

# Do time preferences explain low health insurance take-up?

EsCHER Working Paper No. 2021005  
December 2021

Aurélien Baillon, PhD  
Owen O'Donnell, PhD  
Stella Quimbo, PhD  
Kim van Wilgenburg, PhD



**EsCHER**

ERASMUS CENTRE  
FOR HEALTH ECONOMICS  
ROTTERDAM

**Erasmus University Rotterdam**  
Making Minds Matter



**Title**

Do time preferences explain low health insurance take-up?

**Authors**

Aurélien Baillon, PhD, Erasmus School of Economics, Erasmus University Rotterdam; Tinbergen Institute

Owen O'Donnell, PhD, Erasmus School of Economics and Erasmus School of Health Policy & Management, Erasmus University Rotterdam, Tinbergen Institute; Faculty of Economics and Business, University of Lausanne

Stella Quimbo, PhD, School of Economics, University of the Philippines Diliman

Kim van Wilgenburg, PhD

Corresponding author: Aurélien Baillon, Erasmus School of Economics, Erasmus University Rotterdam, the Netherlands, e-mail: [baillon@ese.eur.nl](mailto:baillon@ese.eur.nl).

**Keywords**

Health insurance, prospect theory, quasi-hyperbolic time preferences, preference elicitation

**JEL classification**

D03, D81, D90, I13

**Cite as**

Baillon A, O'Donnell O, Quimbo S, and van Wilgenburg K. (2021). Do time preferences explain low health insurance take-up? EsCHER Working Paper Series No. 2021005, Erasmus University Rotterdam.

Available from: <https://www.eur.nl/en/research/escher/research/working-papers>

Erasmus Centre for Health Economics Rotterdam (EsCHER) is part of Erasmus University Rotterdam. Want to know more about EsCHER? Visit [www.eur.nl/escher](http://www.eur.nl/escher)  
Want to contact EsCHER? E-mail [escher@eur.nl](mailto:escher@eur.nl)

Interested in more EsCHER Working Papers? Download from [www.eur.nl/escher/research/workingpapers](http://www.eur.nl/escher/research/workingpapers)

© Baillon et al., 2021

All rights reserved. No part of this publication may be reproduced or transmitted in any form or by any means without the written permission of the copyright holder.

## Do time preferences explain low health insurance take-up?

**Aurélien Baillon**  
**Owen O'Donnell**  
**Stella Quimbo**  
**Kim van Wilgenburg<sup>†</sup>**

December 2021

### Abstract

Low insurance take-up in low-income populations is not easily explained by the standard single-period expected utility model of insurance that overlooks the relevance of time preference when liquidity is constrained. We design field survey instruments to elicit quasi-hyperbolic time preferences, as well as prospect theory risk preferences, and use them to examine whether time preferences explain health insurance behavior of low-income Filipinos. Consistent with theory, those who exhibit stronger time preference are less likely to insure and the partial association is most pronounced at low wealth where liquidity is most likely to be constrained. Among those with better understanding of insurance, lower take-up is also associated with present bias. We do not find that insurance is significantly associated with risk preferences.

**JEL Classification:** D03, D81, D90, I13

**Keywords:** health insurance, prospect theory, quasi-hyperbolic time preferences, preference elicitation

**Acknowledgements:** We thank Timo Lambregts and Matthew Robson for comments. We are grateful to the World Bank for funding the Daisy III survey and especially Caryn Bredenkamp for the opportunity to collect the data on risk perceptions and preferences as part of this survey. The research of Aurélien Baillon is made possible by a Vidi grant of the Netherlands Organization for Scientific Research. Owen O'Donnell is supported by the Swiss Agency for Development and Cooperation / National Science Foundation Programme for Research on Global Issues for Development through the grant, "Inclusive social protection for chronic health problems" (400640\_160374, PI: Jürgen Maurer). The data used in this article will be made publicly available. The authors declare no conflict of interest.

<sup>†</sup> Baillon: Erasmus School of Economics, Erasmus University Rotterdam, Tinbergen Institute [baillon@ese.eur.nl](mailto:baillon@ese.eur.nl); O'Donnell: Erasmus School of Economics, Erasmus School of Health Policy and Management, Erasmus University Rotterdam, Tinbergen Institute, Faculty of Economics and Business, University of Lausanne [odonnell@ese.eur.nl](mailto:odonnell@ese.eur.nl); Quimbo: School of Economics, University of the Philippines Diliman [stella\\_quimbo@yahoo.com](mailto:stella_quimbo@yahoo.com); van Wilgenburg: Erasmus School of Health Policy and Management, Erasmus University Rotterdam [vanwilgenburg@eshpm.eur.nl](mailto:vanwilgenburg@eshpm.eur.nl)



# 1 Introduction

Low take-up of insurance against substantial risks related to healthcare and agriculture in developing countries is difficult to explain with the standard single-period expected utility model of insurance. That may be because that model affords no role to time preference despite insurance often requiring upfront payment of a premium to secure entitlement to compensation for a future loss. This paper examines whether time preference can partly explain low insurance take-up.

Evidence that the timing of premium payments influences demand for insurance in low-income settings (Casaburi & Willis, 2018; Belissa et al., 2019; Liu et al., 2020) is consistent with the time dimension of insurance acquiring importance when liquidity is constrained (Ericson & Sydnor, 2018). Both discounting of future compensation when credit cannot be used to pay a premium up front and present bias may reduce demand. However, the explanation for low insurance take-up does not necessarily lie only in time preferences. Compared with expected utility maximization, a more descriptively accurate model of decision under risk may provide greater insight into why so many low-income individuals do not insure. A prospect theory model of insurance in which the premium is perceived as a loss predicts that convex utility over losses will drive demand down (Wakker et al., 1997). Any motivation to insure would then have to come from distorted transformation of loss probabilities into decision weights (Barseghyan et al., 2013; Jaspersen et al. 2021).

To assess empirical support for these explanations of low insurance take-up, we elicit quasi-hyperbolic time preferences and prospect theory risk preferences in a nationwide survey of low-income individuals in the Philippines and examine whether these preferences are associated with the decision to voluntarily insure medical expenses rather than remain uninsured. As far as we know, no previous study has elicited constant discounting, present bias, utility curvature, and probability weighting in a general population survey and estimated associations between insurance and these four dimensions of preferences.

To motivate the empirical analysis, we obtain predictions from a simple model of the decision whether or not to enroll in health insurance. A contract that stipulates a minimum period between payment of a premium and entitlement to make a claim leaves scope for time preference to impinge on the decision to insure if credit cannot be used to smooth the cost of the premium across periods. We show that this intuition is correct irrespective of whether the time dimension of the decision is embedded in an expected utility model of insurance or a

prospect theory model. The insurance probability is predicted to decrease with stronger time preference when there is a binding liquidity constraint. Constrained liquidity is likely to be common in the Filipino population we study and previous evidence, consistent with theory (Ericson & Sydnor, 2018), suggests it is associated with lower demand for insurance (Platteau et al., 2017): poorer households are less likely to insure (Giné & Yang, 2009; Cole et al., 2013); take-up responds positively to cash handouts given immediately before insurance is offered (Cole et al., 2013); and, the opportunity to delay payment of a premium to harvest time raises enrollment substantially (Casaburi & Willis, 2018; Balessi et al., 2019; Liu et al., 2020).<sup>1</sup> Constant discounting is not necessarily the best description of the time dimension of economic behavior (Laibson, 1997; Frederick et al., 2002; Anderson et al., 2008; Dupas, 2011; Burks et al., 2012; Wang et al., 2016). We show that present bias compounds the negative effect of time preference on the demand for insurance unless there is an instrument available to commit to the purchase of insurance.

Consistent with the first prediction, we find that those who discount more aggressively are less likely to purchase health insurance, and this relationship is strongest among the least wealthy who are most likely to be liquidity constrained. In the full sample, insurance take-up is not related to present bias. However, when we restrict attention to respondents who display some understanding of how health insurance operates and what it covers, there is clear evidence that the more present biased are less likely to insure.

Our finding of a negative association between health insurance and discounting is consistent with evidence that an option to delay payment of the premium raises take-up of agricultural insurance (Casaburi & Willis, 2018; Balessi et al., 2019; Liu et al., 2020).<sup>2</sup> Consistent with theory that identifies illiquidity as the mechanism through which the time dimension of insurance acquires relevance (Ericson & Sydnor, 2018) and with our finding that the insurance-discounting association is stronger at lower wealth, Casaburi and Willis (2018) find that the effect of delayed payment is stronger among poorer and liquidity constrained farmers. They also demonstrate that an opportunity to pre-commit can raise take-up, which

---

<sup>1</sup> Illiquidity is not the only possible explanation. Karlan et al. (2014) find that insurance take-up increases with the provision of a timely cash handout but suggest this occurs because the handout builds trust in the insurance or induces reciprocation through buying insurance. Casaburi & Willis (2018) find that more than half of a substantial effect of a handout is removed when control is made for reciprocation.

<sup>2</sup> Casaburi and Willis (2018) find offering Kenyan farmers the opportunity to pay for crop insurance at harvest increased enrollment from 5 percent to 72 percent. Liu et al. (2020) find that a delayed payment option raised enrollment of Chinese (hog) farmers by 10 percentage points (pp); a three-fold increase. Balessi et al. (2019) estimate that this option also produced a three-fold (16 pp) increase in take-up of index insurance in Ethiopia.

suggests that present bias partly explains the large effect of delayed-payment.<sup>3</sup> Unlike these experiment-based studies, this paper does not deliver evidence of the causal effect of an intervention from which preferences can be inferred subject to the validity of assumptions about the mechanism. Rather, we directly elicit preferences in a nationwide survey and examine their associations with insurance behavior.

We do not find evidence of consistent and statistically significant associations between insurance and risk preferences. A point estimate indicates that, in the sample, greater risk seeking (convex utility) over losses is associated with a higher probability of insurance, and this association is significant when the sample is restricted to respondents who show better understanding of the concept and content of insurance. While inconsistent with theory, the direction of this association is consistent with evidence – based on preferences elicited from Holt and Laury (2002) lotteries over gains – that insurance demand is weak among predominantly risk averse individuals (Chemin, 2018) and that demand is decreasing with increasing risk aversion (Giné et al., 2008; Giné & Yang, 2009; Giesbert et al., 2011; Cole et al., 2013; Clarke 2016; Liu et al., 2020). It may be that insurance is viewed as a risky prospect by many with little experience of it.

Besides the finding that low take-up of health insurance in the Philippines is associated with time preference and, to a lesser extent, present bias, the paper introduces a new instrument that makes it feasible to elicit four dimensions preferences in a field survey of the general population. In developing country settings, even standard preferences are usually elicited from samples of students, farmers, or households in small communities (Binswanger, 1980; Cardenas & Carpenter, 2008 & 2013; Tanaka et al., 2010; Vieider et al., 2015; Vieider et al., 2019). Elicitation of quasi-hyperbolic time preferences and prospect theory risk preferences is usually thought to require a laboratory setting and some degree of sophistication on the part of respondents (Charness et al. 2013). To make the exercise feasible in a time-limited field survey, we asked (mostly poorly educated) respondents to make only four sets of choices. From the implied indifference points, we derive non-parametric preference measures. We also identify four preference parameters that rest on assumptions about the nature of utility and probability weighting functions. We obtain a non-parametric estimate of the bivariate relationship between insurance and each dimension of preferences (captured by both the non-parametric measure and

---

<sup>3</sup> Given a choice between free insurance enrollment and cash of equivalent face value, 21 percent more farmers opted for the insurance when told that their choice would be implemented a month later.

the respective parameter) and estimate partial associations from models that include all four preferences and covariates.

Section 2 provides the theoretical motivation. Section 3 presents the preference elicitation instrument and derives the preference measures and parameters. Section 4 provides background on health insurance in the Philippines. Section 5 describes the data. Section 6 describes distributions of the preference measures and parameters before presenting estimates of their bivariate and partial associations with insurance. The final section discusses implications and limitations.

## 2 Theory

We consider a consumer deciding whether to purchase insurance that offers a fixed quantity of cover at a given price. This corresponds to the voluntary social health insurance enrollment decision in the Philippines and elsewhere. Although our focus is on time preferences, we begin with the standard assumption that risk is resolved in the same period that the premium is paid and consider the role of risk preferences according to both expected utility (EU) and (cumulative) prospect theory (PT). We then allow for delay between payment of the premium and resolution of the risk and examine the role of time preferences in each model.<sup>4</sup>

### 2.1 Risk preferences

Under EU, an offer of a fixed quantity of insurance ( $\leq$  loss) will be accepted provided the price is actuarially fair, or subsidized, and utility is concave in the level of consumption. Consider the offer to insure a fraction  $\theta \in (0,1]$  of a loss  $L$  incurred with probability  $p$  at a price  $\pi = \varphi p \theta L$ , where  $\varphi > 0$  is the loading factor. The price is fair if  $\varphi = 1$ , unfair if  $\varphi > 1$ , and subsidized if  $0 < \varphi < 1$ . The difference between expected consumption with insurance ( $y - \pi - p(1-\theta)L$ ), where  $y$  is income, and expected consumption without insurance ( $y - pL$ ) is  $p\theta L(1-\varphi)$ , which is non-negative provided the price is fair or subsidized. The variance of consumption with insurance ( $p(1-p)(1-\theta)^2 L^2$ ) is smaller than the variance without insurance ( $p(1-p)L^2$ ). Since insurance at a price that is not unfair reduces the variance of consumption and does not reduce its expected value, expected utility is greater with insurance provided utility

---

<sup>4</sup> Jaspersen et al. (2021) compare the predictive performance of 17 models of insurance. We restrict attention to EU and PT to explore the consequences of introducing time into two of the main models and because we elicit preferences deemed relevant by these models.

is concave. If the price is unfair, then a higher price necessitates a higher degree of concavity for insurance to be purchased.

In PT, the motivation to insure differs from that identified with EU. Consider the preferences of an individual facing risky outcomes, which are real numbers denoted  $x$  or  $z$  that are defined as changes from some reference situation. Let  $x_p z$  denote a prospect yielding  $x$  with probability  $p$  and  $z$  otherwise. Risk attitudes are represented through a utility function  $v(x)$ , which is anticipated to be concave for gains but convex for losses, and a probability weighting function  $w(p)$  that is increasing and maps cumulative probabilities into decision weights (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). The prospect is valued as  $PT(x_p z) = w(p)v(x) + (1 - w(p))v(z)$ , with  $x \geq z \geq 0$  or  $0 \geq z \geq x$ .

Applied to insurance, the reference point is usually taken to be consumption in the state in which insurance is not purchased and the bad outcome does not occur (Wakker et al. 1997).<sup>5</sup> In that case, the choice is between a small certain loss (the premium) and a larger uncertain loss (medical expenses). If utility is indeed convex for losses, then utility curvature does not motivate insurance. It would generate risk seeking and constrain demand for insurance that carries no default risk. The motivation for insurance can come from the weighting of probabilities. If, as is often found in laboratory experiments (Wakker, 2010 p.204), the weighting function is inverse S-shaped – overweighting smaller probabilities ( $p \lesssim \frac{1}{3}$ ) and underweighting moderate and larger ones – then this would raise demand for insurance against a fixed loss that occurs with a smallish probability.<sup>6</sup> Inverse S-types would be more likely to insure than both EU-types who weight probabilities linearly and S-types who underweight smaller probabilities.<sup>7</sup>

When, as with medical expenses, the loss is not fixed, extreme outcomes in each direction can occur with small probability. Inverse S-shaped probability weighting can then result in the overweighting of both unusually large losses and unusually small ones. Willingness

---

<sup>5</sup> See Jaspersen et al. (2021) for alternatives.

<sup>6</sup> This is because the weight placed on the probability of the loss rises,  $w(p) > p$ , while the weight attached to the prospect of paying the insurance premium is the same as that given under EU,  $w(1) = 1$ .

<sup>7</sup> Exactly how low the loss probability must be for these predictions to hold depends on the precise shape of the weighting function. From previous evidence (Wakker 2010 p.204), if the probability of loss is 10%, then we would expect  $w(0.1) > 0.1$  if  $w(p)$  is inverse S-shaped and  $w(0.1) < 0.1$  if  $w(p)$  is S-shaped.



to pay for insurance then depends on the precise shape of both the distribution of losses and the weighting function (Baillon et al., 2021).

## 2.2 Time preferences

Under EU, time preference is irrelevant to insurance demand if there is no constraint on liquidity; otherwise, time preference reduces demand (Liu & Myers, 2016; Casaburi & Willis, 2018).<sup>8</sup> When liquidity is constrained, insurance must be adjusted to compensate for the reduced opportunity to use credit to make transfers between periods. Purchasing insurance creates imbalance in consumption across periods if the premium must be paid up front and cannot be credit-financed. It also ties resources up in an illiquid asset, raising exposure to (formally) uninsured risks that (constrained) borrowing is insufficient to cope with. Through these direct and indirect mechanisms, insurance affects cross-period, and not only cross-state, consumption levels and so becomes dependent on time preference. Unlike the previous literature that assumes EU maximization, we analyze the influence of time preference on insurance without confining attention to a particular theory of decision under risk.

### 2.2.1 Constant discounting

First, consider a two-period model with no opportunity to borrow or save. With some probability, a fixed loss is incurred in the second period. We assume decisions can be represented by discounted utility which is a function of consumption determined by time- and state-invariant per period income and the risk:

$$V(y, 0) + \delta V(y, -L_p, 0), \quad (1)$$

where  $\delta \in (0, 1]$  is the discount factor.<sup>9</sup>  $V$  can be either EU, with  $V(y, -L_p, 0) = pu(y - L) + (1 - p)u(y)$ , or PT, with  $V(y, -L_p, 0) = w(p)v(-L)$ , where we take income to be the reference point.<sup>10</sup>

---

<sup>8</sup> Liu and Myers (2016) show that when liquidity is constrained full insurance is not optimal at an actuarially fair premium. Their equation (11) implies that the optimal insurance quantity depends on the discount factor. Casaburi and Willis (2018) show (equation (4)) that the insurance probability is decreasing with both the degree of time discounting and present bias.

<sup>9</sup> We assume the discount factor is bounded at 1 in order to examine how insurance varies with the intensity of positive time preference. We do not constrain elicited time preference to be positive.

<sup>10</sup> In general, discounting  $V$  need not be the same as applying PT on discounted utilities. However, given there is no risk in the first period and income is the reference point in each period, the two approaches are consistent in the problem we analyze. The relevant reference point is that contemplated at the time the individual decides whether or not to insure. At this time, the individual compares a prospect with insurance with a prospect without insurance. Evaluation of each prospect is made with respect to the same reference point, which we assume is no

In the first period, there is a take-it-or-leave-it offer to purchase a fixed quantity of insurance at a given price that must be paid up front. Taking the offer yields

$$V(y, -\pi) + \delta V\left(y, -((1-\theta)L)_p, 0\right). \quad (2)$$

The offer is accepted if

$$\Delta_\delta = V(y, -\pi) - V(y, 0) + \delta \left[ V\left(y, -((1-\theta)L)_p, 0\right) - V(y, -L_p, 0) \right] \geq 0. \quad (3)$$

Since  $\Delta_\delta$  is increasing in  $\delta$ , stronger discounting (smaller  $\delta$ ) reduces the propensity to insure.

*OBSERVATION: When it is not possible to borrow or save, individuals who discount the future more heavily are less likely to insure irrespective of whether they behave in accordance with expected utility or prospect theory.*

For some combinations of risk attitudes and price, even someone who does not discount the future will decline the offer of insurance. In such cases, variation in the discount factor will obviously have no influence on the decision. However, provided risk aversion and the price are such that insurance is purchased by someone with no time preference, then an otherwise identical individual will be less likely to insure the more they discount the future. This is because insuring involves making a sacrifice now to cushion a possible loss in the future and there are no other instruments available to offset the intertemporal redistribution.

The analysis assumes there is no opportunity to borrow. Lack of credit to purchase health insurance is not a particularly strong assumption in the context of our empirical analysis. It is critical to the result. The constrained opportunity to borrow to pay the insurance premium creates the dependence of insurance on time preference.<sup>11</sup> To simplify the exposition, we have confined attention to the extreme case in which there is no opportunity to borrow whatsoever. But if a less extreme liquidity constraint were imposed, the logic tying the demand for insurance to the discount factor would hold. Given a large fraction of the Filipino households in our

---

insurance-no loss. By the time the risk is resolved and the insurance is paid out (if there is a loss), the reference point will have shifted. But that is irrelevant to the insurance decision, as modelled.

