645
					(1.1025)
Controls					
Sociodemographics & health		No	Yes	Yes	Yes
Risk attitudes		No	No	Yes	Yes
Risk perceptions		No	No	No	Yes
Control mean		10.895	10.895	10.895	10.895
Weak IV test		435.62	469.21	102.31	N/A
critical value ($\alpha = 0.05, \tau = 0.1$)		[14.19]	[14.19]	[57.32]	
AR test $\sim \chi^2(1)$		0.0226	0.0208	0.4559	3.1701
p-value		[0.8805]	[0.8854]	[0.9936]	0.9232
AR confidence set		[-1.1675, 0.9995]	[-0.4610, 0.5350]		
Observations		3147	3147	3147	3147

Note: 2SLS estimates of effect of a public health clinic visit on CVD risk predicted from sex, age (years), systolic blood pressure, body mass index and current smoking status using the Globorisk algorithm (Ueda et al., 2017). Event predicted is heart attack or stroke within 10 years. See Appendix C and Appendix B, Table A2 for further details of this outcome. Column (4) gives estimates from model eq.(3). Columns (3), (2) and (1) are from restricted models with cumulative exclusion of risk perceptions (& interactions), risk attitudes and covariates, respectively. Columns (1) controls for urban/rural sample strata. Covariates are listed in Appendix B, Table A1, plus the baseline value of the outcome. Age and sex entered as sex-specific 5-year age groups. Top row gives the estimated effect on average in columns (1) and (2) and in the respective reference group in columns (3) and (4). Reference group is risk neutral with linear probability weighting in (3). In (4), it is the subset of this group perceiving CVD risk in the intermediate interval, $p \in (0.1, 0.85]$. Other rows give differential effects of a clinic visit by risk attitude and risk perception categories. In (4), for example, -0.2894 and 0.4305 are the estimates of γ_1 and γ_2, respectively. Cluster (barangay) adjusted standard errors in parentheses. Weak IV test is the (robust) Effective F-statistic (Montiel Olea and Pflueger, 2013) in columns (1) & (2) and an extension for multiple endogenous variables (Lewis and Mertens, 2025) in column (3). Critical values (all columns) from Lewis and Mertens (2025) for bias tolerance (τ) at 10% of worst-case benchmark using 5% significance (α). In column (4), there are too many endogenous variables to compute this test (see fn.[20]). For $VISIT_i$ (not its interactions), first-stage estimates in Table 2, except the model used there does not include baseline outcome. AR test is the (weak IV robust) Anderson and Rubin (1949) test of no effect(s) of the endogenous variable(s) in the reduced form. AR confidence set is the 95% confidence interval for the effect of the endogenous variable derived from this test.