<sup>11</sup> Ericson and Sydnor (2018) show that predictions obtained from the standard single-period expected utility model of insurance differ from those obtained from a multi-period model when liquidity is constrained. By restricting attention to a two-period model with the risk of incurring a loss in the second period, we rule out the possibility of borrowing to smooth consumption over that loss. Allowing for the possibility to self-insure through credit would reduce the demand for formal insurance offered at an actuarially unfair price (Gollier 2003) but would not change our prediction that the propensity to insure falls together with the discount factor unless credit is available to pay the premium.

sample are likely to be liquidity constrained, we expect to find a positive relationship between insurance and the discount factor.

### 2.2.2 *Quasi-hyperbolic discounting*

Extending the two-period model to allow for quasi-hyperbolic discounting (QHD) (Laibson 1997), the condition for accepting a take-it-or-leave-it offer of insurance becomes  $\Delta_{\beta\delta} = V(y, -\pi) - V(y, 0) + \beta\delta \left[ V(y, -((1-\theta)L)_p, 0) - V(y, -L_p, 0) \right] \geq 0$ , where  $\beta \in (0, 1]$  is the present bias parameter. In this case, present bias only increases the degree to which the future is discounted. The propensity to insure is increasing in  $\beta$  and so more present-biased people (smaller  $\beta$ ) are less likely to insure.<sup>12</sup>

The effect of present bias can change in a three-period model. In period 0, the decision to insure is taken. In period 1, the premium must be paid. In period 2, the loss is incurred or not. In period 0, the agent would compare  $\beta\delta V(y, 0) + \beta\delta^2 V(y, -L_p, 0)$  with  $\beta\delta V(y, -\pi) + \beta\delta^2 V(y, -((1-\theta)L)_p, 0)$ . The difference is  $\beta\delta\Delta_{\delta}$ , which has the same sign as  $\Delta_{\delta}$ . Present bias then has no effect on the decision to insure, provided that decision is binding. If the decision taken in period 0 is not binding, then some present-biased individuals – those with  $\Delta_{\delta} \geq 0$  but  $\Delta_{\beta\delta} < 0$  – would change their mind and refuse to pay for the insurance.<sup>13</sup>

To summarize, we expect present bias to reduce the likelihood of enrollment if payment of the premium is simultaneous with the decision to insure (two-period model) or if the initial decision can be revised when payment is due (three-period model without commitment). In the insurance program we study, part of the premium is due upfront and the remainder is paid at intervals over the course of the year. Present bias may therefore reduce the propensity to enroll initially and increase the propensity to drop out before payment is due for all of the premium.

---

<sup>12</sup> Provided the present biased are naïve, allowing saving does not change the argument. With a saving option, present bias could increase the insurance of sophisticated agents. Upfront payment of a one-off premium offers a means of committing to insurance. It is less prone to procrastination than self-insurance through saving (without a saving commitment device). Recognizing this, those with self-awareness of their present bias may opt for formal insurance (Ito and Kono 2010). We might therefore expect the relationship between insurance and present bias to vary between *sophisticates* and *naïfs*, and across contexts distinguished by opportunities to commit to saving. Given the context and our data, we are not able to explore this empirically.

<sup>13</sup> Allowing saving can change these results but the predictions then depend on which (if any) period the liquidity constraint is binding and on assumptions about the specific nature of risk preferences within an EU model (Kifmann et al., 2014).

### 3 Preference elicitation

This section describes instruments we designed to elicit time and risk preferences in a general population field survey. Appendices A and B contain the instruments. We first describe elicitation of risk preferences and identification of respective parameters because one of those parameters is subsequently used to identify time preference parameters.

#### 3.1 Risk preferences

According to PT with a reference point of no insurance-no loss, the insurance decision is between outcomes in the loss domain. We aim to elicit PT risk preferences in that domain. Loss aversion is omitted because it is identified (and relevant) only if there are both gains and losses. We use two independent sets of hypothetical lotteries implemented in a respondent-enumerator interview. Respondents are asked to choose between two jars each containing four balls of two colors. They are told that one ball will be drawn randomly from the chosen jar and the color of that ball will determine the magnitude of the loss (if any) supposedly incurred.

In the first set of lottery choices, we elicit a sure loss  $x$  that leaves the respondent indifferent compared with a 50% chance of losing 400 PHP (pesos) or incurring no loss.

$$\text{Lottery 1: } x \sim -400_{0,5}0$$

$x > -200$  implies risk seeking in the domain of losses, while  $x < -200$  implies risk aversion. In the second lottery, we elicit the loss  $z$  such that the respondent is indifferent between facing a 50% chance of incurring that loss and facing a 25% chance of losing 400.

$$\text{Lottery 2: } z_{0,5}0 \sim -400_{0,25}0$$

Under EU that assumes expectations are formed using untransformed probabilities,  $x = z$ . The sign and magnitude of any difference between the amounts identifies the nature and intensity of probability weighting.

Elicitation was conducted with a bisection method. It starts with a choice between two prospects with the same expected value.<sup>14</sup> Depending on the answer, we either increase or decrease the expected value of the second option while keeping the first option constant until the respondent switches from one to the other. If there is no switching, then the procedure ends after offering four choices (Appendix A Figure A4). From the switching point, we infer a range

---

<sup>14</sup> The expected value (-200 pesos) coincides with the insurance premium per month of the program we study.



in which the value corresponding to indifference lies and use the midpoint as the estimate of that value.

From the estimated points of indifference  $x$  and  $z$ , we infer components of PT risk preferences. We do this both with and without the imposition of parametric functions for utility and probability weighting. In the non-parametric case, we use the average of the indifference points  $((x+z)/2)$  as a measure of *risk tolerance* that reflects both utility curvature and optimism. Larger values (not magnitudes) indicate lower risk tolerance.

We infer probability weighting from the difference between the two indifference points. Fixing  $v(0)=0$  and  $v(-400)=-1$ , the indifference from Lottery 1 implies  $v(x)=-w(0.5)$ , while that from Lottery 2 implies  $v(z)w(0.5)=-w(0.25)$ . Consequently,  $x > z$  if and only if  $w(0.25) > w(0.5)^2$ , which holds for any inverse S-shaped function  $w(p)$  that overweights 0.25 and underweights 0.5. Analogously,  $x < z$  is compatible with 0.25 being underweighted and 0.5 overweighted. For all weighting functions that cross the diagonal between 0.25 and 0.5,  $x - z > 0$  implies that the function is inverse S-shaped, while  $x - z < 0$  implies that it is S-shaped. For EU types who weight probabilities linearly,  $x - z = 0$ . We use  $x - z$  as a measure of *probability weighting*. Larger absolute values indicate greater nonlinear weighting of probabilities. In some analyses, we distinguish between the three types: inverse S-shaped, S-shaped, and linear weighting.

For (tractable) parametric identification of utility curvature and probability weighting, we restrict attention to the single parameter forms of the respective functions that have been demonstrated to perform best among (combinations of) the most popular specifications (Stott 2006). For utility, we use a power function  $v(x)=-(-x)^\gamma$ ,  $x < 0$ , where  $\gamma$  indicates the curvature of utility for losses and utility is convex if  $\gamma \leq 1$ . For probability weighting, we use the one-parameter functional form axiomatized by Prelec (1998):  $w(p)=\exp(-(-\ln p)^\alpha)$ , where  $\alpha > 0$  captures probability sensitivity. If  $\alpha < 1$ , the weighting function is inverse S-shaped, overweighting small probabilities ( $p \lesssim 1/3$ ) and underweighting larger probabilities.<sup>15</sup> If  $\alpha > 1$ , the weighting function is S-shaped, overweighting moderate and large probabilities and underweighting small probabilities. With  $\alpha = 1$ , the function is linear and expectations are taken using untransformed probabilities, as in EU.

---

<sup>15</sup> For  $\alpha < 1$ , this is a special case of all the weighting functions that cross the diagonal between 0.25 and 0.5.

With these functions (and normalizations of utility), the indifference points from Lottery 1 and Lottery 2 give two equations that solve for  $\alpha$  and  $\gamma$  for each combination of  $x$  and  $z$  (Appendix A Text A1 & Table A1).

### 3.2 Time preferences

We elicit time preferences in the gain domain, which is expected to reduce the cognitive burden on respondents. The canonical discounted utility model does not prescribe any difference between discounting of gains and losses. There is evidence that gains are discounted more than losses (Yates & Watts, 1975; Thaler, 1981; Ben Zion et al., 1989). However, this is not a concern since we are interested in the association between insurance and time preference, not the strength of time preference.

We offer two independent sets of hypothetical choices between monetary amounts to be received at different points in time. The first set of choices is designed to elicit the amount  $x_0$  that if received now ( $t=0$ ) would leave the respondent indifferent in comparison with receipt of 200 pesos in half a year from now ( $t = \frac{1}{2}$ ).

$$\text{Choice 1: } x_0 \square 200_{\frac{1}{2}}$$

$x_0 < 200$  indicates of positive time preference. The second choice elicits the amount that if received in half a year from now,  $z_{\frac{1}{2}}$ , would leave the respondent indifferent in comparison with receipt of 200 pesos in one year from now ( $t=1$ ).

$$\text{Choice 2: } z_{\frac{1}{2}} \square 200_1$$

For each choice, we again use a bisection method to identify switching points, infer a range of possible values containing  $x_0$  ( $z_{\frac{1}{2}}$ , respectively), and take the midpoint as the respondent's point of indifference (Appendix B Figure B3).

Time preference is inversely related to the average of the indifference points,  $(x_0 + z_{\frac{1}{2}})/2$ . We use this measure to examine the association between insurance and time preference without making any assumption about the nature of discounting or the functional form of utility.<sup>16</sup> The measure, like all those we use, potentially captures influences of liquidity

---

<sup>16</sup> While we refer to  $(x_0 + z_{\frac{1}{2}})/2$  as a measure of *time preference* (for shorthand), it does not correspond to a discount factor. For analysis of associations, it is sufficient that the measure is monotonically related to the strength of time preference/discounting.

and borrowing costs on temporal choices, in addition to pure time preference (Epper, 2017; Cohen et al., 2020; Dean & Sautmann, 2021). Clearly, this is limiting with respect to identifying mechanisms through which temporal choice impacts the demand for insurance. But it does not prevent examination of how discounting overall – not each of its sources – affects insurance, which, in any case, is hypothesized to rest on constrained liquidity (Lui & Myers, 2016; Casaburi & Willis, 2018; Ericson & Sydnor, 2018).

The difference between the indifference points  $(x_0 - z_{1/2})$  measures *non-stationarity*, with positive, negative, and zero values corresponding to present bias, future bias, and stationary preferences, respectively. If we assume that preferences are time invariant, then non-stationarity implies time inconsistency (Halevy, 2015). We cannot test this assumption because we elicit the preferences of each respondent on only one date. With constrained liquidity, anticipated fluctuation in cash flow may cause non-stationarity without violation of time consistency (Halevy, 2015; Epper, 2017). There is, indeed, evidence of liquidity constrained individuals behaving as if they are present biased (Carvalho et al., 2016; Janssens et al., 2017). Again, from the perspective of this study, this is only a partial limitation since elicitation task choices that appear to reflect present bias, but derive from constrained liquidity, could still help explain low insurance take-up that is caused by the combination of (short-term) discounting and limited opportunity to borrow to pay the premium.

Under the assumption that respondents anticipate immediate consumption of any money offered in the elicitation task (Cohen et al., 2020; Dean & Sautmann, 2021) and subject to the same caveat about the potentially confounding effect of constrained liquidity, the two points of indifference separately identify the *discount factor* ( $\delta$ ) and *present bias* ( $\beta$ ) parameters of the QHD model (Laibson, 1997) when utility is linear ( $\gamma = 1$ ).<sup>17</sup> This assumption risks confounding time preference with ignored utility curvature (Anderson et al., 2008; Attema et al., 2010; Andreoni & Sprenger, 2012; Andreoni et al., 2015). If money is perceived in the same way in the risk and time elicitation tasks, then we can correct for the confounding effect of utility by using the respondent-specific estimates of curvature ( $\gamma$ ) inferred from the risk task, now

---

<sup>17</sup> Under linear utility, the indifference point of Choice 1 gives  $x_0 = \beta\delta^{1/2}200$ , and Choice 2 indifference implies  $\beta\delta^{1/2}z_{1/2} = \beta\delta^{1/2}200$ . Solving gives  $\delta = \left(\frac{z_{1/2}}{200}\right)^2$  and  $\beta = \frac{x_0}{z_{1/2}}$ .

applied to gains,  $v(x_t) = x_t^\gamma$ .<sup>18</sup> The indifference points from Choice 1 and Choice 2 give two equations that solve for the two QHD parameters.<sup>19</sup>

Pretesting of the preference elicitation instruments on convenience samples (in Manila) suggested reasonably good comprehension of the tasks and confirmed the effectiveness of visual aids.<sup>20</sup> As is the norm in field surveys, respondents were not paid to participate. Because we elicited risk preferences in the loss domain, we used hypothetical lotteries without incentives. Such lotteries are sometimes found to increase risk seeking (e.g. Holt & Laury, 2002), although Etchart-Vincent & l'Haridon (2011) found no differences in preferences elicited using hypothetical losses, losses from an initial endowment, and real losses.<sup>21</sup> This is less of a concern because we are not primarily interested in the absolute values of the preference parameters but in their associations with insurance. The hypothetical nature of the questions could, however, increase noise and obfuscate relationships.

#### 4 Health insurance in the Philippines

The National Health Insurance Program (aka PhilHealth) covers most households in the Philippines. Salaried employees are covered by a mandatory employment-based program. Senior citizens are entitled to cover at no charge and the indigent are covered (subject to a means-test conducted infrequently) by another fully subsidized program. Other disadvantaged groups also get cover without charge. The remainder – informal workers and the self-employed considered insufficiently poor to qualify for the indigent program – can enroll in PhilHealth

---

<sup>18</sup> Since we elicit risk preferences in the loss domain, we are assuming that utility curvature is the same in both domains. As previously mentioned, loss aversion is irrelevant under the assumptions made.

<sup>19</sup> The indifference points from Choice 1 and Choice 2 imply  $x_0^\gamma = \beta\delta^{1/2}200^\gamma$  and  $\beta\delta^{1/2}z_{1/2}^\gamma = \beta\delta^1 200^\gamma$ , which solve for  $\delta = (z_{1/2}/200)^{2\gamma}$  and  $\beta = (x_0/z_{1/2})^\gamma$ . The values of parameters for different combinations of  $x_0$  and  $z_{1/2}$  are given in Appendix B Table B1.

<sup>20</sup> Comprehension was demonstrated by most pretest respondents switching at some point and the others being able to rationalize extreme choices. Those opting for a small amount of money rather wait for a much larger amount explained that they needed money immediately. Those opting for a smaller amount in the future explained they were taking the opportunity to save. Those making choices that implied extreme risk seeking explained that they enjoyed the thrill of gambling. Effectiveness of the visual aids was evident from finding a greater propensity to switch when they were used. After pretesting, adjustments were made to some of the amounts used in the Choices/Lotteries to increase the scope for respondents to switch.

<sup>21</sup> Incentivizing choices in the loss domain would involve compensating for all losses, which would be extremely expensive in a field survey. Incentivizing time preference choices is difficult with this type of study because it requires finding the respondents again.



voluntarily through the Individual Paying Program (IPP).<sup>22</sup> Only one third of the eligible population joins this program (Manasan, 2011; Capuno et al., 2016). We examine whether the decision to enroll rather than remain uninsured is associated with preferences.

The IPP premium is 2,400 PHP per year (~\$50) if average monthly income is no more than 25,000 PHP (\$540) and is 3,600 PHP otherwise. In practice, given the difficulty of verifying informal sector incomes, almost all who enroll do so at the lower premium. At the time of application, the premium for one month or a quarter must be paid. Subsequently, the premium is paid at monthly or quarterly intervals. A claim can only be made if the premium has been paid for four months continuously in the last six months. Hence, anyone enrolling in the program for the first time would have to wait for half a year before filing a claim. This creates substantial delay between paying for the insurance and benefiting from it.<sup>23</sup> It also leaves scope for enrolling but not following through with payment of all installments of the premium, and so losing cover. There is potential for time preferences – discounting and present bias – to influence the decisions to insure and to maintain cover through continued payment of the premium.

As with all PhilHealth programs, anyone who becomes a member of the IPP obtains cover for their spouse, children (<21 years old), and parents ( $\geq 65$  years). The insurance benefit package includes inpatient treatments at accredited hospitals as well as some outpatient services and primary care. Limited coverage of ambulatory care and medicines, as well as reimbursement ceilings, means that the insured are still exposed to the risk of incurring medical expenses that will not be reimbursed (Bredenkamp & Buisman, 2016).

---

<sup>22</sup> The means-test that gives cover through the indigent program is conducted nationwide only infrequently. Hence, a household impoverished through medical expenses would not immediately qualify for this program. Years may pass before entitlement is acquired. This limits the extent to which the indigent program crowds-out insurance through the IPP.

<sup>23</sup> Ericson and Sydnor (2018) show that a liquidity constraint increases the value of insurance that can be paid for smoothly over the contract period because it provides a means of smoothing the consumption impact of a loss that cannot be self-insured through borrowing. However, not allowing a claim to be filed for some time after payment of the first instalment of a premium shuts down this mechanism for the duration of the waiting period. Hence, there is a large upfront element to payment for the IPP that in combination with a constraint on liquidity is expected to reduce the value of the insurance.

## 5 Data

### 5.1 Sample design

Data on time and risk preferences, as well as insurance and covariates, were collected in a nationwide survey of Filipino households conducted in 2015. The surveyed households had initially been interviewed in 2011 as part of a randomized experiment that estimated effects of incentives – a premium subsidy and application assistance – on enrollment in the IPP (Capuno et al., 2016). The 2015 survey has been used to test for persistent effects of the incentives (Baillon et al., 2019).

In 2011, after stratification by 15 regions, 243 municipalities were randomly sampled and randomly assigned to treatment (n=179) and control (n=64) sites. Within the sampled municipalities, a random sample of 2,950 households was drawn. In the treatment sites, uninsured households were offered a 50% discount on the IPP premium for one year, along with information on this program. A randomly selected half of those who initially did not take up this offer were offered one-time assistance with application (Baillon et al., 2019).

The 2015 survey aimed to re-interview all 1,975 households that were not covered by mandatory, employment-based health insurance in 2011. Interviews were conducted with 1,513 (77%) of the targeted households. Attrition is higher for urban, younger, and better educated households (Appendix Table D1). We control for these characteristics. To increase the size of the sample, a random selection of 267 households that did have mandatory insurance in 2011 was added.

In 2011, the head of each household or their spouse was targeted for interview. If neither could be interviewed, another adult ( $\geq 21$  years) was selected as the respondent. In 2015, enumerators were instructed to interview the same person in each household. If that person was unavailable, the spouse was to be interviewed.

For each of the 1780 (1513+267) households in the 2015 sample, we define insurance status by the cover of the respondent – the person whose preferences were elicited. The sample used to examine associations between preferences and insurance consists of 807 households that either voluntarily purchased health insurance (n=176) or were uninsured (n=631).<sup>24</sup> The remaining 973 households are excluded because they did not face an insurance decision – they

---

<sup>24</sup> Of the 1780 household respondents interviewed in 2015, 48 reported not knowing if they had health insurance. The insurance status of 31 of these respondents could be determined using that reported for another household member. We assume that the remaining 17 were uninsured.

had mandatory or fully subsidized insurance. The 807 households in the analysis sample are spread over all 15 regions and 222 of the 243 municipalities originally sampled. Most of the voluntarily insured were covered by the IPP (158/176) – the others had private insurance – and most had enrolled themselves (108/176) – the others were covered through enrollment of a relative. We find some evidence that insurance obtained through self enrollment is more strongly associated with time preference than is insurance acquired through enrollment of a relative (Appendix E).

## 5.2 Sample characteristics

Table 1 reports means of covariates used as controls in multivariable analysis of the association between insurance and preferences. A majority of respondents are female; the proportion female is lower among the uninsured. More than a third of the respondents are heads of their households. Almost a fifth of the uninsured, and around an eighth of the insured, have not completed elementary schooling.

To capture risk perceptions, we asked each respondent to compare their household's risk of incurring at least 8000 PHP of out-of-pocket (OOP) medical expenses next year with the risk faced by other households (Appendix C). We use an indicator of perceived own risk lower than the risk of other households. The uninsured, despite their lack of protection, are more likely to report facing a lower risk, which may reflect optimism bias or adverse selection.

We asked respondents whether each of five statements about the operation of health insurance was true or false (Appendix C). Those giving three or more incorrect answers are categorized as having low health insurance literacy. We also asked respondents whether the social health insurance program covers 18 treatments and categorize those giving seven or more incorrect answers as having poor knowledge of insurance benefits (Appendix C). The uninsured are slightly more likely to display low insurance literacy and poor knowledge of insurance benefits, but not significantly.

To control for health, we use indicators of whether anyone in the household a) was sick in the last 30 days, b) has a disability or a chronic illness, and c) was admitted to hospital in the last year. In the sample, b) is more prevalent among the insured, which may also indicate adverse selection.

Table 1. Sample characteristics by insurance status (means)

	Total	Insured		t-test
	(1)	No (2)	Yes (3)	p-value (2)=(3)
<i>Respondent</i>				
female	0.711	0.696	0.767	0.041
age (years)	45.507 [13.962]	45.361 [14.468]	46.028 [11.578]	0.520
head of household	0.356	0.374	0.290	0.025
< elementary education	0.178	0.192	0.131	0.043
elementary education	0.230	0.239	0.199	0.254
high school graduate	0.485	0.487	0.477	0.820
college graduate	0.107	0.082	0.193	<0.001
perceive OOP risk lower than average	0.346	0.369	0.261	0.009
low health insurance literacy	0.304	0.311	0.278	0.379
poor knowledge of insurance benefits	0.294	0.300	0.273	0.530
smokes currently	0.131	0.151	0.063	<0.001
drinks alcohol regularly	0.043	0.041	0.051	0.597
<i>Household</i>				
no. persons	4.979 [2.430]	4.973 [2.423]	5.000 [2.004]	0.874
no. persons $\geq$ 65 yrs. / total	0.052 [0.145]	0.050 [0.149]	0.059 [0.162]	0.547
head is female	0.177	0.187	0.142	0.157
anyone sick in last 30 days	0.038	0.040	0.034	0.743
anyone disabled or chronically sick	0.059	0.054	0.080	0.296
anyone admitted to hospital last year	0.074	0.073	0.080	0.769
urban	0.481	0.464	0.540	0.147
wealth index quartile score (1=poorest quartile, ..., 4=richest quartile)	2.498 [1.779]	2.369 [1.642]	2.960 [1.202]	<0.001
annual income per capita (PHP)	43,370 [71,428]	40,540 [59,674]	53,514 [84,604]	0.043
experiment treatment site	0.778	0.753	0.869	0.006
N	807	631	176	807

*Notes:* Sample is restricted to those voluntarily insured or uninsured. Standard deviations of continuous variables in brackets. Right-hand column gives p-values from a t-test of no difference in the means between the insured and uninsured. Adjustment is made for clustering at the municipality level. The uninsured and the insured are drawn from 206 and 101 clusters, respectively. Definitions of variables related to perceptions of out-of-pocket (OOP) medical expenditure risk, health insurance literacy and knowledge of insurance benefits in Appendix C.

We control for measures of both wealth and household income per capita. Wealth is proxied by the first principal component from a factor analysis of housing materials, sanitation, water source, and possession of durable assets (Filmer & Pritchett, 2001). In the analysis, we control for quartile group of this wealth index. In Table 1, we show means of a score that goes from 1 for the least wealthy quartile group to 4 for the wealthiest. The mean is 2.5 in the full sample by construction. The uninsured are less wealthy than the insured. Income is reported household annual income from all sources divided by the number of persons in the household. The mean incomes presented in Table 1 confirm that uninsured households are poorer. In the analysis, we control for income quartile groups.



Insured households are more than ten percentage points more likely to be located in municipalities randomly selected as treatment sites in the experiment (Baillon et al., 2019).

## 6 Results

### 6.1 Preferences

Table 2 shows summary statistics of the choices made in the preference elicitation tasks and the non-parametric preference measures derived from them. Distributions of the latter are shown in Figure 1. In Choice 1 of the time preference task, the average respondent is indifferent between receiving 93.5 pesos now ( $x_0$ ) and waiting half a year to get 200 pesos. The median response implies even stronger time preference. In Choice 2, the average respondent is indifferent between receiving 99 pesos in half a year ( $z_{1/2}$ ) and 200 pesos in one year. Consequently, the mean and median of the non-parametric measure  $\left(\frac{(x_0 + z_{1/2})}{2}\right)$  are well below the threshold (200) up to which time preference is positive.

Table 2. Choices in preference elicitation tasks and non-parametric preference measures

	Time preferences				Risk preferences			
	Choice		$\frac{x_0 + z_{1/2}}{2}$	$x_0 - z_{1/2}$	Lottery		$\frac{x + z}{2}$	$x - z$
	1 ( $x_0$ )	2 ( $z_{1/2}$ )			1 ( $x$ )	2 ( $z$ )		
Median	62.5	87.5	75.0	0	-49.5	-125.0	-112.8	0
Mean	93.5	98.8	96.2	-5.3	-96.7	-138.8	-117.8	42.1
Std. Dev.	92.8	89.5	82.4	78.0	104.2	127.9	97.5	128.0
N	807	807	807	807	807	807	807	807
	Total		Exclude		Total		Exclude	
<i>Discounting</i>			dominated	extreme	<i>Probability weighting</i>			
stationary ( $x_0 - z_{1/2} = 0$ )	50.5%		50.7%	28.4%	linear ( $x - z = 0$ )	45.1%	48.6%	26.5%
present bias ( $x_0 - z_{1/2} < 0$ )	28.1%		28.6%	40.7%	inverse S ( $x - z > 0$ )	36.6%	31.9%	48.9%
future bias ( $x_0 - z_{1/2} > 0$ )	21.3%		20.7%	30.9%	S-shaped ( $x - z < 0$ )	18.3%	19.5%	24.5%
N	807		730	557	N	807		730 603

Notes: Top panel summarizes the indifference points from the preference elicitation tasks. Bottom panel shows the distribution of respondents across discounting and probability weighting types. *Exclude dominated* drops respondents who choose dominated prospects on the risk task. *Exclude extreme* drops other respondents who do not switch in both Choices/Lotteries.

On average, preferences for gratification sooner are only slightly more intense when the earlier period is the present (Choice 1,  $x_0$ ) rather than in the future (Choice 2,  $z_{1/2}$ ) ( $H_0: \mu_{x_0} - \mu_{z_{1/2}} = 0, p = 0.081$ ), indicating only a small degree of present bias ( $x_0 - z_{1/2} < 0$ ). Less than 30 percent of the respondents make choices that are consistent with present bias. The median respondent, and around a half of the sample, have the same indifference point on both choices, implying stationary preferences. Around a fifth of respondents appear to be more impatient in the future than in the present, which is consistent with several studies that allow

for future bias (Loewenstein, 1987; Scholten & Read, 2006; Sayman & Öncüler, 2009; Attema et al., 2010; Takeuchi, 2011; Bleichrodt et al., 2016; Delaney & Lades, 2017).

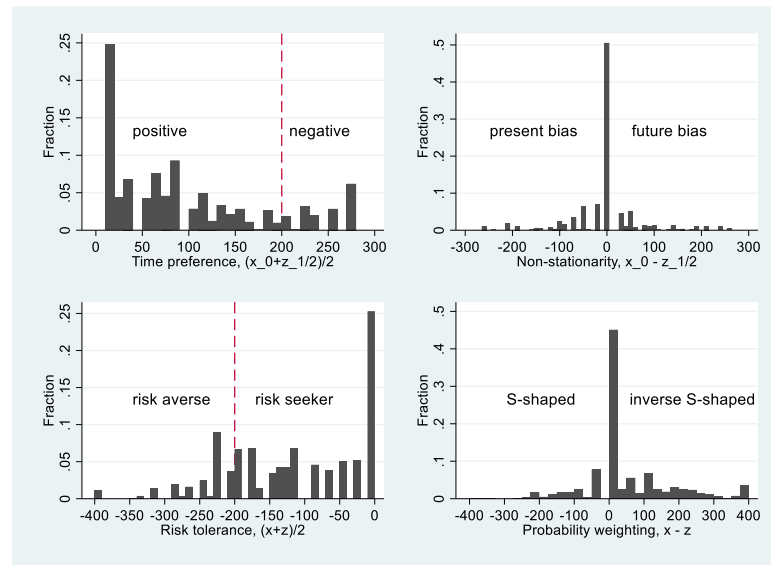


Figure 1. Histograms of non-parametric preference measures

There are 250 respondents who consistently display either extreme patience or extreme impatience by not switching on both Choice 1 and Choice 2.<sup>25</sup> While these responses could reflect extreme negative and positive time preference, respectively, they may also arise from misunderstanding or low cognitive effort. Respondents who consistently go for the extremes account for 61% of all those who apparently have stationary preferences, and so dropping those consistently taking extreme options reduces the sample proportion of this preference category and increases the prevalence of present bias (Table 2).<sup>26</sup>

On the risk preference elicitation task, the median point of indifference is about -50 for Lottery 1 ( $x$ ) and -125 for Lottery 2 ( $z$ ) (Table 2). Both the median and the mean of the individual-specific averages of the indifference points – our non-parametric measure of risk tolerance ( $((x+z)/2)$ ) – are greater than -200, reflecting the anticipated predominance of risk seeking in the loss domain. The median difference between the indifference points is 0, indicating that the median respondent weights probabilities linearly, consistent with EU. However, the mean point of indifference in Lottery 1 is 42 pesos greater than the mean for

<sup>25</sup> 200 are extremely impatient: consistently opt for 25 pesos rather than wait 6 months for 200 pesos. Other 50 extremely patient: consistently opt to wait 6 months for 200 pesos rather than take 250 pesos (Table D2).

<sup>26</sup> Those taking the same extreme option on both Choice 1 and Choice 2 do not differ significantly from other respondents in the proportion insured or in the means of covariates, except that they are older (2 years), and are more likely to be admitted to hospital last year, rural, and poorer (Appendix Table D3).

Lottery 2 ( $p\text{-value} < 0.001$ ), implying that there is inverse S-shaped probability weighting, on average. The bottom right panel of Table 2 shows that more than two fifths of the sample respondents make choices consistent with linear weighting, more than a third are classified as inverse S-shaped types, and less than a fifth are S-shaped (see also Figure 1).

In Lottery 1, 15 out of the 807 respondents choose a dominated prospect, preferring a loss of 400 pesos for sure over a 50% chance to lose the same amount (or nothing) (Appendix Table D4). In the more cognitively demanding Lottery 2, a greater number of respondents (71) violate monotonicity by choosing a dominated prospect. The risk preference parameters are not defined for the 77 respondents who opt for a dominated prospect in either lottery, forcing us to drop these cases from analyses that use these parameters.<sup>27</sup> Since a large majority of those who choose dominated prospects do so only on Lottery 2 (62/77), most are classified as exhibiting inverse S-shaped probability distortion. Dropping them reduces the prevalence of this type. Around a quarter of respondents consistently make choices that imply extreme risk seeking: on both lotteries, they never switch to a less risky prospect.<sup>28</sup> Dropping them reduces the proportion categorized as exhibiting linear probability weighting.

Figure 2 shows distributions of the derived preference parameters.

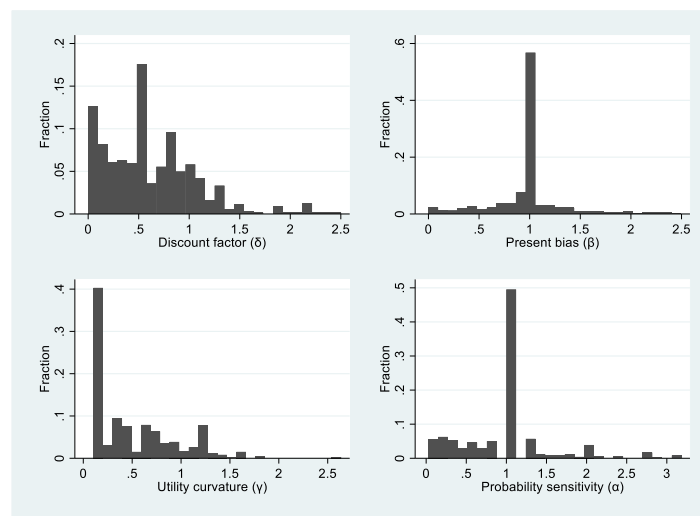


Figure 2. Histograms of preference parameters

*Notes.* Distributions of  $\delta$ ,  $\gamma$ , and  $\alpha$  are censored at the 99<sup>th</sup> percentile. Distribution of  $\beta$  is censored at the 97<sup>th</sup> percentile.  $N=730$

<sup>27</sup> The proportion insured and covariate means do not differ significantly between those taking a dominated prospect and those not (Appendix Table D5). Less educated are more likely to take a dominated prospect.

<sup>28</sup> These respondents do not differ significantly from others, except they are less likely to have poor knowledge of insurance benefits and more likely to perceive their OOP risk as lower than average (Table D6).

## 6.2 Bivariate associations of insurance with preferences

Figure 3 shows the estimated probability of being voluntarily insured (vs uninsured) as a function of each of the four non-parametric preference measures. Each conditional mean function is estimated by a bivariate local linear regression (Fan & Gijbels, 1996) that makes no assumptions about the nature of the respective relationship.<sup>29</sup> Each panel of the figure shows the estimated probabilities of insurance (and 95% confidence intervals) at the 5<sup>th</sup>, 10<sup>th</sup>, ..., 95<sup>th</sup> percentiles of the respective preference measure. The top left graph reveals that respondents with the strongest positive time preference (smallest  $(x_0 + z_{1/2})/2$ ) have the lowest probability of being insured. While all the 95% confidence intervals overlap, the point estimates suggest that the insurance probability rises as time preference weakens over much of its positive range in which most respondents are located, before falling in the region of zero time preference ( $(x_0 + z_{1/2})/2 = 200$ ) and rising again in the sparsely populated negative range ( $(x_0 + z_{1/2})/2 > 200$ ). The top right graph shows that individuals who are close to exhibiting stationarity ( $(x_0 - z_{1/2})/2 \approx 0$ ) – a majority – have a lower probability of being insured compared with those who exhibit stronger present bias ( $(x_0 - z_{1/2})/2 < 0$ ) and most of those who are future biased. But all the confidence intervals are wide and overlapping. There is no apparent association between insurance and risk tolerance. The bottom right graph reveals that the insurance probability is lowest for those with slightly inverse S-shaped probability weighting ( $(x - z) \approx 50$ ) and increases with greater intensity of both inverse S-shaped (up to a point) and S-shaped ( $(x - z) < 0$ ) probability distortion. Again, all confidence intervals are overlapping.

---

<sup>29</sup> The conditional mean functions are robust to estimation by local constant regression (Watson, 1964; Nadarya, 1965) rather than local linear regression (Appendix Figure D1).



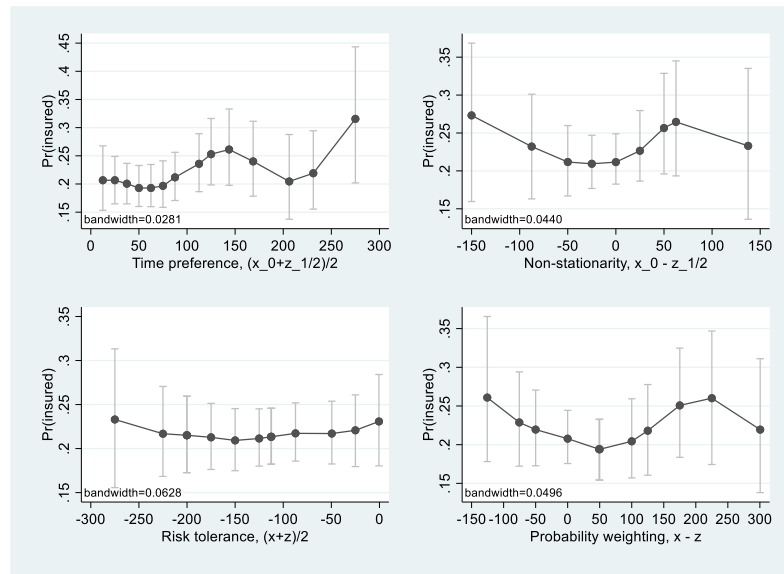


Figure 3. Probability of insurance as function of each non-parametric preference measure

*Notes:* The graph in each panel is obtained from a bivariate local linear regression of an insurance indicator on the respective preference measure. Dots indicate point estimates of conditional means at the 5<sup>th</sup>, 10<sup>th</sup>, and 95<sup>th</sup> percentiles of the respective measure. The number of dots is less than 19 in some panels because of equal percentile values. The Epanechnikov kernel function is used. Bandwidth is selected by the plugin estimator of the asymptotically optimal constant bandwidth because cross-validation (Li & Racine, 2004) produced very wide bandwidths for the non-stationarity and risk tolerance measures. To aid convergence, each measure was scaled through division by 1000, but the x-axes in the figure are on the original scales. Whiskers show 95% confidence intervals (CI) obtained from a bootstrap percentile method (Cattaneo & Jansson, 2018) with 500 replications.

The top row of Table 3 panel A shows estimates of the marginal change in the conditional probability of insurance with respect to each non-parametric preference measure calculated at each value of that measure and averaged. Each estimate is from the bivariate local linear regression used to estimate the conditional mean function in the respective panel of Figure 3. For shorthand, we refer to these estimates as “effects” without inferring causality. We scale all measures through division by 1000. Hence, the estimate in the first column indicates that a standard deviation increase in the time preference measure is associated with a 1.5 percentage point ( $0.186 \times (82.4/1000) \times 100$ ) increase the probability of insurance, on average. That is 7% of an estimated insurance probability of 22.1 percent. However, this averaged estimate is not remotely significant and should be interpreted bearing in mind the nonlinearity observed in Figure 3. The estimated associations of insurance with the other non-parametric preference measures are also not at all significant. The negative point estimates for non-stationarity and probability weighting indicate that, in the sample, the negative relationships observed on the left of the respective graphs in Figure 3 predominate: the insurance probability decreases with weaker present bias and with less intense S-shaped probability weighting.

Table 3. Effects of preference measures and parameters on probability of insurance  
– bivariate local linear regression estimates

<i>A. Non-parametric measures</i>				
	Time preference $((x_0 + z_{1/2})/2)/1000$	Non-stationarity $(x_0 - z_{1/2})/1000$	Risk tolerance $((x + z)/2)/1000$	Probability weighting $(x - z)/1000$
Effect	0.186 (0.302)	-0.0417 (0.190)	0.0035 (0.157)	-0.137 (0.167)
Predicted mean	0.221*** (0.0157)	0.220*** (0.0157)	0.221*** (0.0159)	0.220*** (0.0153)
Bandwidth	0.0449	1.040	0.0938	0.0732
$R^2$	0.0076	0.0071	0.0018	0.0115
$N$	807	807	807	807
<i>B. Parameters</i>				
	Discount factor $(\delta)$	Present bias $(\beta)$	Utility curvature $(\gamma)$	Probability sensitivity $(\alpha)$
Effect	0.0792** (0.0395)	0.0206 (0.0655)	-0.0262 (0.0373)	0.0154 (0.0348)
Predicted mean	0.211*** (0.0155)	0.215*** (0.0159)	0.216*** (0.0154)	0.214*** (0.0160)
Bandwidth	0.4074	0.4970	0.9294	0.4702
$R^2$	0.0168	0.0175	0.00684	0.0185
$N$	729	730	729	730

*Notes.* The rows labelled “Effect” show estimates of the marginal change in the probability of insurance associated with a unit increase in the respective scaled preference measure (top panel) or preference parameter (bottom panel). The marginal changes are estimated at all values of the respective measure/parameter and averaged. The rows labelled “Predicted mean” show the average of the predictions from the respective estimated mean function. The estimates are from the bivariate local linear regressions used to produce Figures 3 and 4. See notes to those figures for details of computation. The bandwidths shown in the table are those used for estimation of derivatives of the mean function. They are obtained by cross-validation (Henderson et al., 2015). Bootstrap standard errors in parentheses (500 replications). Statistical significance indicated by \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Figure 4 shows bivariate local linear regression estimates of the conditional probability of insurance as a function of each of the four preference parameters.<sup>30</sup> Each panel shows the estimated probability of insurance at percentiles (5<sup>th</sup> to 95<sup>th</sup>) of the respective parameter. From the top right panel, it is clear that the insurance probability is a quadratic function of the (long-term) discount factor ( $\delta$ ). The probability of insurance is lowest for those with the strongest positive time preference ( $\delta \square 0$ ). It is around 9 percentage points (pp) higher at the point where there is no (long-term) discounting ( $\delta=1$ ). Thereafter, over a range of the parameter distribution that is much less dense (Figure 2), the insurance probability declines as discounting becomes increasingly negative. The statistically significant estimate in the first column of Table 3 panel

<sup>30</sup> The conditional mean functions are generally robust to estimation by local constant regression, rather than local linear regression. Two differences are that the local constant regression estimator gives a slightly flatter function of insurance with respect to the present bias parameter and a function that displays somewhat more of a negative slope for the utility curvature parameter (Appendix Figure D2).