H. Additional figures

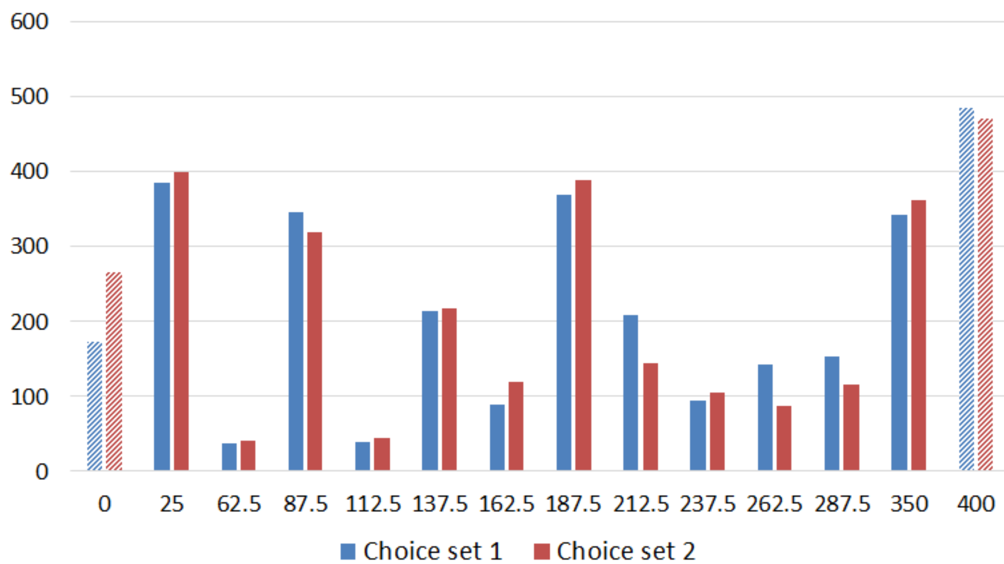


Figure A7. : Histogram of indifference points, x and z, from risk elicitation task

Note: x elicited from Choice Set 1. z