B indicates that a standard deviation increase in  $\delta$  is associated with a 5.7 pp ( $7.92 \times 0.7163$ ) increase in the probability of insurance, on average. There is no clear relationship between insurance and the present bias parameter. As with the non-parametric measure, compared with stationary types, both those who display more present bias and (up to a point) those more future biased are more likely to be insured.<sup>31</sup>

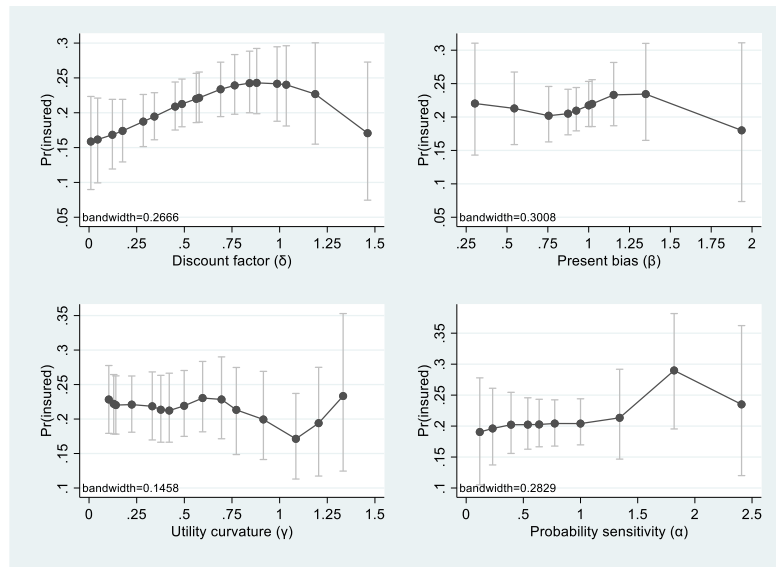


Figure 4. Probability of insurance as function of each preference parameter

Notes: Notes to Figure 3 apply except that here bandwidths are selected optimally by cross-validation (Li & Racine, 2004).

The bottom right graph in Figure 3 shows that the probability of being insured is lowest for those who are close to having linear utility ( $\gamma \approx 1$ ). From this point, the probability rises, although not continuously, with more convex utility in the domain of losses ( $\downarrow \gamma$ ). That is, risk seekers in this domain are more likely to be insured than the risk neutral. However, the confidence intervals are wide and overlapping, and the negative point estimate of the average effect of utility curvature on the probability is not remotely significant (Table 3). There is little or no variation in the probability of insurance as probability sensitivity varies over the range of inverse S-shaped distortion up to linear weighting ( $\alpha \leq 1$ ) (Figure 4). Thereafter, the probability

<sup>31</sup> Conditional mean functions with respect to time preference parameters derived under the restriction of linear utility have similar shapes to those shown in the top row of Figure 4 (Appendix Figure D3), except that the mean is a less smooth function of  $\delta$ , which is more right-skewed under this restriction. The estimated marginal change in the insurance probability with respect to  $\delta$  derived under linear utility is about one third of the respective estimate shown in Table 3 (Table D7), which could be due to confounding by utility curvature.

increases with more S-shaped weighting, although not at the extreme and the average effect is not significant (Table 3).

### 6.3 Partial associations of insurance with preferences

#### 6.3.1 Main estimates

We estimate partial associations of insurance with all preferences simultaneously using probit models of a binary insurance indicator,  $y_i = 1(y_i^* > 0)$ , specified as follows,

$$y_i^* = \text{time}(x_{0_i}, z_{1/2_i}) + \text{risk}(x_i, z_i) + \mathbf{X}_i\boldsymbol{\beta} + \mathbf{S}_i\boldsymbol{\lambda} + \varepsilon_i, \quad (4)$$

where  $\text{time}(x_{0_i}, z_{1/2_i})$  represents the influence of time preference measures or parameters derived from the indifference points  $x_{0_i}$  and  $z_{1/2_i}$  elicited from respondent  $i$ ,  $\text{risk}(x_i, z_i)$  represents the influence of the respective risk preference measures or parameters,  $\mathbf{X}_i$  is a vector of the covariates listed in Table 1 (with age in quadratic form, and wealth and income each represented by respective quartile group indicators),  $\mathbf{S}_i$  is a vector of strata (province) indicators, and  $\varepsilon_i$  is a standard normal distributed error that possibly exhibits dependence within sample clusters. While controlling for covariates reduces the risk of confounding, it increases the risk of introducing bad controls. Preferences potentially influence insurance through education, health behavior, and health, for example. For this reason, we also present estimates obtained with no covariate controls (other than strata indicators). We continue to refer to estimates as “effects” but interpret them only as partial associations.

Table 4 panel A gives estimates of average partial effects from models that use the non-parametric preference measures. In columns (1)-(3), each measure enters the linear index function (4) linearly. In column (1), where there is no control for covariates (other than strata), none of the preference measures has a remotely significant partial effect. As with the bivariate estimates (Table 3), the point estimate is largest in magnitude for the effect of the time preference measure. This estimate suggests that, in the sample, a standard deviation increase in the direction of weaker time preference is associated with a 1.2 pp  $((0.1405/1000) \times 82.4 \times 100)$  increase in the probability of being insured, conditional on measures of other preferences. After controlling for covariates (column (2)), the time preference measure still has the largest (absolute) point estimate and all the estimates remain insignificant.

Table 4. Partial effects of preference measures and parameters on probability of insurance

	(1)	(2)	(3)	(4)
--	-----	-----	-----	-----

<i>A. Non-parametric measures</i>				
Time preference	0.1405	0.1050	0.1769	0.0649
$\left(\frac{x_0 + z_{1/2}}{2}\right)/1000$	(0.1736)	(0.1556)	(0.1528)	(0.1624)
Non-stationarity	-0.0566	-0.0538	-0.0027	
$(x_0 - z_{1/2})/1000$	(0.1667)	(0.1664)	(0.1852)	
- Present biased				0.0429
$1(x_0 - z_{1/2} < 0)$				(0.0304)
- Future biased				0.0274
$1(x_0 - z_{1/2} > 0)$				(0.0365)
Risk tolerance	0.0556	0.0278	0.2373	0.0511
$\left(\frac{x + z}{2}\right)/1000$	(0.1757)	(0.1624)	(0.1827)	(0.1798)
Probability weighting	-0.0138	0.0469	-0.0395	
$(x - z)/1000$	(0.1140)	(0.1051)	(0.1200)	
- Inverse S-shaped				0.0151
$1(x - z > 0)$				(0.0317)
- S-shaped				0.0167
$1(x - z < 0)$				(0.0347)
Pseudo R <sup>2</sup>	0.0658	0.1977	0.1955	0.2000
N	807	807	730	807
Covariates	No	Yes	Yes	Yes
Dominated	Included	Included	Excluded	Included
<i>B. Parameters</i>				
Discount factor ( $\delta$ )	0.0304*	0.0378**	0.0568**	0.0349**
	(0.0170)	(0.0155)	(0.0283)	(0.0152)
Present bias ( $\beta$ )	0.0063	0.0111	0.0123	
	(0.0098)	(0.0083)	(0.0082)	
- present biased				0.0386
$1(\beta < 1)$				(0.0317)
- future biased				0.0530
$1(\beta > 1)$				(0.0389)
Utility curvature	-0.0601*	-0.0470	-0.0396	-0.0504
( $\gamma$ )	(0.0342)	(0.0351)	(0.0360)	(0.0368)
Probability	0.0396*	0.0220	0.0228	
sensitivity ( $\alpha$ )	(0.0204)	(0.0181)	(0.0180)	
- inverse S-shaped				0.0007
$1(\alpha < 1)$				(0.0294)
- S-shaped				0.0431
$1(\alpha > 1)$				(0.0366)
Pseudo R <sup>2</sup>	0.0703	0.1991	0.2001	0.2009
N	730	730	730	730
$\delta$ specification	Linear	Linear	Quadratic	Linear
Covariates	No	Yes	Yes	Yes
Dominated	Excluded	Excluded	Excluded	Excluded

*Notes:* Partial effects derived from probit estimates and are averaged over the respective sample. Robust standard errors adjusted for clustering at the municipality level in parentheses. Except for column (1), models include covariates in Table 1 (with age quadratic and quartile group indicators for each of wealth and income). All models include strata indicators. Partial effects of covariates in Appendix D Table D8.  $x_0$ ,  $z_{1/2}$ ,  $x$ , and  $z$  are the indifference points elicited from Choice 1, Choice 2, Lottery 1, and Lottery 2, respectively. In column (4), reference groups are stationary preferences ( $x_0 = z_{1/2}$  and  $\beta = 1$ ) and linear probability weighting ( $x = z$  and  $\alpha = 1$ ). *Dominated* refers to respondents who choose a dominated prospect on either lottery.  *$\delta$  specification* refers to how the long-term discount factor enters the latent index. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Dropping respondents who choose a dominated prospect on the risk elicitation task (column (3)) increases the estimated effects of time preference and, to a greater extent, risk tolerance. The positive point estimate of the effect of the latter implies that, in the sample, a



standard deviation increase in the direction of greater risk seeking in the loss domain is associated with a 2.1 pp increase in the conditional probability of being insured.

In column (4), we replace the continuous measure of non-stationarity with indicators of present bias and future bias, and we use indicators of inverse S-shaped and S-shaped probability weighting instead of the respective continuous measure. Consistent with Figure 3, the point estimates suggest that both the present and future biased are more likely to insure than the unbiased, and both inverse S-shaped and S-shaped weighting types are more likely to insure than the linear weighting (EU) types. However, none of these differences is statistically significant.

Panel B presents estimates from models that use the preference parameters, and so exclude respondents who opt for dominated prospects. In columns (1) and (2), each parameter enters the latent index linearly. Without control for covariates (column (1)), there are marginally significant estimated effects of the parameters for long-term discounting ( $\delta$ ), utility curvature ( $\gamma$ ), and probability sensitivity ( $\alpha$ ). The respective signs imply that the conditional probability of insurance is higher for those who exhibit a) less discounting of future returns, b) more risk seeking over losses, and c) less inclination toward inverse S-shaped probability weighting.

With the addition of covariates (column (2)), the discounting effect strengthens in magnitude and gains some precision, while the other two effects weaken. A standard deviation increase in the long-term discount factor, which for given present bias implies weaker time preference, is associated with a 2.7 pp increase in the probability of insurance. This is around half the magnitude of the bivariate estimate (Table 3), which may be because the specification used in column (2) does not allow sufficiently for the nonlinearity observed in Figure 4. When the index function is specified as a quadratic function of  $\delta$ , the average partial effect of this parameter increases by 50% (column (3)). With this specification, we estimate that a standard deviation increase in  $\delta$  is associated with a 4 pp increase in the insurance probability.

In column (4), we return to a linear specification for  $\delta$  and allow nonlinearity (of the index function) in both  $\beta$  and  $\alpha$  by replacing those parameters with indicators of present/future bias and inverse S-shaped/S-shaped probability weighting, respectively. This again shows that, in the sample, both present bias and future bias are associated with a higher probability of insurance compared with stationarity, and that S-shaped weighting types are more likely to insure, although neither difference is significant. The estimated effect of the discount factor is robust to this specification.

### 6.3.2 Robustness

We assess robustness of the estimates given in Table 4 column (2) (see Appendix Table D9). Linear probability model (LPM) estimates differ little in size and significance from the probit estimates, particularly for the model that uses parameters. The LPM estimate of the partial effect of the long-term discounting parameter  $\delta$  (0.0388, SE=0.0162) is extremely close to the respective probit estimate (0.0378, SE=0.0155).

Using probit and controlling for a more limited set of covariates (sex, age, and random assignment to an experiment treatment site) that are almost certainly not determined by preferences produces estimates that generally lie between those given in column (2) (full controls) and column (1) (no controls) of Table 4. The effects of the utility curvature and probability sensitivity parameters are marginally significant with this specification.

Excluding respondents who make choices that imply extremely strong or extremely weak time preference (because they do not switch in the elicitation task) reduces the estimated effect of the non-parametric time preference measure by 46% but reduces the effect of  $\delta$  by 15%. The standard error of the latter estimate increases and it loses statistical significance because of a 30% reduction in the sample size. Exclusion of respondents who make choices that imply extreme risk seeking has relatively little impact on the estimates.

To further assess robustness of the finding that the probability of insurance rises with the discounting factor  $\delta$ , we estimate probit models with alternative transformations of the parameters (Table D10). First, we confirm that the effect is not driven by outliers by censoring (winsorizing)  $\delta$ , and the other parameters, at the 99<sup>th</sup> percentile. This substantially increases the magnitude of the partial effect of  $\delta$ , bringing it closer to the estimate obtained with a quadratic specification shown in Table 4 column (3). Allowing for nonlinearity by entering the inverse hyperbolic sine of  $\delta$ , and each of the other parameters, into the probit latent index function also produces a larger and significant average partial effect of  $\delta$  similar to the Table 4 column (3) estimate.<sup>32</sup> This is also true if we replace the value of  $\delta$  with its relative rank, except that the average effect is no longer significant in this case.

---

<sup>32</sup> We use the inverse hyperbolic sine rather than the log transformation because there are some extremely small (close to zero) values of  $\delta$ . Because of these values, the log transformation turns a right-skewed distribution into a left-skewed one. Further, if the log transformation is used, then the expression for the partial effect of  $\delta$  on the probability of insurance includes division by  $\delta$ . This produces huge partial effects for a few respondents and distorts the average partial effect.

Using time preference parameters derived under the assumption of linear utility reduces the average effect of  $\delta$  to 0.0226 and renders it insignificant. This may be due to confounding by utility curvature. With this one caveat, which may itself be due to a misspecification, we conclude that the finding of a positive association between insurance and the long-term discount factor (weaker time preference) does not appear to be sensitive to the empirical specification or the treatment of extreme/outlier responses.

### 6.3.3 *Heterogeneity*

Theory predicts that time preference influences insurance when liquidity is constrained. While we do not observe liquidity constraints, we do have a proxy measure of wealth. Less wealthy households are more likely to be liquidity constrained. Insurance is expected to be more strongly associated with the time preference of these households. To test this, we extend the model used to produce the estimates in Table 4 Panel B column (2) by including interactions between each preference parameter and an indicator of being below the median of the wealth index.<sup>33</sup> Consistent with the theory, estimates in Table 5 columns (1) and (2) show that the effect of the discount factor  $\delta$  is much larger, and only significant, at lower wealth. A standard deviation increase in  $\delta$  is associated with a 4.9 pp increase in the probability that a low-wealth household insures, which is a 36% increase from an enrollment rate of 13.6%. At low wealth, there is even a significant partial association between insurance and the non-parametric time preference measure that also suggests that stronger time preference reduces the probability of insurance among households that are more likely to be liquidity constrained.<sup>34</sup>

Time and risk preferences may have little impact on the insurance decision of someone who does not fully comprehend that insurance involves making an up-front non-refundable payment to reduce, but not eliminate, liability for losses that they are not certain to incur in the future. To test this hypothesis, we allow interactions between each preference parameter and an indicator of low health insurance literacy or poor knowledge of the medical expenses covered by the insurance program. The estimates in Table 5 columns (3)-(4) reveal that the positive effect the discount factor  $\delta$  is much stronger and only significant when insurance literacy and

---

<sup>33</sup> We also explore heterogeneity in the partial effects of the non-parametric preference measures by estimating extended versions of the model used to produce the Table 4 Panel A column (2) estimates that include interactions between each of those measures and characteristics, such as low wealth. See Appendix Table D11.

<sup>34</sup> The stronger partial association between insurance and time preference at low wealth is also evident in LPM estimates. See Table D12, which gives LPM estimates for all the heterogenous effects.

knowledge are high. In that case, the estimated effect of  $\delta$  is almost 2.5 times larger than its average effect over all individuals.

There is a positive and significant effect of the present bias parameter  $\beta$  only for those who do not lack insurance literacy and knowledge. For this group, a standard deviation increase in  $\beta$ , which corresponds to less present bias, is associated with an estimated 6.7 pp increase in the probability of insurance. The relationship has the opposite sign and is weaker when insurance literacy/knowledge is low.

**Table 5. Partial effects of preference parameters on probability of insurance - heterogeneity**

	Wealth		Insurance literacy / knowledge		Education	
	Low (1)	High (2)	Low (3)	High (4)	Low (5)	High (6)
Discount factor ( $\delta$ )	0.0540*** (0.0176)	0.0103 (0.0408)	0.0085 (0.0200)	0.0914*** (0.0283)	0.0126 (0.0429)	0.0391** (0.0182)
Present bias ( $\beta$ )	0.0106 (0.0114)	0.0113 (0.0135)	-0.0100 (0.0192)	0.0680** (0.0345)	-0.0135 (0.0228)	0.0197* (0.0119)
Utility curvature ( $\gamma$ )	-0.0663 (0.0439)	-0.0485 (0.0484)	0.0017 (0.0413)	-0.1257*** (0.0475)	-0.1406** (0.0571)	-0.0243 (0.0390)
Probability sensitivity ( $\alpha$ )	-0.0339 (0.0296)	0.0626** (0.0254)	0.0058 (0.0280)	0.0330 (0.0229)	0.0066 (0.0284)	0.0445* (0.0249)
N	361	369	356	374	292	438

*Notes:* Average partial effects from probit models like that used for Table 4 Panel B column (2) but extended to include interactions with each preference parameter. Model for columns (1) and (2) includes interactions with indicator of below (low) wealth index median. Model for columns (3) and (4) has interactions with indicator of low health insurance literacy/knowledge (Appendix C). Model for columns (5) and (6) has interactions with indicator of high school/college graduates. Robust standard errors adjusted for clustering in parentheses. N indicates the size of the respective group. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

The significant, negative relationship between insurance and utility curvature in column (4) suggests that among people with reasonable understanding of the concept and content of insurance, those with more intense risk seeking preferences (conditional on all else) are more likely to insure. This is similar to puzzling evidence from other studies that greater risk aversion in the domain of gains is associated with a smaller likelihood of insurance (Giné et al., 2008; Giesbert et al., 2011; Cole et al., 2013; Dercon et al., 2015). One possible explanation is that those with little experience of insurance view it as a risky prospect. Another is that the risk of default on the payment of compensation deters the risk averse. This is a plausible scenario in the Philippines, where healthcare providers are permitted to charge in excess of reimbursement rates paid by the insurer.

Associations between preferences and insurance may also be obscured by low education if this impedes comprehension of the preference elicitation tasks and results in noisier measures of preferences. To test this, we allow interactions between each preference parameter and an

indicator that distinguishes high school and college graduates (high) from those with less education (low).<sup>35</sup> Estimates in columns (5)-(6) confirm that effects of the time preference parameters are larger in magnitude when education is high, and both of these effects are positive and significant only for this group. The puzzling association between insurance and risk seeking is much weaker and not significant among the better educated.

Almost four fifths (78%) of the sample households were located in treatment sites where those eligible were offered incentives to insure in 2011. These temporary incentives had persistent effects on enrollment in 2015 (Baillon et al. 2019): the partial effect of being located in a treatment site is around 14 pp (Table D8). We find stronger relationships between insurance and preferences in the control sites (Table D13), which suggests that our central finding that insurance is associated with time preference is not attributable to using a sample that was previously incentivized to insure. If anything, this may have weakened the association.

There is some support for the hypothesis that elicited preferences are more strongly associated with insurance when respondents obtain it through enrolling in the program themselves rather than through enrollment of a family member (Appendix E). In particular, the discount factor is significantly associated only with the probability of being insured directly and the point estimate of this effect is twice as large as the estimated effect on the probability of being insured indirectly (Table E1).

## **7 Conclusion**

Finding stronger time preference is associated with a lower probability of insurance confirms the theoretical prediction (of both expected utility and prospect theory) obtained when the newly insured must wait before making a claim and are unable to borrow (at a reasonable interest rate) to pay the premium. The waiting period is six months in the health insurance program we study, many of the low-income Filipinos in our sample are likely to be liquidity constrained, and we find an even stronger association between insurance and time preference amongst least wealthy. While the study does not have a design capable of delivering causal effects, the estimated positive association between insurance and elicited discount factors is consistent with time preference influencing the decision to insure, and theory gives grounds for this interpretation. If it were accepted, it would imply that one of the reasons many low-income,

---

<sup>35</sup> Among those who did not graduate from high school or college, 49.3% score low on insurance literacy or knowledge, compared with 48.4% among graduates. Hence, insurance literacy/knowledge and education are distinct dimensions of potential heterogeneity.

potentially liquidity constrained Filipinos do not insure medical expenses is that they value the premium due at enrollment above highly discounted benefits they would enjoy at least six months later, if at all. In addition to the premium, up-front indirect effort costs of applying for insurance may deter low-income individuals with strong time preference and little cognitive bandwidth to contemplate future circumstances (Mullainathan & Shafir, 2014; Schilbach et al., 2016). Randomized experiments, including in the Philippines, demonstrate that assistance that reduces application costs can be highly effective (at least initially) in increasing insurance take-up (Thornton et al. 2010, Capuno et al. 2016, Banerjee et al. 2021, Baillon et al. 2019).