elicited from Choice Set 2. Light shading indicates dominated choices.

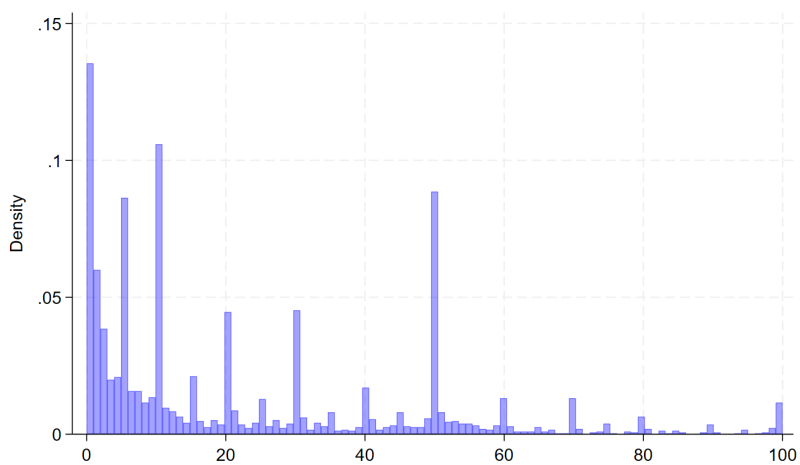
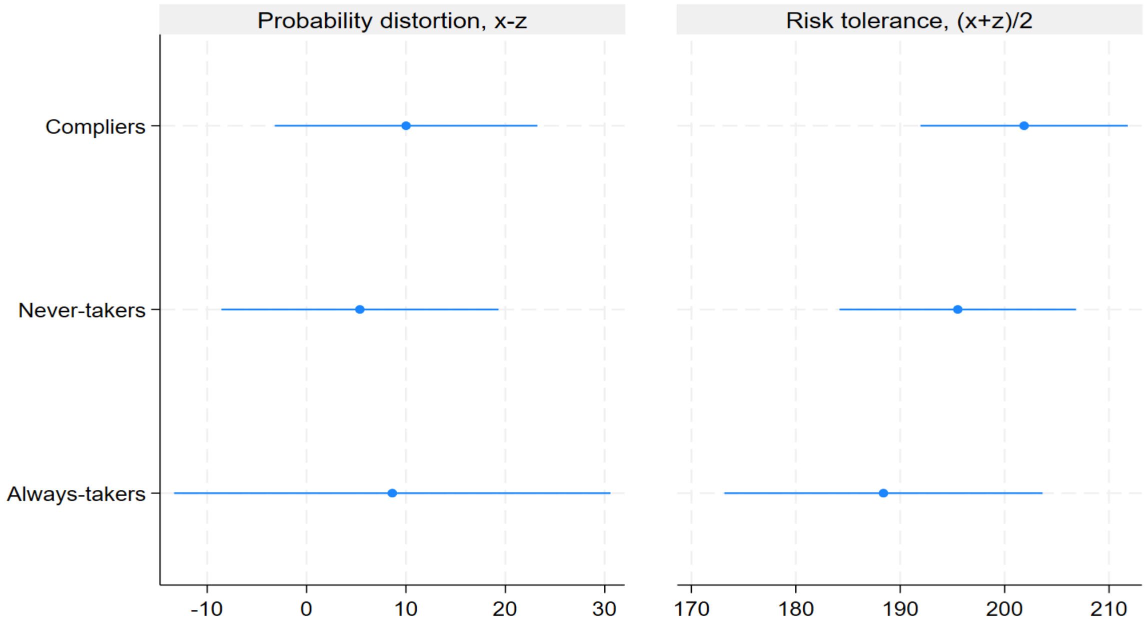
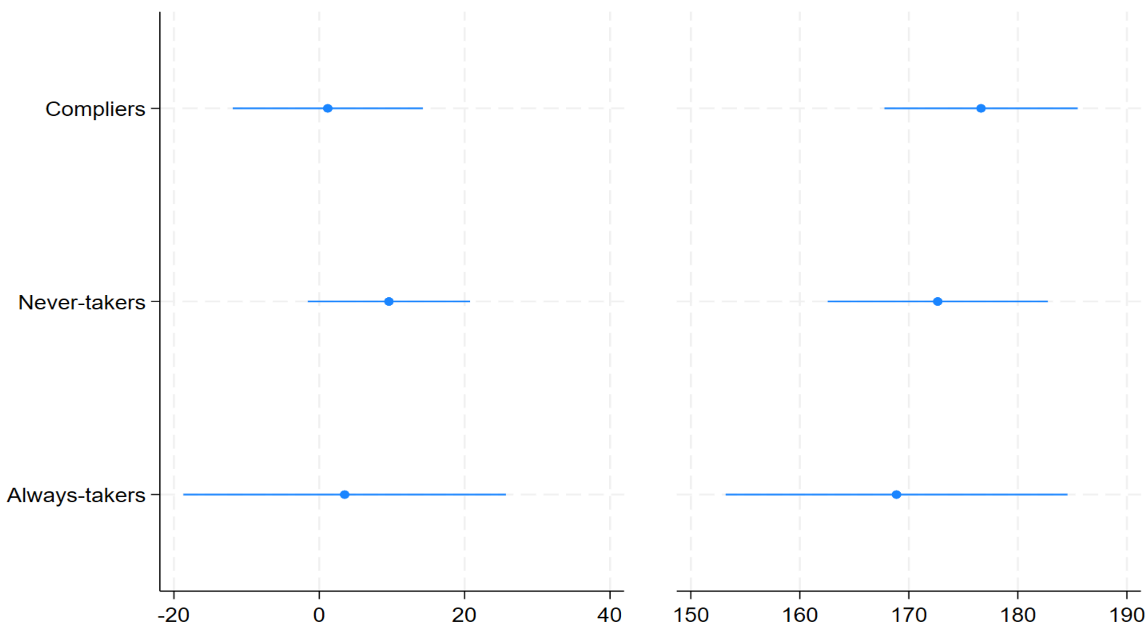