Constrained liquidity can cause the propensity to take up-front payment insurance to decrease with the intensity of time preference and it can raise the value of a more flexible insurance contract that allows the premium to be paid at times of liquidity (Casaburi & Willis, 2018; Belissa et al., 2019; Liu et al., 2020). Redesigning contracts with respect to the timing of premium payments and claim entitlements may increase take-up of health insurance in countries, such as the Philippines, that are striving for Universal Health Coverage. The welfare gains from such contracts potentially extend beyond smoothing consumption over medical expense shocks to health improvements produced by more affordable healthcare. This inference is supported by US evidence that more comprehensive, subsidized health insurance weakens the extent to which the utilization of medicines is sensitivity to the liquidity of low-income households (Gross et al., 2021). Liquidity constraints are barriers to both healthcare consumption and health insurance.

We find that the probability of insurance is negatively associated with present bias only among those who appears to understand how insurance operates and what it delivers. While a negative association is consistent with predictions obtained from the quasi-hyperbolic discounting model, it does not necessarily follow that insurance take-up would be raised by redesigning contracts to counter time inconsistency. We infer present bias from violation of stationarity, which implies time inconsistency only if preferences are time invariant (Halevy, 2015). Constrained liquidity may induce time varying preferences (Janssens et al., 2017) and cause people to behave as if their preferences are present biased (Epper, 2017), including in preference elicitation tasks (Dean & Sautmann, 2021). Consequently, attempts to raise insurance demand by offering commitment devices may fail not only because of a lack of sophistication but also because some of those who appear to be present biased are actually time consistent. If illiquidity is the source of the problem, then there will be little interest in committing any liquid assets that are at hand. It would be more effective to either loosen the



constraint on liquidity or redesign insurance such illiquidity is less of a barrier to its purchase. A combination of the two would not necessarily be even more effective since illiquidity raises the value of insurance that can be paid for smoothly over a contract period (Ericson & Sydnor, 2018).

We do not find strong associations between insurance and risk preferences. Barseghyan et al. (2013) and Sydnor (2010) find that concave utility over final consumption cannot account for patterns of demand for home and automobile insurance in the US. The first study infers from revealed preferences that there is overweighting small probabilities and this drives insurance demand. Jaspersen et al. (2021) find that each of three dimensions of elicited risk preferences – utility curvature, probability weighting, and loss aversion – correlate with insurance behavior in a laboratory experiment. However, collectively these three components of risk preferences can explain only a small fraction of the variation in insurance. Our study adds to accumulating evidence (Casaburi & Willis, 2018; Belissa et al., 2019; Liu et al., 2020) that time preferences may be an important missing ingredient to explain the (low) demand for insurance.

We treat time preferences as distinct from risk preferences. An alternative view is that time preferences are inherently connected to risk preferences because any future prospect carries risk (Epper & Fehr-Duda, 2021). One might wonder whether this explains our main finding. That is, insurance associated with elicited time preference because the latter captures risk attitudes. This interpretation is inconsistent with the direction of the association we find. If insurance is associated with risk aversion and the more risk averse display stronger time preference, then the positive association between insurance and the elicited discount factor will underestimate the strength of the association between insurance and pure time preference.

Consistent with causal evidence emerging from field experiments (Casaburi & Willis, 2018; Belissa et al., 2019; Liu et al., 2020), our correlation analysis points to the importance of the time dimension of insurance combined with strong time preference of low-income people who are likely to be liquidity constrained as an explanation for the low insurance take-up that is frequently observed in such populations.

## References

- Andersen, S., Harrison, G. W., Lau, M. I., & Rutström, E. E. (2008). Eliciting risk and time preferences. *Econometrica*, 76(3), 583-618.
- Andreoni, J. and Sprenger, C. (2012). Estimating time preferences from convex budgets. *American Economic Review*, 102 (7), 3333-56.
- Andreoni, J., Kuhn, M. A., & Sprenger, C. (2015). Measuring time preferences: A comparison of experimental methods. *Journal of Economic Behavior & Organization*, 116, 451-464.
- Attema, A. E., Bleichrodt, H., Rohde, K. I. M., & Wakker, P. P. (2010). Time-tradeoff sequences for analyzing discounting and time inconsistency. *Management Science*, 56(11), 2015–2030.
- Baillon, A., Capuno, J., O'Donnell, O., Tan Jr., C., & van Wilgenburg, K. (2019). Persistent effects of temporary incentives: evidence from a nationwide health insurance experiment. *Tinbergen Institute Discussion Paper TI 2019-078/V* <https://papers.tinbergen.nl/19078.pdf>
- Baillon, A., Kraft, A., O'Donnell, O., & van Wilgenburg, K. (2021). A behavioral decomposition of willingness to pay for health insurance. *Journal of Risk and Uncertainty*, forthcoming.
- Banerjee, A., Finkelstein, A., Hanna, R., Olken, B.A., Ornaghi, A., and Sumarto, S. (2021). The Challenges of Universal Health Insurance in Developing Countries: Evidence from a Large-scale Randomized Experiment in Indonesia. *American Economic Review*, 111(9):3035-3063.
- Barseghyan, L., Molinari, F., O'Donoghue, T., & Teitelbaum, J. C. (2013). The nature of risk preferences: Evidence from insurance choices. *The American Economic Review*, 103(6), 2499-2529.
- Belissa, T., Bulte, E., Cecchi, F., Gangopadhyay, S., & Lensink, R. (2019). Liquidity constraints, informal institutions, and the adoption of weather insurance: A randomized controlled trial in Ethiopia. *Journal of Development Economics*, 140, 269-278
- Benzion, U., Rapoport, A., & Yagil, J. (1989). Discount rates inferred from decisions: An experimental study. *Management Science*, 35(3), 270-284.
- Binswanger, H. P. (1980). Attitudes toward risk: experimental measurement in rural India. *American Journal of Agricultural Economics*, 62(3), 395-407.
- Bleichrodt, H., Gao, Y., & Rohde, K. I. (2016). A measurement of decreasing impatience for health and money. *Journal of Risk and Uncertainty*, 52(3), 213-231.
- Bredenkamp, C., & Buisman, L. R. (2016). Financial protection from health spending in the Philippines: policies and progress. *Health Policy and Planning*, 31(7), 919-927.
- Burks, S., Carpenter, J., Götte, L., & Rustichini, A. (2012). Which measures of time preference best predict outcomes: Evidence from a large-scale field experiment. *Journal of Economic Behavior & Organization*, 84(1), 308-320.
- Capuno, J. J., Kraft, A. D., Quimbo, S., Jr. Tan, C. R., & Wagstaff, A. (2016) Effects of price, information, and transactions cost interventions to raise voluntary enrollment in a social health insurance scheme: a randomized experiment in the Philippines. *Health Economics*, 25(6), 650–662.
- Cardenas, J. C., & Carpenter, J. (2008). Behavioral development economics: lessons from field labs in the developing world. *The Journal of Development Studies*, 44(3), 311-338.
- Cardenas, J. C., & Carpenter, J. (2013). Risk attitudes and economic well-being in Latin America. *Journal of Development Economics*, 103, 52-61.
- Carvalho, L.S., Meier, S. & Wang, S.W. (2016). Poverty and economic decision making: Evidence from changes in financial resources at payday. *American Economic Review* 106(2), 260–84.

- Casaburi, L., & Willis, J. (2018). Time vs. state in insurance: Experimental evidence from contract farming in Kenya. *American Economic Review* 108(12), 3778-3813.
- Cattaneo, M. D., & Jansson, M. (2018). Kernel-based semiparametric estimators: small bandwidth asymptotics and bootstrap consistency. *Econometrica*, 86, 955-995.
- Charness, G., Gneezy, U., & Imas, A. (2013). Experimental methods: Eliciting risk preferences. *Journal of Economic Behavior & Organization*, 87, 43-51.
- Chemin, M. (2018). Informal groups and health insurance take-up: evidence from a field experiment, *World Development* 101, 54-72
- Clarke, D.J. (2016). A theory of rational demand for index insurance. *American Economic Journal: Microeconomics*, 8(1): 283-306.
- Cohen, J., Ericson, K.M., Laibson, D., & White, J.M. (2020). Measuring Time Preferences. *Journal of Economic Literature*, 58 (2): 299-347.
- Cole, S., Giné, X., Tobacman, J., Topalova, P., Townsend, R., & Vickery, J. (2013). Barriers to household risk management: Evidence from India. *American Economic Journal: Applied Economics*, 5(1), 104-135.
- Dean, M. & Sautmann, A. (2021). Credit constraints and the measurement of time preferences. *Review of Economics and Statistics*, 103(1): 119–135.
- Delaney, L., & Lades, L. K. (2017). Present bias and everyday self-control failures: a day reconstruction study. *Journal of Behavioral Decision Making*, 30:1157–1167.
- Dercon, S., Gunning, J.W. & Zeitlin, A. (2015). The demand for insurance under limited trust: Evidence from a field experiment in Kenya. mimeo Georgetown University [https://site.stanford.edu/sites/default/files/dgz\\_201503.pdf](https://site.stanford.edu/sites/default/files/dgz_201503.pdf)
- Dupas, P. (2011). Health behavior in developing countries. *Annual Review of Economics*, 3(1), 425-449.
- Epper, T. (2017). Income expectations, limited liquidity, and anomalies in intertemporal choice. Mimeo University of St. Gallen <https://www.thomasepper.com/papers/TaR2Theory.pdf>
- Epper, T. & Fehr-Duda, H. (2020). Risk in time: the intertwined nature of risk taking and time discounting. mimeo University of St. Gallen <https://www.thomasepper.com/papers/RiskInTime.pdf>
- Ericson, K.M., & Sydnor, J. (2018). Liquidity constraints and the value of insurance. *NBER Working Paper 24993*. Cambridge, MA: NBER.
- Etchart-Vincent, N., & l'Haridon, O. (2011). Monetary incentives in the loss domain and behavior toward risk: An experimental comparison of three reward schemes including real losses. *Journal of Risk and Uncertainty*, 42(1), 61-83.
- Fan, J., & Gijbels, I. (1996). *Local Polynomial Modelling and Its Applications*. London: Chapman & Hall.
- Filmer, D. & Pritchett, L. (2001). Estimating wealth effects without expenditure data – or tears: an application to educational enrollments in states of India. *Demography* 38(1), 115-133.
- Frederick, S., Loewenstein, G., & O'Donoghue, T. (2002). Time discounting and time preference: A critical review. *Journal of Economic Literature*, 40(2), 351-401.
- Giesbert, L., Steiner, S., & Bendig, M. (2011). Participation in micro life insurance and the use of other financial services in Ghana. *Journal of Risk and Insurance*, 78(1), 7-35.
- Giné, X., Townsend, R., & Vickery, J. (2008). Patterns of rainfall insurance participation in rural India. *The World Bank Economic Review*, 22(3), 539-566.

- Giné, X., & Yang, D. (2009). Insurance, credit, and technology adoption: Field experimental evidence from Malawi? *Journal of Development Economics*, 89(1), 1–11.
- Gollier, C. (2003). To insure or not to insure? An insurance puzzle. *The Geneva Papers on Risk and Insurance Theory*, 28, 5-24.
- Gross, T., Layton, T. & Prinz, D. (2021). The liquidity sensitivity of healthcare consumption: evidence from Social Security payments. *American Economic Review: Insights*, forthcoming
- Halevy, Y. (2015). Time consistency: Stationarity and time invariance. *Econometrica*, 83(1), 335-352.
- Henderson, D. J., Li, Q., Parmeter, C. F., & Yao, S. (2015). Gradient-based smoothing parameter selection for non-parametric regression estimation. *Journal of Econometrics* 184, 233–241.
- Holt, C. A., & Laury, S. K. (2002). Risk aversion and incentive effects. *American Economic Review*, 92(5), 1644-1655.
- Ito, S. & Kono, H. (2010). Why is the take-up of microinsurance so low? Evidence from a health insurance scheme in India. *The Developing Economies* 48 (1), 74–101
- Janssens, W., Kramer, B., & Swart, L. (2017). Be patient when measuring hyperbolic discounting: Stationarity, time consistency and time invariance in a field experiment. *Journal of Development Economics*, 126, 77-90.
- Jaspersen, J. G., Ragin, M. A. & Sydnor, J. R. (2021). Predicting insurance demand from risk attitudes. *Journal of Risk and Insurance*, 1–34. <https://doi.org/10.1111/jori.12342>
- Kahneman, D., & Tversky, A. (1979). Prospect theory: an analysis of decision under risk. *Econometrica*, 47, 263-291.
- Karlan, D., Osei, R., Osei-Akoto, I., & Udry, C. (2014). Agricultural decisions after relaxing credit and risk constraints. *Quarterly Journal of Economics*, 129(2), 597–652.
- Kifman, M., Roeder, K., & Schumacher, C. (2014). A note on quasi-hyperbolic discounting, risk aversion, and the demand for insurance. *Economics Bulletin*, 34(2), 772-783.
- Laibson, D. (1997). Golden eggs and hyperbolic discounting. *Quarterly Journal of Economics*, 112(2), 443-477.
- Li, Q., & Racine, J.S. (2004). Cross-validated local linear non-parametric regression. *Statistica Sinica* 14, 485–512.
- Liu, Y. and R. J. Myers (2016). The dynamics of insurance demand under liquidity constraints and insurer default risk. *Journal of Risk and Insurance*, 83(1), 121–138.
- Liu, Y., Chen, K., & Hill, R.V. (2020). Delayed premium payment, insurance adoption, and household investment in rural China. *American Journal of Agricultural Economics*, 102(4), 1177-1197
- Loewenstein, G. F. (1987). Anticipation and the valuation of delayed consumption. *Economic Journal*, 97(387), 666–684.
- Manasan RG. 2011. *Expanding Social Health Insurance Coverage: New Issues and Challenges*, Discussion Paper Series No. 2011-21, Philippine Institute for Development Studies: Manila.
- Mullainathan, S., & Shafir, E.(2014). *Scarcity: The New Science of Having Less and How It Defines Our Lives* (4th ed) . London: Macmillan/Picador.
- Nadaraya, E. A. 1965. On non-parametric estimates of density functions and regression curves. *Theory of Probability and Its Applications* 10, 186–190.
- Platteau, J.-P., De Bock, O., & Gelade, W. (2017). The demand for microinsurance: a literature review. *World Development* 94, 139-156.
- Prelec, D. (1998). The probability weighting function. *Econometrica*, 66, 497-527.

- Sayman, S., & Öncüler, A. (2009). An investigation of time-inconsistency. *Management Science*, 55, 470–482.
- Schilbach, F., Schofield, H., & Mullainathan, S. (2016). The psychological lives of the poor. *American Economic Review: Papers & Proceedings*, 106(5), 435-440.
- Scholten, M., & Read, D. (2006). Discounting by intervals: A generalized model of intertemporal choice. *Management Science*, 52(9), 1424–1436
- Stott, H. P. (2006). Cumulative prospect theory's functional menagerie. *Journal of Risk and Uncertainty*, 32(2), 101-130.
- Sydnor, J. (2010). (Over) insuring modest risks. *American Economic Journal: Applied Economics*, 2(4), 177-199.
- Takeuchi, K. (2011). Non-parametric test of time consistency: Present bias and future bias. *Games and Economic Behavior*, 71(2), 456–478.
- Tanaka, T., Camerer, C. F., & Nguyen, Q. (2010). Risk and time preferences: linking experimental and household survey data from Vietnam. *American Economic Review*, 100(1), 557-571.
- Thaler, R. H. (1981). Some empirical evidence on dynamic inconsistency. *Economic Letters*, 8(3), 201–207.
- Thornton, R. L., Hatt, L. E., Field, E. M., Islam, M., Solís Diaz, F., & González, M. A. (2010). Social security health insurance for the informal sector in Nicaragua: a randomized evaluation. *Health Economics*, 19(S1), 181-206.
- Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, 5(4), 297-323.
- Vieider, F. M., Lefebvre, M., Bouchouicha, R., Chmura, T., Hakimov, R., Krawczyk, M., & Martinsson, P. (2015). Common components of risk and uncertainty attitudes across contexts and domains: Evidence from 30 countries. *Journal of the European Economic Association*, 13(3), 421-452.
- Vieider, F.M., Martinsson, P., Nam, P.K., & Truong, N. (2019). Risk preferences and development revisited. *Theory and Decision*, 86, 1–21
- Wang, M., Rieger, M. O., & Hens, T. (2016). How time preferences differ: Evidence from 53 countries. *Journal of Economic Psychology*, 52, 115-135.
- Wakker, P., Thaler, R., & Tversky, A. (1997). Probabilistic insurance. *Journal of Risk and Uncertainty*, 15(1), 7-28.
- Wakker, P. P. (2010). *Prospect theory for risk and ambiguity*. Cambridge University Press: Cambridge.
- Watson, G. S. (1964). Smooth regression analysis. *Sankhya Series A* 26, 359–372.
- Yates, F. J., & Watts, R. A. (1975). Preferences for deferred losses. *Organizational Behavior and Human Performance*, 13(2), 294–306.

## **Supplementary Material**

### **Do time preferences explain low health insurance take-up?**

#### **APPENDICES**

**Appendix A** Survey instruments for elicitation of risk preferences

**Appendix B** Survey instruments for elicitation of time preferences

**Appendix C** Variable definitions

**Appendix D** Additional tables and figures

**Appendix E** Partial associations of preferences with insurance obtained as a program member and as a member's dependent



## Appendix A Survey instruments for elicitation of risk preferences

### **RISK AVERSION (1) [Lottery 1]**

**NOTE TO THE INTERVIEWER: Present the respondent with the visual support. The visual support for option 1 stays the same throughout the question, but the visual support for option 2 needs to be changed for every sub question.**

I am now going to ask you some questions which are a little bit similar to “pera o bayong”, but they are about losing money as opposed to winning money. There is no right or wrong answer, I am just curious to hear what you prefer.

<b>A.</b>		
I am going to ask you to make the choice between two options, represented by these two jars. The first jar contains 4 balls. If you choose the first jar, one ball will be drawn from the jar. If a black ball is drawn you will lose 400 pesos and if a white ball is drawn you will lose nothing. This means there is an equal chance of losing 400 pesos and losing nothing (fifty-fifty). If you choose the second jar you will lose 200 pesos for sure. If you were to choose between these two jars, which one would you choose?		
An equal chance (fifty-fifty) of <u>losing</u> 400 pesos and <u>losing</u> nothing	1	<b>CONTINUE TO B</b>
<u>Lose</u> 200 pesos for sure	2	<b>SKIP TO E</b>
<b>B.</b>		
<b>NOTE TO THE INTERVIEWER: Change the visual support for only the second option</b>		
What if the first jar stays the same, but if you choose the second jar you will now lose 150 pesos for sure. If you were to choose between these two jars, which one will you choose?		
Again, an equal chance (fifty-fifty) of <u>losing</u> 400 pesos and <u>losing</u> nothing	1	<b>CONTINUE TO C</b>
Lose 150 pesos for sure	2	<b>PROCEED TO NEXT SET</b>

<b>C.</b>		
<b>NOTE TO THE INTERVIEWER: Change the visual support for only the second option</b>		
What if the first jar stays the same, but if you choose the second jar you will now lose 100 pesos for sure. If you were to choose between these two jars, which one will you choose?		
Again, an equal chance (fifty-fifty) of <u>losing</u> 400 pesos and <u>losing</u> nothing	1	<b>CONTINUE TO D</b>
Lose 100 pesos for sure	2	<b>PROCEED TO NEXT SET</b>

<b>D.</b>		
<b>NOTE TO THE INTERVIEWER: Change the visual support for only the second option</b>		
What if the first jar stays the same, but if you choose the second jar you will now lose 1 peso for sure. If you were to choose between these two jars, which one will you choose?		
Again, an equal chance (fifty-fifty) of <u>losing</u> 400 pesos and <u>losing</u> nothing	1	<b>PROCEED TO NEXT SET</b>
Lose 1 peso for sure	2	<b>PROCEED TO NEXT SET</b>

<b>E.</b>		
<b>NOTE TO THE INTERVIEWER: Change the visual support for only the second option</b>		
What if the first jar stays the same, but if you choose the second jar you will now lose 250 pesos for sure. If you were to choose between these two jars, which one will you choose?		
Again, an equal chance (fifty-fifty) of <u>losing</u> 400 pesos and <u>losing</u> nothing	1	<b>PROCEED TO NEXT SET</b>
<u>Lose</u> 250 pesos for sure	2	<b>CONTINUE TO F</b>

<b>F.</b>		
<b>NOTE TO THE INTERVIEWER: Change the visual support for only the second option</b>		
What if the first jar stays the same, but if you choose the second jar you will now lose 300 pesos for sure. If you were to choose between these two jars, which one will you choose?		
Again, an equal chance (fifty-fifty) of <u>losing</u> 400 pesos and <u>losing</u> nothing	1	<b>PROCEED TO NEXT SET</b>
<u>Lose</u> 300 pesos for sure	2	<b>CONTINUE TO G</b>

<b>G.</b>		
<b>NOTE TO THE INTERVIEWER: Change the visual support for only the second option</b>		
What if the first jar stays the same, but if you choose the second jar you will now lose 400 pesos for sure. If you were to choose between these two jars, which one will you choose?		
Again, an equal chance (fifty-fifty) of <u>losing</u> 400 pesos and <u>losing</u> nothing	1	<b>PROCEED TO NEXT SET</b>
Lose 400 pesos for sure	2	<b>PROCEED TO NEXT SET</b>

Figure A1. Questionnaire for Lottery 1 used to elicit risk preferences

**RISK AVERSION(2) [Lottery 2]**

**NOTE TO THE INTERVIEWER: Present the respondent with the visual support. The visual support for option 1 stays the same throughout the question, but the visual support for option 2 needs to be changed for every sub question.**

<b>A.</b>		
<p>In this question I am again going to ask you to make the choice between two options, represented by these two jars. The first jar again contains 4 balls. If you choose the first jar, one ball will be drawn from the jar. If a black ball is drawn you will lose 400 pesos and if a white ball is drawn you will lose nothing. This means there is a chance of 1 out of 4 (25%) of losing 400 pesos and 3 out of 4 (75%) losing nothing. The second jar also contains 4 balls. If you choose the second jar also one ball will be drawn from the jar. If a black ball is drawn you will lose 200 pesos and if a white ball is drawn you will lose nothing. This means there is an equal chance of losing 200 pesos and losing nothing (fifty-fifty). If you were to choose between these two jars, which one would you choose?</p>		
A chance of 1 out of 4 (25%) of losing 400 pesos and 3 out of 4 (75%) losing nothing	1	<b>CONTINUE TO B</b>
An equal chance (fifty-fifty) of losing 200 pesos and losing nothing	2	<b>SKIP TO E</b>
<b>B.</b>		
<b>NOTE TO THE INTERVIEWER: Change the visual support for only the second option</b>		
<p>What if the first jar stays the same but the second jar changes? If a black ball is drawn from the second jar it now means you lose 150 pesos. If you were to choose between these two jars, which one will you choose?</p>		
Again, a chance of 1 out of 4 (25%) of losing 400 pesos and 3 out of 4 (75%) losing nothing	1	<b>CONTINUE TO C</b>
An equal chance (fifty-fifty) of losing 150 pesos and losing nothing	2	<b>PROCEED TO NEXT SET</b>

<b>C.</b>		
<b>NOTE TO THE INTERVIEWER: Change the visual support for only the second option</b>		
<p>What if the first jar stays the same but the second jar changes? If a black ball is drawn from the second jar it now means you lose 100 pesos. If you were to choose between these two jars, which one will you choose?</p>		
Again, a chance of 1 out of 4 (25%) of losing 400 pesos and 3 out of 4 (75%) losing nothing	1	<b>CONTINUE TO D</b>
An equal chance (fifty-fifty) of losing 100 pesos and losing nothing	2	<b>PROCEED TO NEXT SET</b>

<b>D.</b>		
<b>NOTE TO THE INTERVIEWER: Change the visual support for only the second option</b>		
What if the first jar stays the same but the second jar changes? If a black ball is drawn from the second jar it now means you lose 1 peso. If you were to choose between these two jars, which one will you choose?		
Again, a chance of 1 out of 4 (25%) of losing 400 pesos and 3 out of 4 (75%) losing nothing	1	<b>PROCEED TO NEXT SET</b>
An equal chance (fifty-fifty) of losing 1 peso and losing nothing	2	<b>PROCEED TO NEXT SET</b>

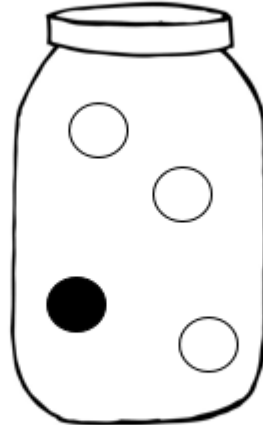
<b>E.</b>		
<b>NOTE TO THE INTERVIEWER: Change the visual support for only the second option</b>		
What if the first jar stays the same but the second jar changes? If a black ball is drawn from the second jar it now means you lose 250 pesos. If you were to choose between these two jars, which one will you choose?		
Again, a chance of 1 out of 4 (25%) of losing 400 pesos and 3 out of 4 (75%) losing nothing	1	<b>PROCEED TO NEXT SET</b>
An equal chance (fifty-fifty) of losing 250 pesos and losing nothing	2	<b>CONTINUE TO F</b>

<b>F.</b>		
<b>NOTE TO THE INTERVIEWER: Change the visual support for only the second option</b>		
What if the first jar stays the same but the second jar changes? If a black ball is drawn from the second jar it now means you lose 300 pesos. If you were to choose between these two jars, which one will you choose?		
Again, a chance of 1 out of 4 (25%) of losing 400 pesos and 3 out of 4 (75%) losing nothing	1	<b>PROCEED TO NEXT SET</b>
An equal chance (fifty-fifty) of losing 300 pesos and losing nothing	2	<b>CONTINUE TO G</b>

<b>G.</b>		
<b>NOTE TO THE INTERVIEWER: Change the visual support for only the second option</b>		
What if the first jar stays the same but the second jar changes? If a black ball is drawn from the second jar it now means you lose 400 pesos. If you were to choose between these two jars, which one will you choose?		
Again, a chance of 1 out of 4 (25%) of losing 400 pesos and 3 out of 4 (75%) losing nothing	1	<b>PROCEED TO NEXT SET</b>
An equal chance (fifty-fifty) of losing 400 pesos and losing nothing	2	<b>PROCEED TO NEXT SET</b>

Figure A2. Questionnaire for Lottery 2 used to elicit risk preferences

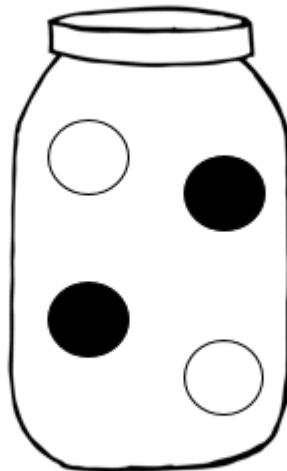
**1**



● Lose **400** pesos

○ Lose **nothing**

**2**

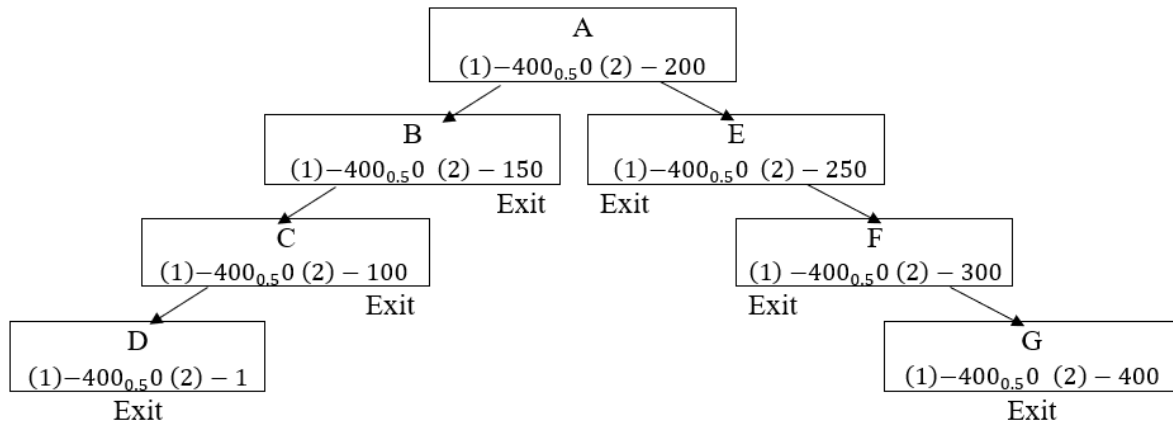


● Lose **200** pesos

○ Lose **nothing**

Figure A3. Example of visual support for risk elicitation task

### Lottery 1



### Lottery 2

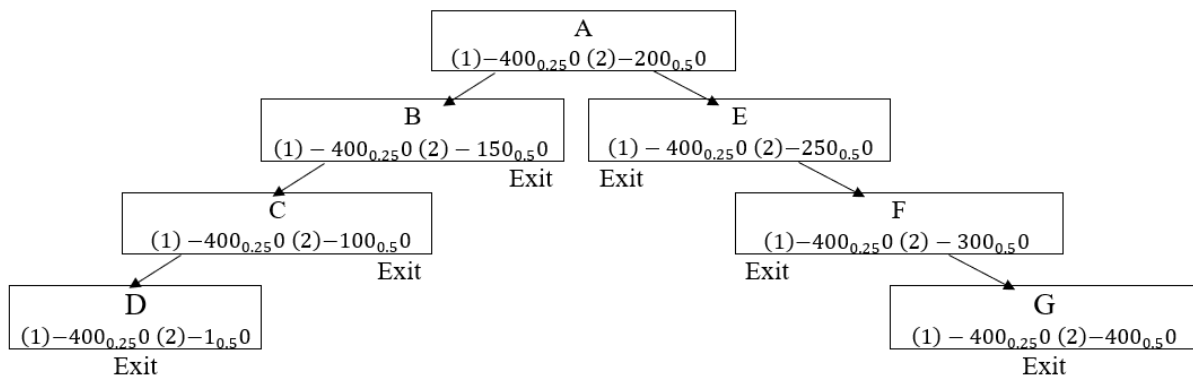


Figure A4. Lotteries used to elicit risk preferences

*Note.* From the switching point, we infer a range in which the value corresponding to indifference lies and use the midpoint as the estimate of that value. For example, (2) at A and (1) at E  $\rightarrow x = -225$  or  $z = -225$  in Lottery 1 and Lottery 2, respectively. For those who do not switch at D, we impose  $x = -0.5$  (or  $z = -0.5$ ). For those who do not switch at G, we impose  $x = -400$  (or  $z = -400$ ).



### Text A1. Derivation of risk preference parameters

The indifference from Lottery 1 implies

$$\begin{aligned} (-x)^\gamma &= \exp(-(-\ln 0.5)^\alpha) \\ \gamma \ln(-x) &= -(-\ln 0.5)^\alpha, \end{aligned} \quad (1)$$

while the indifference from Lottery 2 implies

$$\begin{aligned} (-z)^\gamma &= \frac{\exp(-(-\ln 0.25)^\alpha)}{\exp(-(-\ln 0.5)^\alpha)} \\ \gamma \ln(-z) &= (-\ln 0.5)^\alpha - (-\ln 0.25)^\alpha. \end{aligned} \quad (2)$$

From (1) and (2), we have  $\gamma(\ln(-x) + \ln(-z)) = -(-\ln 0.25)^\alpha$  and  $\frac{\ln(-x)}{\ln(-x) + \ln(-z)} = \frac{(-\ln 0.5)^\alpha}{(-\ln 0.25)^\alpha}$ ,

which solve for

$$\alpha = \frac{\ln\left(\frac{\ln(-x)}{\ln(-x) + \ln(-z)}\right)}{\ln\left(\frac{\ln 0.5}{\ln 0.25}\right)},$$

and

$$\gamma = \frac{-(-\ln 0.5)^\alpha}{\ln(-x)}.$$

Table A1: Utility curvature ( $\gamma$ ) and probability weighting ( $\alpha$ ) for all combinations of Lottery 1 ( $x$ ) and Lottery 2 ( $z$ ) indifference points

Utility curvature ( $\gamma$ )

		Set 2 $z_{0.5} \sim -400_{0.25} 0$						
		-0.5	-50	-125	-175	-225	-275	-350
Set 1 $x \sim -400_{0.5} 0$	-0.5	0.10	0.13	0.14	0.14	0.14	0.15	0.15
	-50	0.22	0.33	0.38	0.40	0.42	0.44	0.47
	-125	0.31	0.50	0.60	0.65	0.70	0.74	0.81
	-175	0.38	0.62	0.76	0.84	0.91	0.99	1.12
	-225	0.45	0.77	0.97	1.09	1.20	1.33	1.56
	-275	0.57	0.99	1.26	1.44	1.63	1.85	2.27
	-350	0.94	1.70	2.25	2.64	3.10	3.69	5.19

Probability weighting ( $\alpha$ )

		Set 2 $z_{0.5} \sim -400_{0.25} 0$						
		-0.5	-50	-125	-175	-225	-275	-350
Set 1 $x \sim -400_{0.5} 0$	-0.5	1.00	0.39	0.23	0.17	0.12	0.08	0.03
	-50	2.08	1.00	0.64	0.48	0.35	0.24	0.09
	-125	2.75	1.48	1.00	0.77	0.58	0.40	0.16
	-175	3.18	1.81	1.27	1.00	0.76	0.54	0.22
	-225	3.66	2.21	1.60	1.28	1.00	0.72	0.30
	-275	4.24	2.71	2.04	1.68	1.34	1.00	0.44
	-350	5.67	4.05	3.28	2.85	2.41	1.93	1.00

## Appendix B Survey instruments for elicitation of time preferences

### TIME PREFERENCE (1) [Choice 1] SHOWCARD

Now I will ask you to make some choices between receiving money at different points in time, either now or half a year from now. There is no right or wrong answer, I am just curious to hear what you prefer. If you were to choose between the following two options, which one will you choose?

<b>A.</b>		
Receive 200 pesos now	1	<b>CONTINUE TO B</b>
Receive 200 pesos half a year from now	2	<b>SKIP TO I</b>

<b>B.</b>		
Receive 100 pesos now	1	<b>CONTINUE TO C</b>
Receive 200 pesos half a year from now	2	<b>SKIP TO F</b>

<b>C.</b>		
Receive 50 pesos now	1	<b>CONTINUE TO D</b>
Receive 200 pesos half a year from now	2	<b>SKIP TO E</b>

<b>D.</b>		
Receive 25 pesos now	1	<b>PROCEED TO NEXT SET</b>
Receive 200 pesos half a year from now	2	<b>PROCEED TO NEXT SET</b>

<b>E.</b>		
Receive 75 pesos now	1	<b>PROCEED TO NEXT SET</b>
Receive 200 pesos half a year from now	2	<b>PROCEED TO NEXT SET</b>

<b>F.</b>		
Receive 150 pesos now	1	<b>CONTINUE TO G</b>
Receive 200 pesos half a year from now	2	<b>SKIP TO H</b>

<b>G.</b>		
Receive 125 pesos now	1	<b>PROCEED TO NEXT SET</b>
Receive 200 pesos half a year from now	2	<b>PROCEED TO NEXT SET</b>

<b>H.</b>		
Receive 175 pesos now	1	<b>PROCEED TO NEXT SET</b>
Receive 200 pesos half a year from now	2	<b>PROCEED TO NEXT SET</b>

<b>I.</b>		
Receive 250 pesos now	1	<b>PROCEED TO NEXT SET</b>
Receive 200 pesos half a year from now	2	<b>PROCEED TO NEXT SET</b>

Figure B1. Questionnaire for Choice 1 used to elicit time preferences

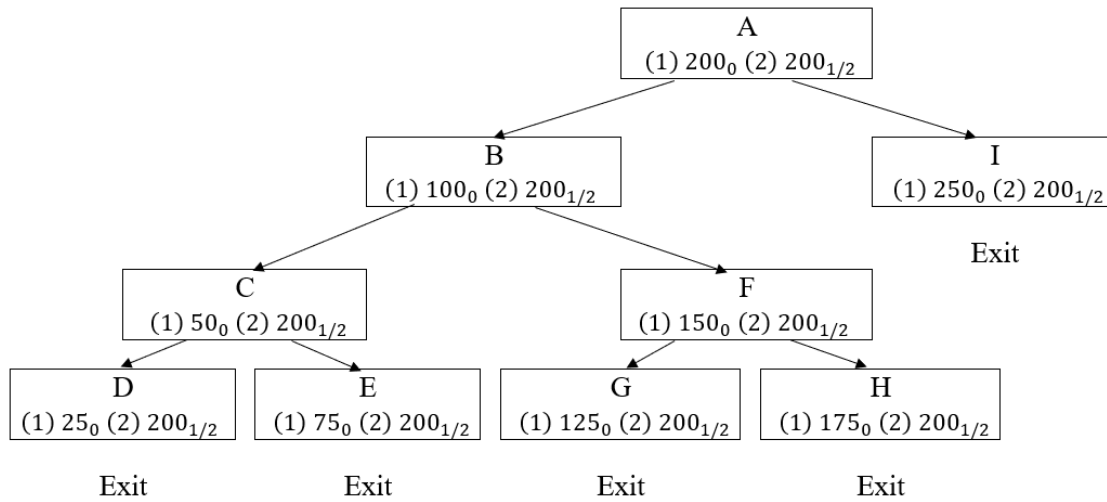
**TIME PREFERENCE (2) [Choice 2]**  
**SHOWCARD.**

Again, I will ask you to make some choices between receiving money at different points in time, now they concern choices between half a year from now and one year from now. Again, there is no right or wrong answer. If you were to choose between the following two options, which one will you choose?

<b>A.</b>		
Receive 200 pesos half a year from now	1	<b>CONTINUE TO B</b>
Receive 200 pesos one year from now	2	<b>SKIP TO I</b>
<b>B.</b>		
Receive 100 pesos half a year from now	1	<b>CONTINUE TO C</b>
Receive 200 pesos one year from now	2	<b>SKIP TO F</b>
<b>C.</b>		
Receive 50 pesos half a year from now	1	<b>CONTINUE TO D</b>
Receive 200 pesos one year from now	2	<b>SKIP TO E</b>
<b>D.</b>		
Receive 25 pesos half a year from now	1	<b>PROCEED TO NEXT SET</b>
Receive 200 pesos one year from now	2	<b>PROCEED TO NEXT SET</b>
<b>E.</b>		
Receive 75 pesos half a year from now	1	<b>PROCEED TO NEXT SET</b>
Receive 200 pesos one year from now	2	<b>PROCEED TO NEXT SET</b>
<b>F.</b>		
Receive 150 pesos half a year from now	1	<b>CONTINUE TO G</b>
Receive 200 pesos one year from now	2	<b>SKIP TO H</b>
<b>G.</b>		
Receive 125 pesos half a year from now	1	<b>PROCEED TO NEXT SET</b>
Receive 200 pesos one year from now	2	<b>PROCEED TO NEXT SET</b>
<b>H.</b>		
Receive 175 pesos half a year from now	1	<b>PROCEED TO NEXT SET</b>
Receive 200 pesos one year from now	2	<b>PROCEED TO NEXT SET</b>
<b>I.</b>		
Receive 250 pesos half a year from now	1	<b>PROCEED TO NEXT SET</b>
Receive 200 pesos one year from now	2	<b>PROCEED TO NEXT SET</b>

Figure B2. Questionnaire for Choice 2 used to elicit time preferences

### Choice 1



### Choice 2

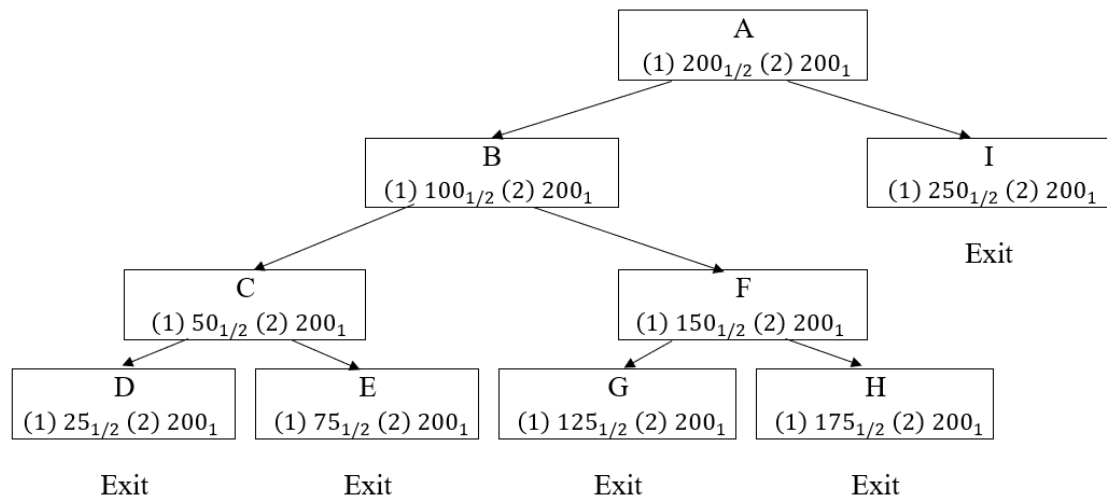


Figure B3. Choices used to elicit time preferences

Note. From the switching point, we infer a range in which the value corresponding to indifference lies and use the midpoint as the estimate of that value. For example, (2) at A and (1) at I  $\rightarrow x_0=225$  and  $y=225$  in Choice 1 and Choice 2, respectively. For respondents who opt for (2) 200 pesos at I on Choice 1 or 2, we impose a switching point of 275. For those who opt for (1) 25 pesos at D on Choice 1 or 2, we impose a switching point of 12.5.