Figure A8. : Perceived CVD risk - empirical distribution

Note: Histogram of reported percentage chance of having a heart attack or stroke within 10 years. Analysis sample (N = 3,147) at baseline. See Table A3 for sample selection.



A. Overall



B. Dominated excluded

Figure A9. : Probability distortion & risk tolerance means by CCL principal strata

Note: Estimated means of the probability distortion measure, $x-z$, and the risk tolerance measure, $(x+z)/2$, among conditional cash lottery (CCL) compliers, never-takers and always-takers. Appendix J for identification and estimation. Interval lines show bootstrapped 95% confidence intervals that account for sample clustering and stratification (percentile method, 1000 repetitions). Panels give estimates: A) from full analysis sample (N = 3,147), B) excluding those taking dominated options in risk attitude elicitation tasks (N = 2,113). Appendix G, Tables A18 and A19 give numerical estimates.

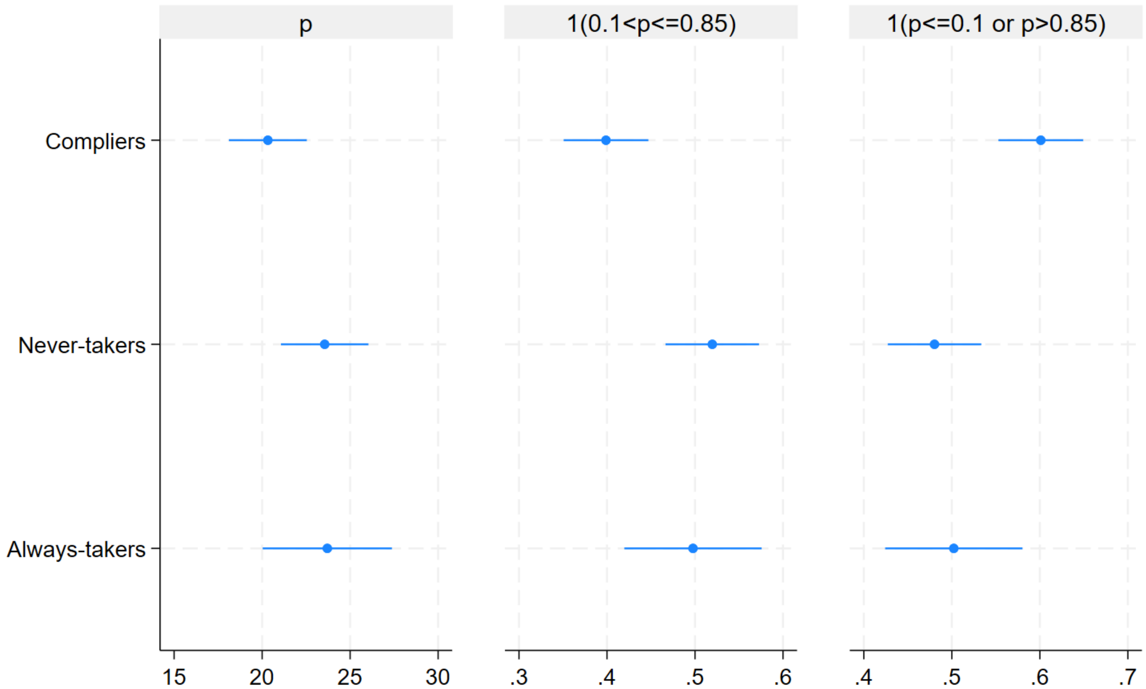
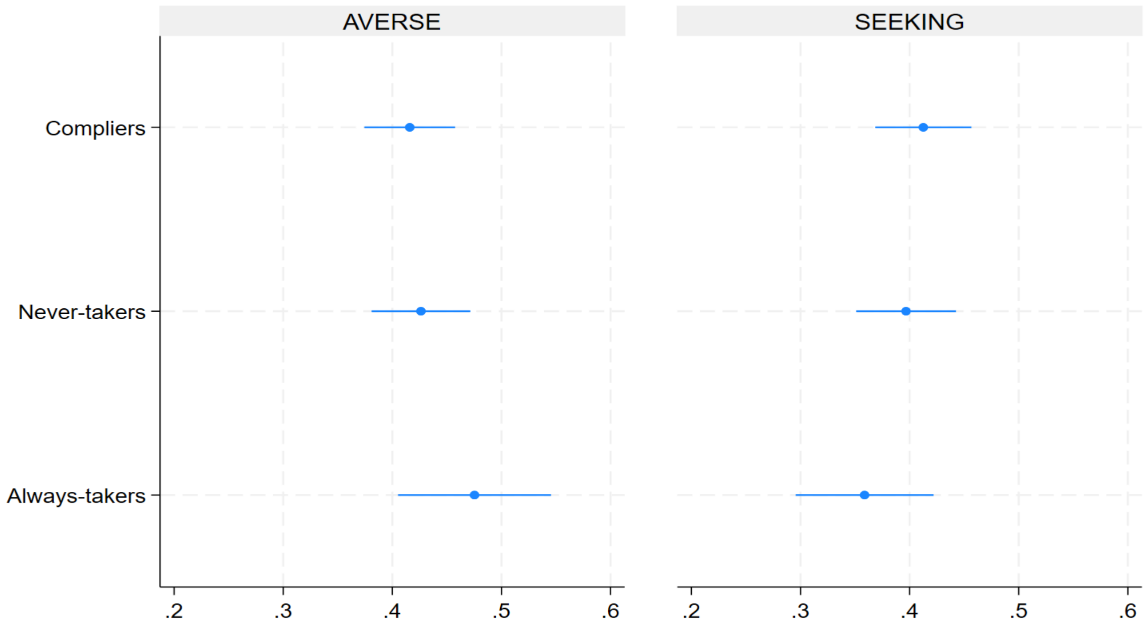
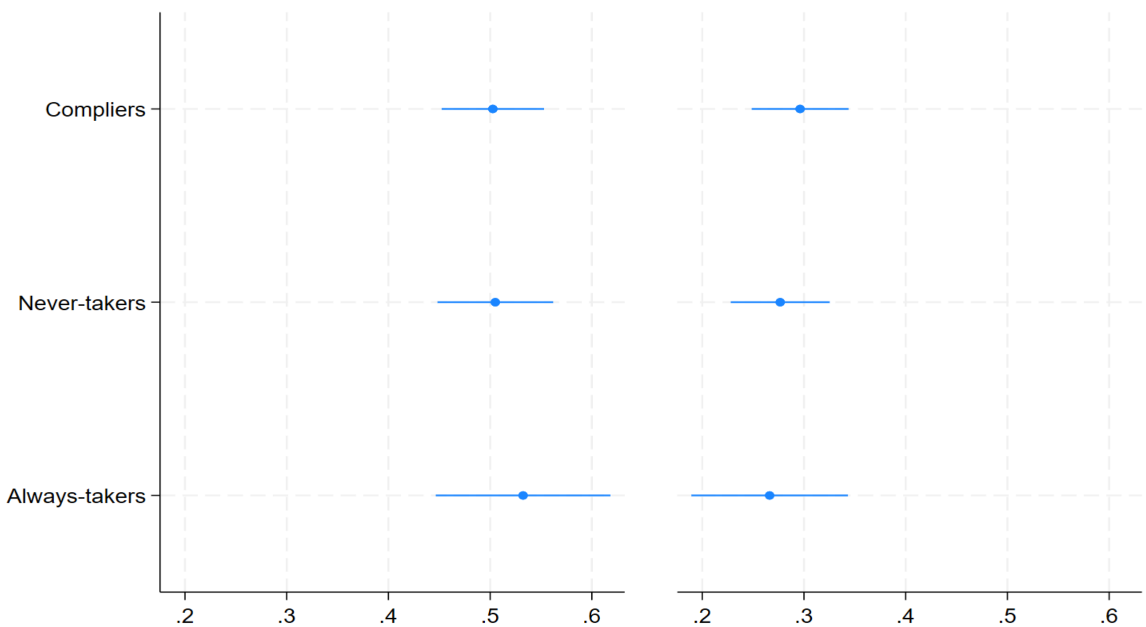


Figure A10. : Perceived CVD risk (p) - means and interval proportions by CCL principal strata

Note: Estimated means of perceived CVD risk (p) and proportions perceiving risk in the *Intermediate* ($p \in (0.1, 0.85]$) and *Low/High* ($p \notin (0.1, 0.85]$) intervals among conditional cash lottery (CCL) compliers, never-takers and always-takers. Appendix J for identification and estimation. Interval lines show bootstrapped 95% confidence intervals that account for sample clustering and stratification (percentile method, 1000 repetitions). Full analysis sample estimates (N = 3,147). Appendix G, Table A18 gives numerical estimates.



A. Overall



B. Dominated excluded

Figure A11. : Risk tolerance category proportions by CCL principal strata

Note: Estimated proportions in risk $AVERSE$ and $SEEKING$ categories of risk tolerance among conditional cash lottery (CCL) compliers, never-takers and always-takers. Appendix J for identification and estimation. Interval lines show bootstrapped 95% confidence intervals that account for sample clustering and stratification (percentile method, 1000 repetitions). Panels give estimates: A) from full analysis sample (N = 3,147), B) excluding those taking dominated options in risk attitude elicitation tasks (N = 2,113). Appendix G, Tables A18 and A19 give numerical estimates. Figure A9 gives respective means for the continuous risk tolerance measure, $(x + z)/2$.

I. Deviations from pre-analysis plan

The study is registered at the AEA RCT Registry: AEARCTR-0002867. It is multi-purposed. This paper addresses hypotheses H6c and H6e in the pre-analysis plan (PAP) (pages 11-15). The particular focus is on the part of H6c concerning probability distortion: inverse S distortion reduces prevention of intermediate risks and increases compliance with a conditional cash lottery (CCL) (p. 12).

Regrettably, the PAP has deficiencies in the logic of some predictions and some methods proposed to test them. Logical errors are partly due to the PAP preceding publication of Baillon et al. (2022*a*) that derives predictions we test, although we knew the main results of that publication when writing the PAP. We believe it is better to correct the deficiencies of the PAP, while acknowledging that this renders the analysis somewhat exploratory. This appendix describes and justifies the deviations we make from the PAP.

Prevention by risk attitudes and perceptions.—The PAP does not specify a method to be used to test an association between baseline prevention and probability distortion. This makes the correlational analysis reported in section III.A even more exploratory. Nonetheless, the evidence presented is consistent with the PAP prediction that inverse-S probability distortion reduces prevention of intermediate risks and it is robust to the method of estimation, controls and alternative indicators of prevention.

The PAP suggests intermediate risks are loss probabilities approximately in the interval of 15-80%. Based on a comprehensive review of the evidence on likelihood insensitivity in Baillon et al. (2022*a*), we use 10-85% for the main analysis and demonstrate robustness to using 5-80% (Table A10). The latter interval is based on theoretical results (ibid.).

In the simple model used in section I to demonstrate the logic that likelihood insensitivity leads to underprevention, we assume that the utility function is additively separable in utility from a risky binary outcome and the utility cost of preventive effort exerted to reduce the known probability of a loss from the bad outcome. In that case, the marginal (utility) cost of effort is the same in the two states and the loss probability interval within which there is underprevention is the same as the likelihood insensitivity region. If we do not impose additive separability and make the plausible alternative assumption that the marginal cost of effort is higher in the bad state, then the underprevention interval is to the left of the likelihood insensitivity region (ibid. Proposition 2i). Further, the underprevention interval moves to the left when a) the marginal cost of effort increases more rapidly in the bad state and, for that case, b) the loss (health or monetary) is larger (ibid. Proposition 3). Finally, greater ambiguity about the loss probability increases underprevention, including at lower probabilities (ibid. Corollary 1). These are all plausible scenarios in which inverse S types may do too little prevention even for risks smaller than 10%.

Lottery compliance by risk attitudes and perceptions.—The regression eq.(2) we use to test heterogeneity in CCL compliance by risk attitudes differs from that specified in the PAP, eq.(6.4). The latter included participant-specific estimates of power-utility curvature, instead of the $AVERSE_i$ and $SEEKING_i$ indicators based on the non-parametric risk tolerance measure, $\frac{x_i+z_i}{2}$. We prefer the latter because using these indicators avoids imposition of a functional form for utility. Also, the measure captures risk tolerance through optimism, not only utility curvature. In any case, Appendix G, Table A17 demonstrates robustness to various specifications that use power-utility curvature.