Table B1: Time preference parameters  $\delta_1$  and  $\beta_1$  for all combinations Choice 1 ( $x_0$ ) and Choice 2 ( $y$ ) indifference points assuming linear utility

Discount factor ( $\delta$ )

Set 2		$y_{1/2} \sim 200_{1/2}$									
		12.5	37.5	62.5	87.5	112.5	137.5	162.5	187.5	225	275
		0.00	0.04	0.10	0.19	0.32	0.47	0.66	0.88	1.27	1.89

Present bias ( $\beta$ )

Set 2		$y_{1/2} \sim 200_{1/2}$										
		12.5	37.5	62.5	87.5	112.5	137.5	162.5	187.5	225	275	
Set 1	$x_0 \sim 200_{1/2}$	12.5	1.00	0.33	0.20	0.14	0.11	0.09	0.08	0.07	0.06	0.05
		37.5	3.00	1.00	0.60	0.43	0.33	0.27	0.23	0.20	0.17	0.14
		62.5	5.00	1.67	1.00	0.71	0.56	0.45	0.38	0.33	0.28	0.23
		87.5	7.00	2.33	1.40	1.00	0.78	0.64	0.54	0.47	0.39	0.32
		113	9.00	3.00	1.80	1.29	1.00	0.82	0.69	0.60	0.50	0.41
		138	11.00	3.67	2.20	1.57	1.22	1.00	0.85	0.73	0.61	0.50
		163	13.00	4.33	2.60	1.86	1.44	1.18	1.00	0.87	0.72	0.59
		188	15.00	5.00	3.00	2.14	1.67	1.36	1.15	1.00	0.83	0.68
		225	18.00	6.00	3.60	2.57	2.00	1.64	1.38	1.20	1.00	0.82
		275	22.00	7.33	4.40	3.14	2.44	2.00	1.69	1.47	1.22	1.00

*Note:* To obtain the parameters under power utility, raise each entry in the tables above to a power given by any value of utility curvature ( $\gamma$ ) given in Table A1.

## Appendix C Variable definitions

### Perceived comparative risk of medical spending

Respondents were asked:

“Compared with other households similar to yours, do you think the chance that your household will incur more than 8000 pesos out-of-pocket expenditure on healthcare, medicines and maintenance drugs in the next year is”

- Smaller
- The same
- Larger

In the analysis, we use an indicator of reporting “Smaller”, which we label “perceive lower OOP risk than average”.

### Health insurance literacy

Respondents were asked to judge whether each of five statements relating to health insurance was true or false.

They also had the option answer “don’t know”. The statements were as follows:

- Health insurance is a financial arrangement where an individual contributes a small certain payment on a regular basis in exchange for reductions in medical expenses in case of illness or hospitalization.
- Health insurance contribution is something you must pay only in months when you use medical services.
- With health insurance, the insurer pays for a portion of your medical expenses in case you get sick.
- A health insurance is an individual savings account from which you can withdraw the total amount of your contributions in times of illness and hospitalization.
- An insured person can claim back her health insurance contributions for the year if she did not get ill or hospitalized and did not claim benefits.

A respondent is categorized as having *low health insurance literacy* if no more than 2 of the answers are correct.

### Knowledge of insurance program benefits

Respondents were asked whether the Philhealth (fully or partially) covers 18 medical treatments/services.

Answers could be “yes”, “no” or “don’t know”. A respondent is categorized as having *low knowledge of insurance benefits* if no more than 6 answers are correct.



## Appendix D Additional Figures & Tables

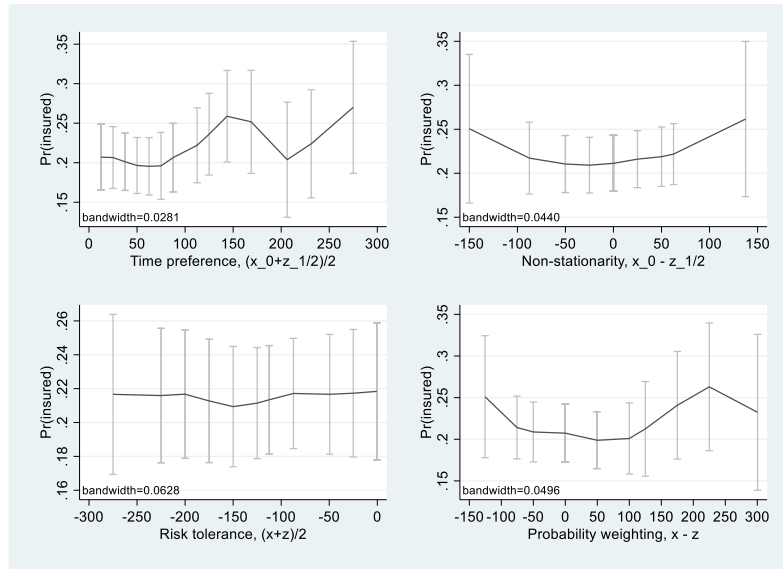


Figure D1. Conditional probability of insurance as function of each non-parametric preference measures – Local constant regression estimates

*Notes:* The graph in each panel is obtained from a bivariate local constant regression of an insurance indicator on the respective preference measure. It shows estimates of conditional means at the 5<sup>th</sup>, 10<sup>th</sup>, .., 95<sup>th</sup> percentiles of the respective measure. The number of estimates is less than 19 in some panels because of equal percentile values. The Epanechnikov kernel function is used and the bandwidth is selected by the plugin estimator of the asymptotically optimal constant bandwidth. In computation, each measure was scaled through division by 1000, but the x-axes in the figure are on the original scales. Whiskers show 95% confidence intervals (CI).

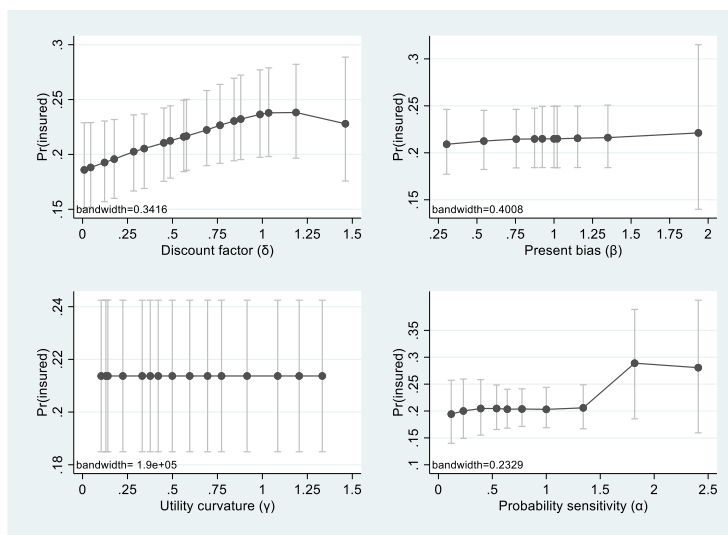


Figure D2. Conditional probability of insurance as function of each preference parameter  
Local constant regression estimates

*Notes:* The graph in each panel is obtained from a bivariate local constant regression of an insurance indicator on the respective preference parameter. It shows estimates of conditional means at the 5<sup>th</sup>, 10<sup>th</sup>,,, 95<sup>th</sup> percentiles of the respective parameter. The number of estimates is less than 19 in some panels because of equal percentile values. The Epanechnikov kernel function is used. For  $\delta$ ,  $\beta$  and  $\alpha$ , the bandwidth is selected optimally by cross-validation (Li & Racine, 2004). This method produced very wide bandwidth for  $\gamma$ , and so for this parameter, the bandwidth is selected by the plugin estimator of the asymptotically optimal constant bandwidth. Whiskers show 95% confidence intervals (CI).

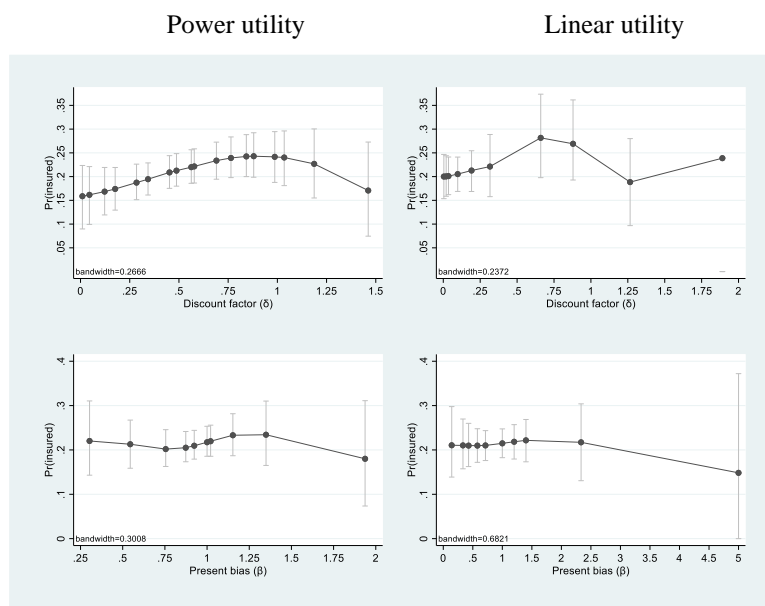


Figure D3. Conditional probability of insurance as function of time preference parameters —  
 comparison of parameters derived assuming power (left) and linear (right) utility

*Notes:* The graph in each panel is obtained from a bivariate local linear regression of an insurance indicator on the respective preference parameter. The graphs in the left-hand column are the same as those in the top row of Figure 4. They use time preference parameters that are derived under the assumption of power utility, using individual-specific estimates of utility curvature. The graphs in the right-hand column use parameters derived under the assumption of linear utility. Dots indicate point estimates of conditional means at the 5<sup>th</sup>, 10<sup>th</sup>, ..., 95<sup>th</sup> percentiles of the respective measure. The number of dots is less than 19 in some panels because of equal percentile values. The Epanechnikov kernel function is used. Bandwidths are selected optimally by cross-validation (Li & Racine, 2004). Whiskers show 95% confidence intervals (CI) obtained from a bootstrap percentile method (Cattaneo & Jansson, 2018) with 500 replications.

Table D1: Characteristics in 2011 by whether interviewed in 2015 (means)

	Interviewed 2015		t-test
	No (1)	Yes (2)	p-value (1)=(2)
<b>Voluntary/subsidized insurance or uninsured</b>			
<i>Respondent</i>			
female	0.742	0.755	0.590
age	41.41	43.05	0.015
head of household	0.355	0.318	0.137
< elementary school	0.169	0.182	0.505
elementary school	0.268	0.318	0.043
high school graduate	0.411	0.396	0.556
college graduate	0.152	0.104	0.005
<i>Household</i>			
no. persons	4.582	5.245	0.000
no. persons $\geq 65$ / total	0.066	0.050	0.040
anyone admitted to hospital last year	0.132	0.145	0.493
urban	0.617	0.424	0.000
experiment treatment site	0.755	0.751	0.842
<i>N</i>	462	1513	1975
<b>Mandatory insurance</b>			
<i>Respondent</i>			
female	0.753	0.768	0.628
age	40.20	40.65	0.600
head of household	0.284	0.281	0.926
< elementary school	0.093	0.075	0.369
elementary school	0.201	0.225	0.407
high school graduate	0.463	0.427	0.310
college graduate	0.243	0.273	0.328
<i>Household</i>			
no. persons	5.006	5.210	0.175
no. persons $\geq 65$ / total	0.027	0.033	0.439
anyone admitted to hospital last year	0.148	0.169	0.435
urban	0.523	0.652	0.000
experiment treatment site	0.746	0.775	0.341
<i>N</i>	708	267	975

Notes: Top panel – uninsured or with voluntary/subsidized health insurance in 2011. All these households were targeted for interview in 2015. Bottom panel – mandatory, employment-based health insurance in 2011. A random (supplementary) sample of 267 households from those with mandatory insurance in 2011 was targeted for interview in 2015. Any such household that was randomly selected for interview in 2015 but could not be traced or refused was replaced with another random draw from those initially with mandatory insurance. The 708 of these households not interviewed in 2015 either were not selected or could not be traced/refused. Table does not include covariates listed in Table 1 that were not measured in 2011. p-values adjusted for clustering at the municipality level.

Table D2: Frequencies of points of indifference in choices used to elicit time preferences

Choice 1 $x_0 \sim 200_{1/2}$	Choice 2 $y_{1/2} \sim 200_1$										N
	12.5	37.5	62.5	87.5	112.5	137.5	162.5	187.5	225	275	
12.5	200	21	4	14	8	4	1	0	15	9	276
37.5	14	45	5	29	7	4	1	4	6	2	117
62.5	6	7	9	18	3	1	2	1	2	0	49
87.5	8	13	6	65	11	5	5	6	3	3	125
112.5	2	2	1	7	1	0	2	1	3	0	19
137.5	0	1	0	3	2	0	2	1	3	1	13
162.5	0	1	1	1	3	0	2	0	1	0	9
187.5	2	1	1	6	0	1	1	10	2	9	33
225	8	4	2	7	1	1	6	9	26	8	72
275	4	8	1	4	1	3	1	7	15	50	94
N	244	103	30	154	37	19	23	39	76	82	807

Notes: Sample comprises voluntarily insured and uninsured respondents.

Table D3: Characteristics by whether choose same extreme option on both Choice 1 and Choice 2 of time preference elicitation task (means)

	Choose same extreme option		t-test
	No (1)	Yes (2)	p-value (1)=(2)
<i>Respondent</i>			
insured	0.212	0.232	0.517
female	0.725	0.680	0.216
age (years)	44.908	46.840	0.040
head of household	0.343	0.384	0.241
< elementary education	0.172	0.192	0.516
elementary education	0.214	0.268	0.136
high school graduate	0.504	0.440	0.114
college graduate	0.110	0.100	0.700
perceive OOP risk lower than average	0.354	0.328	0.493
low health insurance literacy	0.294	0.324	0.412
poor knowledge of insurance benefits	0.303	0.272	0.425
smokes currently	0.124	0.148	0.383
drinks alcohol regularly	0.045	0.040	0.764
<i>Household</i>			
no. persons	4.973	4.992	0.919
no. persons $\geq$ 65 yrs. / total	0.048	0.063	0.154
head is female	0.189	0.152	0.209
anyone sick in last 30 days	0.039	0.036	0.844
anyone disabled or chronically sick	0.063	0.052	0.508
anyone admitted to hospital last year	0.061	0.104	0.064
urban	0.512	0.412	0.044
wealth index quartile score (1=poorest quartile, ..., 4=richest quartile)	2.553	2.376	0.048
annual income per capita (PHP)	42515.505	45273.468	0.569
experiment treatment site	0.765	0.808	0.250
<b>N</b>	<b>557</b>	<b>250</b>	<b>807</b>

Notes: Sample includes respondents voluntarily insured or uninsured at follow up. Choosing the same extreme option corresponds to not switching either at a) D in both Choice 1 and Choice 2 (extreme impatience) or b) I in both Choice 1 and Choice 2 (extreme patience) (see Appendix B Figure B3). All covariates measured at follow-up. p-values adjusted for clustering at municipality level.

Table D4: Frequencies of points of indifference in lottery choices used to elicit risk preferences

Lottery 1 $x \sim -400_{0.5}0$	Lottery 2 $z_{0.5}0 \sim -400_{0.25}0$								N
	-400	-350	-275	-225	-175	-125	-49.5	-0.5	
-400	9	0	0	1	3	0	1	1	15
-350	0	1	3	4	2	0	0	1	11
-275	3	0	3	11	6	6	3	2	34
-225	7	1	9	50	17	6	4	10	104
-175	8	2	9	21	22	13	8	6	89
-125	9	3	5	24	15	34	9	9	108
-49.5	6	5	8	16	16	12	41	22	126
-0.5	29	2	12	21	10	22	20	204	320
N	71	14	49	148	91	93	86	255	807

Notes: Sample comprises voluntarily insured and uninsured respondents.



Table D5: Characteristics by whether choose dominated prospect on risk elicitation task (means)

	Choose dominated prospect		t-test
	No (1)	Yes (2)	p-value (1)=(2)
<i>Respondent</i>			
insured	0.214	0.260	0.344
female	0.712	0.701	0.825
age (years)	45.60	44.68	0.566
head of household	0.351	0.403	0.381
< elementary education	0.173	0.234	0.217
elementary education	0.227	0.260	0.559
high school graduate	0.489	0.442	0.431
college graduate	0.111	0.065	0.127
perceive OOP risk lower than average	0.340	0.403	0.330
low health insurance literacy	0.308	0.260	0.407
poor knowledge of insurance benefits	0.284	0.390	0.152
smokes currently	0.127	0.169	0.337
drinks alcohol regularly	0.042	0.052	0.733
<i>Household</i>			
no. persons	4.960	5.156	0.426
no. persons $\geq$ 65 yrs. / total	0.054	0.040	0.291
head is female	0.175	0.195	0.687
anyone sick in last 30 days	0.038	0.039	0.980
anyone disabled or chronically sick	0.058	0.078	0.536
anyone admitted to hospital last year	0.075	0.065	0.716
urban	0.479	0.494	0.847
wealth index quartile score (1=poorest quartile, ..., 4=richest quartile)	2.504	2.442	0.698
annual income per capita (PHP)	42,702	49,700	0.538
experiment treatment site	0.782	0.740	0.474
N	631	176	807

Notes: Sample includes respondents voluntarily insured or uninsured at follow up. Choosing a dominated prospect corresponds to selecting option G in either Lottery 1 or Lottery 2 (see Appendix A Figure A4). All covariates measured at follow-up. p-values adjusted for clustering at municipality level.

Table D6: Characteristics by whether choose same extreme risk seeking prospect on both tasks

	Choose same extreme risk seeking		t-test
	No (1)	Yes (2)	p-value (1)=(2)
<i>Respondent</i>			
insured	0.211	0.240	0.439
female	0.713	0.706	0.842
age (years)	45.44	45.71	0.778
head of household	0.350	0.373	0.563
< elementary education	0.177	0.181	0.912
elementary education	0.222	0.255	0.424
high school graduate	0.499	0.441	0.205
college graduate	0.101	0.123	0.428
perceive OOP risk lower than average	0.325	0.407	0.084
low health insurance literacy	0.300	0.314	0.750
poor knowledge of insurance benefits	0.335	0.172	0.000
smokes currently	0.119	0.167	0.166
drinks alcohol regularly	0.048	0.029	0.286
<i>Household</i>			
no. persons	5.002	4.912	0.623
no. persons $\geq$ 65 yrs. / total	0.055	0.044	0.277
head of household is female	0.176	0.181	0.856
anyone sick in last 30 days	0.036	0.044	0.645
anyone disabled or chronically sick	0.060	0.059	0.963
anyone admitted to hospital last year	0.068	0.093	0.291
urban	0.476	0.495	0.700
wealth index quartile score (1=poorest quartile, ..., 4=richest quartile)	2.511	2.461	0.651
annual income per capita (PHP)	42,345	46,399	0.482
experiment treatment site	0.773	0.794	0.652
<b>N</b>	<b>603</b>	<b>204</b>	<b>807</b>

Notes: Sample includes respondents voluntarily insured or uninsured at follow up. Choosing the same extreme risk seeking prospect corresponds to not switching either at D in both Lottery 1 and Lottery 2 (see Appendix A Figure A4). All covariates measured at follow-up. p-values adjusted for clustering at municipality level.

Table D7. Effects of time preference parameters on probability of insurance – bivariate local linear regression estimates. Robustness to specification of utility.