To estimate this parameter for each participant, we must also choose a functional form for the probability weighting function (PWF), $w(p)$. Consistent with the PAP, we use Prelec's 1998 single-parameter function. In the PAP (eq.(6.4)), the proposed test for differential compliance by probability distortion is based on an interaction between the CCL treatment indicator and an indicator of Prelec's $\alpha < 1$. Conditional on restricting attention to this PWF, $INVERSE\text{-}S_i = \mathbb{1}_{\{x_i - z_i < 0\}} = \mathbb{1}_{\{\alpha_i < 1\}}$ (Appendix E). Hence, in this respect, there is no discrepancy between our analysis of compliance and the PAP.

In the PAP, eq.(6.4) omits an indicator of S-shaped probability distortion (equivalently, $\mathbb{1}_{\{\alpha_i > 1\}}$) interacted with the CCL indicator. Implementation of this specification would be a mistake that we choose to avoid. Theory predicts that, compared with no probability distortion ($\alpha_i = 1$), inverse S causes underprevention of intermediate risks and overweighting of lottery chances, while S causes overprevention of intermediate risks and underweighting of lottery chances. Hence, the appropriate reference group is those with no distortion, not a mixture of this group and S types.

The PAP specification given by eq.(6.4) includes the baseline value of an outcome, while we do not include this in the specification estimated, eq.(2). This is because the PAP regression (6.4) is a first stage of an instrumental variable (IV) estimate of the effect of a clinic visit on the respective outcome, as in section III.C of this paper, where we do include the baseline outcome. In section III.B, regression (2) is not a first stage. We do include an indicator of having visited a clinic before baseline in this regression.

The PAP states that heterogeneity in compliance by risk attitudes would also be tested using a risk premium as a composite measure capturing both utility curvature and likelihood insensitivity (eq.(6.3)). We decided to drop this idea because it is more restrictive than the approach we take in regression eq.2 using non-parametric measures of probability distortion and risk tolerance. Estimating a (participant-specific) risk premium would require imposition of functional form for both utility and the PWF. It would not distinguish variation in compliance by probability distortion from that by risk tolerance. Further, the control group is not offered the CCL. In this group, a risk premium for the CCL (included in eq.(6.3)) would be relevant to the decision to visit a clinic between baseline and endline only to the extent that it reflects the risk attitudes, in general, that are elicited. In sum, eq.(6.3) was a bad idea not worth pursuing.

In any case, our risk tolerance measure is a linear function of the average risk premium from the two choice sets in the elicitation task: $\frac{x_i+z_i}{2}= 200 - \frac{\pi_{1i}+\pi_{2i}}{2}$, where $\pi_{1i} = 200 - x_i$ and $\pi_{2i} = 200 - z_i$ are the risk premia from choice sets 1 and 2, respectively. For Set 2, $\pi_{2i} = 2\left(\pi_{Mi} - \pi_{Li}\right)$, where π_{Mi} and π_{Li} are the premia for the more ($400_{0.25}0$) and less ($z_{i0.5}0$) risky lotteries, respectively. π_{2i} is the willingness to pay to face the least risky of the two lotteries.

The PAP states that characterization of compliers would be done by estimating regressions of a clinic visit on the CCL indicator using samples stratified by risk attitudes, then taking ratios of the estimated effects. This is the procedure of Angrist and Pischke (2008). We opted to use the less restrictive approach of Marbach and Hangartner (2020), which was published after the PAP was written. This allows identification of means of risk attitudes (and covariates) of compliers, as well as always-takers and never-takers, while avoiding model specification and stratification, and it allows testing for significant differences in means (Appendix J).

Clinic visit effects by risk attitudes and perceptions.—In the PAP, hypothesis H6e postulates that individuals who underweight low probabilities would gain more from a CCL-induced clinic visit because they would otherwise underinvest in prevention. The logic of this hypothesis is incorrect. It is likelihood insensitivity, not underweighting of a risk, that causes underprevention (Baillon et al., 2022*a*). The PAP-proposed test of this hypothesis is also flawed. It would involve comparison of estimated effects of a clinic visit across categories of probability distortion irrespective of the level of perceived CVD risk. Yet, it is the combination of likelihood insensitivity and the perceived risk level that result in underprevention, giving scope for increased prevention to be particularly effective.

The first paragraph of section III.C provides a corrected rationale for expecting the effect of a CCL-induced clinic visit to vary with probability distortion and CVD risk perception. Regression eq.(3), in which a visit is interacted with both probability distortion and risk perception categories, is an appropriate specification for testing the corrected hypothesis.

J. Characterizing compliers and other principal strata

This appendix explains the approach (Marbach and Hangartner, 2020) we use to identify and estimate means of measured risk attitudes and covariates for subpopulations defined by (potential) response to the conditional cash lottery (CCL).

The indicator of the randomly assigned CCL offer, $LOTTERY_i$, is an instrumental variable (IV) for a binary treatment indicator – a public health clinic visit, $VISIT_i$. For consistency with conventional notation and to save space in the expressions below, we relabel these indicators: $Z_i \equiv LOTTERY_i$ and $D_i \equiv VISIT_i$. Dropping the generic individual index, i, let $D(1)$ and $D(0)$ indicate potential treatment with and without receipt of a CCL offer, respectively.

We assume *monotonicity* of the effect of the CCL offer on occurrence of a clinic visit: $D(1) \geq D(0)$. Then, there are only three subpopulations (principal strata):

1) *Compliers* who would be induced by a CCL offer to visit a public health clinic but would not do so otherwise: $D(1) = 1$ amd $D(0) = 0$.

2) *Always-takers* who would visit a clinic even without a CCL offer: $D(1) = D(0) = 1$.

3) *Never-takers* who would not visit a clinic even with a CCL offer: $D(1) = D(0) = 0$.

Let $\mathbf{X}$ be a vector that includes measures of risk attitudes and covariates. Given the CCL offer is randomly assigned, we assume *independence* of these characteristics and of the potential treatments from that instrument: $\mathbf{X}, D(1), D(0) \perp\!\!\!\perp Z$ (Marbach and Hangartner, 2020).

In addition to the monotonicity and independence assumptions, we assume compliers exist. That is, there is a *first stage*: $\mathbb{E}[D \mid Z = 1] \neq \mathbb{E}[D \mid Z = 0]$. With these assumptions, the means of each X for always-takers and never-takers are identified from the subset of the control group that visit a clinic and the subset of the treatment group that does not, respectively:

$$\mathbb{E}[X|D(1) = D(0) = 1] = \mathbb{E}[X|D = 1, Z = 0]\,, \tag{A6}$$

$$\mathbb{E}[X|D(1) = D(0) = 0] = \mathbb{E}[X|D = 0, Z = 1]\,. \tag{A7}$$

Writing the overall mean as the weighted (by population proportions) means of the subpopulations and using eq.(A6) and eq.(A7) identifies the mean for compliers (Marbach and Hangartner, 2020):

$$
\begin{aligned}
\mathbb{E}[X|D(1) > D(0)] = &(\mathbb{E}[X] - \mathbb{E}[X|D = 1, Z = 0]P[D = 1|Z = 0] \\
&- \mathbb{E}[X|D = 0, Z = 1]P[D = 0|Z = 1]) \\
&(\mathbb{E}[D|Z = 1] - \mathbb{E}[D|Z = 0])^{-1} ,
\end{aligned} \tag{A8}
$$

where P is a probability.

To estimate the means for the three principal strata, we replace the (sub)population means and shares in equations (A6)-(A8) by their sample counterparts. As the shares need to be estimated, there is no closed-form solution for the variance of the estimate of the mean for compliers. We use the bootstrap method (1,000 replications) to compute 95% confidence intervals (percentile method) for the estimated means.

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