Effect	Discount factor ( $\delta$ )		Present bias ( $\beta$ )	
	Power utility	Linear utility	Power utility	Linear utility
	0.0792** (0.0395)	0.0234 (0.0398)	0.0206 (0.0655)	0.0100 (0.0309)
Predicted mean	0.211*** (0.0155)	0.213*** (0.0166)	0.215*** (0.0159)	0.214*** (0.0155)
Bandwidth	0.4074	0.908	0.4970	1.043
$R^2$	0.0168	0.0042	0.0175	0.0095
$N$	729	713	730	726

*Notes.* The rows labelled “Effect” show estimates of the marginal change in the probability of insurance associated with a unit increase in the respective time preference parameter. The marginal changes are estimated at all values of the respective parameter and averaged. The columns headed “Power utility” reproduce estimates from Table 3, that correspond to the conditional mean functions shown in Figure 4. They utilize estimates of the time preference parameters derived under the assumption of power utility, using individual-specific estimates of utility curvature. The estimates in the columns headed “Linear utility” use preference parameter estimates derived under the assumption of linear utility. They correspond to the conditional mean functions shown in the right-hand column of Figure D3. All estimates are from bivariate local linear regressions. See notes to the respective figures for details of computation. The bandwidths shown in the table are those used for estimation of derivatives of the mean function. They are obtained by cross-validation (Henderson et al., 2015). Bootstrap standard errors in parentheses (500 replications). Statistical significance indicated by \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table D8. Partial effects of covariates on probability of insurance

	Non-parametric preference measures		Preference parameters	
<i>Respondent</i>				
female	0.0470	(0.0462)	0.0446	(0.0500)
age	0.0011	(0.0011)	0.0011	(0.0012)
head of household	0.0246	(0.0470)	0.0248	(0.0494)
< elementary education	-0.1419**	(0.0564)	-0.1633***	(0.0599)
elementary education	-0.1353***	(0.0493)	-0.1342**	(0.0533)
high school graduate	-0.1300***	(0.0476)	-0.1320***	(0.0496)
perceive OOP risk lower than average	-0.0531*	(0.0290)	-0.0662**	(0.0313)
low health insurance literacy	-0.0170	(0.0287)	0.0014	(0.0315)
poor knowledge of insurance benefits	-0.0405	(0.0306)	-0.0404	(0.0317)
smokes currently	-0.1057***	(0.0389)	-0.1055**	(0.0414)
drinks alcohol regularly	0.0878	(0.0686)	0.1133	(0.0709)
<i>Household</i>				
no. persons = 2	0.1933***	(0.0618)	0.1466**	(0.0705)
no. persons = 3-6	0.1512**	(0.0603)	0.1240*	(0.0753)
no. persons > 6	0.1106*	(0.0651)	0.0932	(0.0785)
no. persons ≥ 65 yrs. / total	0.2556**	(0.1255)	0.2082	(0.1352)
head of household is female	-0.0564	(0.0377)	-0.0575	(0.0385)
anyone sick in last 30 days	-0.0715	(0.0660)	-0.0489	(0.0743)
anyone disabled or chronically sick	0.0450	(0.0587)	0.0683	(0.0642)
anyone admitted to hospital last year	-0.0188	(0.0484)	-0.0667	(0.0424)
urban	-0.0056	(0.0348)	-0.0097	(0.0346)
Poorest wealth quartile group	-0.2044***	(0.0431)	-0.1924***	(0.0483)
2 <sup>nd</sup> poorest wealth quartile group	-0.1653***	(0.0416)	-0.1691***	(0.0454)
2 <sup>nd</sup> richest wealth quartile group	-0.0959***	(0.0371)	-0.1081***	(0.0401)
Poorest income quartile group	-0.0596	(0.0372)	-0.0333	(0.0410)
2 <sup>nd</sup> poorest income quartile group	0.0194	(0.0400)	0.0445	(0.0421)
2 <sup>nd</sup> richest income quartile group	-0.0740**	(0.0332)	-0.0641*	(0.0353)
experiment treatment site	0.1440***	(0.0292)	0.1474***	(0.0290)
Pseudo R <sup>2</sup>	0.1977		0.1991	
N	807		730	

*Notes:* Probit estimates of (averaged) partial effects on probability of being insured for covariates used as controls in models used to produce Table 4. Estimates under “Non-parametric preference measures” go with Panel A, column (2) estimates in Table 4. Estimates under “Preference parameters” go with Panel B, column (2) estimates in Table 4. Estimates for 14 strata indicators also included in the models are not presented. Age enters all models with a quadratic specification. Reference categories: education - college graduate; household size – no. persons =1; wealth index quartile – richest 25%; income per capita quartile group – richest 25%. Definitions of variables related to perceptions of out-of-pocket (OOP) medical expenditure risk, health insurance literacy and knowledge of insurance benefits in Appendix C. Robust standard errors adjusted for clustering at the municipality level in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table D9. Partial effects of preference measures and parameters on probability of insurance – robustness to controls, estimator, and exclusion of extreme preferences

	(1) Linear probability model	(2) Limited controls	(3) Probit Excluding extreme time preferences	(4) Excluding extreme risk preferences
<i>A. Non-parametric measures</i>				
Time preference $\left(\frac{x_0 + z_{1/2}}{2}\right)/1000$	0.1176 (0.1733)	0.1327 (0.1692)	0.0564 (0.2454)	0.1531 (0.1761)
Non-stationarity $(x_0 - z_{1/2})/1000$	-0.0380 (0.1652)	-0.0793 (0.1674)	-0.0854 (0.1621)	-0.1015 (0.1698)
Risk tolerance $\left(\frac{x + z}{2}\right)/1000$	0.0366 (0.1675)	0.0741 (0.1720)	0.1717 (0.1912)	-0.2047 (0.2123)
Probability weighting $(x - z)/1000$	0.0359 (0.1143)	0.0194 (0.1119)	0.1629 (0.1276)	0.0482 (0.1044)
(Pseudo) R <sup>2</sup>	0.1860	0.0939	0.1931	0.2272
N	807	807	557	603
Covariates	As Table 4 col. (2)	Limited	As Table 4 col. (2)	As Table 4 col. (2)
Dominated	Included	Included	Included	Included
<i>B. Parameters</i>				
Discount factor ( $\delta$ )	0.0388** (0.0162)	0.0376** (0.0173)	0.0319 (0.0316)	0.0327** (0.0160)
Present bias ( $\beta$ )	0.0123 (0.0101)	0.0072 (0.0098)	0.0099 (0.0097)	0.0105 (0.0080)
Utility curvature ( $\gamma$ )	-0.0458 (0.0307)	-0.0620* (0.0346)	-0.0440 (0.0411)	-0.0340 (0.0372)
Probability sensitivity ( $\alpha$ )	0.0244 (0.0230)	0.0349* (0.0207)	-0.0003 (0.0224)	0.0193 (0.0179)
(Pseudo) R <sup>2</sup>	0.1866	0.0968	0.1846	0.2202
N	730	730	509	526
Covariates	As Table 4 col. (2)	Limited	As Table 4 col. (2)	As Table 4 col. (2)
Dominated	Excluded	Excluded	Excluded	Excluded

*Notes:* Table assesses robustness of estimates in Table 4, column (2). Column (1) shows estimates obtained using the same covariate specification and samples as Table 4, column (2) but estimated as linear probability model by ordinary least squares. Column (2) uses same (probit) estimator as Table 4 but with a more restricted set of controls comprising sex, age (quadratic), experiment treatment site indicator and strata indicators. Column (3) estimated by probit with covariates as Table 4, column (2) but excluding respondents who do not switch in both Choice 1 & Choice 2 of the time preference elicitation task. Column (4) excludes respondents who do not switch in both Lottery 1 & Lottery 2 of the risk preference elicitation task. Robust standard errors adjusted for clustering at the municipality level in parentheses.  $x_0$ ,  $z_{1/2}$ ,  $x$ , and  $z$  are the indifference points elicited from Choice 1, Choice 2, Lottery 1, and Lottery 2, respectively. *Dominated* refers to respondents who choose a dominated prospect on either lottery. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table D10. Partial effects of preference parameters on probability of insurance  
– robustness to parameter transformations in probit latent index

	(1) Winsorized at 99 <sup>th</sup> percentile	(2) Inverse hyperbolic sine	(3) Relative rank	(4) Time preferences derived under linear utility
Discount factor ( $\delta$ )	0.0523** (0.0263)	0.0541** (0.0268)	0.0557 (0.0399)	0.0226 (0.0210)
Present bias ( $\beta$ )	0.0149 (0.0133)	0.0189 (0.0255)	0.0101 (0.0397)	0.0034 (0.0055)
Utility curvature ( $\gamma$ )	-0.0445 (0.0342)	-0.0448 (0.0385)	-0.0477 (0.0504)	-0.0382 (0.0337)
Probability sensitivity ( $\alpha$ )	0.0259 (0.0187)	0.0287 (0.0224)	0.0356 (0.0367)	0.0221 (0.0181)
Pseudo R <sup>2</sup>	0.1997	0.1991	0.1973	0.1962
N	730	730	730	730
Covariates	Yes	Yes	Yes	Yes
Dominated	Excluded	Excluded	Excluded	Excluded

*Notes:* Table assesses robustness of estimates in Table 4, columns (2)-(3), Panel B. This table uses same (probit) estimator and covariate specification as Table 4 columns (2)-(3) but differs in how the preferences parameters enter the latent index function. In column (1), all parameters are winsorized at the respective 99<sup>th</sup> percentile. In column (2), the inverse hyperbolic spline (IHS) of each parameter is used. In column (3), the relative rank of each parameter is used. In column (4), we enter the time preference parameters ( $\delta$  and  $\beta$ ) that are derived in the money domain under the assumption of linear utility. In columns (2) and (3), we still show the average partial effect of a unit change in each parameter, not the effect of the transformation of the parameter that enters the probit latent index. For the IHS, the estimated partial effect of  $\delta$ , for example, is  $\phi(\hat{y}_i^*)b_\delta/\sqrt{\delta^2+1}$  where  $\phi(\cdot)$  is the standard normal probability density function,  $\hat{y}_i^*$  is the predicted value of the latent index from the probit estimate of (4), and  $b_\delta$  is the coefficient on the IHS transformation of  $\delta$  included in the latent index. For the relative rank, we obtain the partial effect of a unit change in the relative rank, which corresponds to moving from the minimum to the maximum value, and scale this by the relative rank (percentile) change that corresponds to a unit change in the parameter from the minimum value. Robust standard errors adjusted for clustering at the municipality level in parentheses. *Dominated* refers to respondents who choose a dominated prospect on either lottery. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table D11. Partial effects of non-parametric preference measures on probability of insurance - heterogeneity

	Wealth		Insurance literacy / knowledge		Education	
	Low (1)	High (2)	Low (3)	High (4)	Low (5)	High (6)
Time preference $\left(\frac{x_0 + z_{1/2}}{2}\right)/1000$	0.4534** (0.1953)	-0.1942 (0.2117)	0.1255 (0.2073)	0.1067 (0.2270)	0.1531 (0.2511)	0.0675 (0.1800)
Non-stationarity $(x_0 - z_{1/2})/1000$	-0.1881 (0.2101)	0.1446 (0.2731)	-0.2566 (0.2120)	0.2089 (0.2874)	0.1843 (0.2873)	-0.1770 (0.2235)
Risk tolerance $\left(\frac{x + z}{2}\right)/1000$	0.2741 (0.1931)	-0.1580 (0.2525)	-0.0530 (0.1942)	0.1654 (0.2331)	0.2985 (0.2269)	-0.0991 (0.2134)
Probability weighting $(x - z)/1000$	0.2180 (0.1337)	-0.1040 (0.1580)	-0.0397 (0.1397)	0.1479 (0.1500)	0.2008 (0.1668)	-0.0830 (0.1260)
N	404	403	398	409	330	477

*Notes:* Tables shows average partial effects from probit models like that used to produce the estimates in Panel A column (2) of Table 4 but extended to include interactions with each preference measure. Model used for columns (1) and (2) includes interactions with an indicator of low health insurance literacy and/or knowledge (Appendix C for definitions). Model for columns (3) and (4) has interactions with an indicator that distinguishes high school and college graduates (high) from those with less education (low). Model for columns (5) and (6) has interactions with an indicator of below (low) and above (high) median of wealth index. Models include the covariates used for Table 4, column (2) estimates, except in columns (1)-(2) one indicator of low literacy or low knowledge replaces separate indicators of low insurance literacy and knowledge, in columns (3)-(4) one indicator of high school/college graduate replaces separate indicators of four levels of education, and in (5)-(6) one indicator of below/above median wealth replaces indicators for wealth quartile groups. All models include indicators of the sample strata. Robust standard errors adjusted for clustering at the municipality level in parentheses. N indicates the size of the respective group, although the full sample is used to estimate each model. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1



Table D12. Linear probability model estimates of partial effects of preference measures and parameters on probability of insurance - heterogeneity

	Wealth		Insurance literacy / knowledge		Education	
	Low	High	Low	High	Low	High
<i>A. Non-parametric</i>	(1)	(2)	(3)	(4)	(5)	(6)
Time preference $\left(\frac{x_0 + z_{1/2}}{2}\right)/1000$	0.5206** (0.2203)	-0.1853 (0.2385)	0.1448 (0.2472)	0.1235 (0.2396)	0.2025 (0.2632)	0.0861 (0.2108)
Non-stationarity $(x_0 - z_{1/2})/1000$	-0.1777 (0.2179)	0.1502 (0.3033)	-0.3051 (0.2249)	0.2700 (0.2780)	0.1668 (0.2811)	-0.1305 (0.2189)
Risk tolerance $\left(\frac{x + z}{2}\right)/1000$	0.3335* (0.1860)	-0.2198 (0.2742)	-0.0527 (0.2153)	0.1541 (0.2259)	0.2895 (0.2037)	-0.1124 (0.2432)
Prob. weighting $(x - z)/1000$	0.1896 (0.1410)	-0.1031 (0.1771)	-0.0610 (0.1406)	0.1448 (0.1640)	0.1945 (0.1679)	-0.0978 (0.1402)
N	404	403	398	409	330	477
<i>B. Parameters</i>						
Discount factor ( $\delta$ )	0.0606*** (0.0170)	0.0112 (0.0490)	0.0109 (0.0231)	0.0793*** (0.0302)	0.0213 (0.0279)	0.0419* (0.0219)
Present bias ( $\beta$ )	0.0110 (0.0095)	0.0166 (0.0153)	-0.0043 (0.0099)	0.0535*** (0.0101)	0.0019 (0.0064)	0.0274* (0.0142)
Utility curvature ( $\gamma$ )	-0.0696* (0.0355)	-0.0356 (0.0463)	0.0008 (0.0478)	-0.0864** (0.0373)	-0.0877** (0.0363)	-0.0271 (0.0444)
Probability sensitivity ( $\alpha$ )	-0.0326 (0.0282)	0.0701** (0.0318)	0.0092 (0.0335)	0.0351 (0.0299)	-0.0011 (0.0295)	0.0567* (0.0341)
N	361	369	356	374	292	438

*Notes:* Table shows OLS estimates of partial effects from LPM like those used to produce the estimates in column (1) of Table D9 but extended to include interactions with each preference measure. Models used for columns (1) and (2) include interactions with an indicator of below (low) and above (high) median of wealth index. Models for columns (3) and (4) have interactions with an indicator of low health insurance literacy and/or knowledge (Appendix C for definitions). Models for columns (5) and (6) have interactions with an indicator that distinguishes high school and college graduates (high) from those with less education (low). Models include the covariates used for Table D9 column (1) (and Table 4, column (2)) estimates, except in columns (1)-(2) one indicator of below/above median wealth replaces indicators for wealth quartile groups, in columns (3)-(4) one indicator of low literacy or low knowledge replaces separate indicators of low insurance literacy and knowledge, and in (5)-(6) one indicator of high school/college graduate replaces separate indicators of four levels of education. All models include indicators of the sample strata. Robust standard errors adjusted for clustering at the municipality level in parentheses. N indicates the size of the respective group, although the full sample is used to estimate each model. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table D13. Partial effects of preference measures and parameters on probability of insurance – heterogeneity by insurance experiment treatment site

	Probit		Linear probability model	
	Control (1)	Treatment (2)	Control (3)	Treatment (4)
<i>A. Non-parametric</i>				
Time preference $\left(\frac{x_0 + z_{1/2}}{2}\right)/1000$	0.2516 (0.2990)	0.0650 (0.1781)	0.1459 (0.4280)	0.1153 (0.1890)
Non-stationarity $(x_0 - z_{1/2})/1000$	0.3039 (0.2340)	-0.2381 (0.2115)	0.4355* (0.2548)	-0.2413 (0.2123)
Risk tolerance $\left(\frac{x + z}{2}\right)/1000$	-0.0256 (0.2304)	0.0516 (0.1973)	-0.0253 (0.2701)	0.0529 (0.2020)
Prob. weighting $(x - z)/1000$	0.0913 (0.1338)	0.0422 (0.1240)	0.0352 (0.1934)	0.0337 (0.1311)
N	179	628	179	628
<i>B. Parameters</i>				
Discount factor ( $\delta$ )	0.0471*** (0.0175)	0.0276 (0.0257)	0.0564*** (0.0195)	0.0328 (0.0266)
Present bias ( $\beta$ )	0.0197 (0.0173)	0.0109 (0.0096)	0.0268 (0.0233)	0.0120 (0.0106)
Utility curvature ( $\gamma$ )	-0.0957** (0.0460)	-0.0401 (0.0433)	-0.1205** (0.0471)	-0.0325 (0.0368)
Probability sensitivity ( $\alpha$ )	0.0520* (0.0316)	0.0115 (0.0210)	0.0945 (0.0590)	0.0101 (0.0238)
N	159	571	159	571

*Notes:* Table shows Probit and LPM estimates of partial effects from models like those used to produce the estimates in column (2) of Table 4 and column (1) of Table D9, respectively, but extended to include interactions between each preference measure/parameter and an indicator of being located in a treatment site of the insurance experiment conducted in 2011/12. Models include the covariates used for Table 4 column (2) and Table D9 column (1) estimates. All models include indicators of the sample strata. Robust standard errors adjusted for clustering at the municipality level in parentheses. N indicates the size of the respective group, although the full sample is used to estimate each model. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

## **Appendix E Partial associations of preferences with insurance obtained as a program member and as a member's dependent**

A respondent can obtain insurance directly through their own membership of a PhilHealth program (or a private policy) or indirectly through the membership of someone else in their household. Over three fifths of the insured respondents in our sample are direct members of a program. While a respondent's (elicited) preferences need not be irrelevant to becoming insured indirectly as a dependent – insurance may be a household decision, particularly since cover is extended to a member's household – the influence of those preferences would be weakened if the respondent negotiates over whether to insure with a spouse, who possibly holds different preferences. In that case, the associations of the elicited preferences with the acquisition of insurance through direct membership would be stronger than the associations with insurance obtained as a dependent.

To explore this potential heterogeneity, we estimate multinomial probit models of a three-category outcome: i) insured as a member, ii) insured as a dependent, and iii) uninsured. Average partial effects derived from these models are given in Table E1.

As expected, the partial effect of the discount factor on the probability of being insured as a member is greater than the effect on the probability of being insured as a dependent, although the difference appears to arise from a much larger effect of extreme negative time preference on direct insurance as a member. The parameter  $\beta$  has a positive partial effect only on the probability of being insured as a member, indicating that this probability increases with decreasing present bias, although not significantly. This parameter has a puzzling nonlinear relationship only with the probability of insurance as a dependent. The effect of present bias is more in line with expectations when attention is confined to direct insurance as a member and to respondents who have greater insurance literacy and knowledge (see Table 5).

The point estimate of the partial effect of extreme risk seeking is larger on the probability of direct insurance. Without controlling for this, utility curvature is estimated to have a stronger negative effect on the probability of insurance as a member. Both types of probability weighting are more strongly associated with the probability of being insured as a dependent, which may cast doubt on the extent to which these associations do reflect effects of probability weighting on the decision to insure.

Table E1. Partial effects of preference measures and parameters on probability of being uninsured, insured as a program member, and insured as a member's dependent

	Uninsured	Insured as	
	(1)	member (2)	dependent (3)
<i>A. Non-parametric</i>			
Time preference $\left(\frac{x_0 + z_{1/2}}{2}\right)/1000$	-0.2293 (0.1743)	0.2104 (0.1288)	0.0189 (0.1257)
Non-stationarity $(x_0 - z_{1/2})/1000$	0.0631 (0.1803)	0.0482 (0.1688)	-0.1112 (0.1374)
Risk tolerance $\left(\frac{x + z}{2}\right)/1000$	0.0025 (0.1696)	0.0375 (0.1232)	-0.0401 (0.1137)
Prob. weighting $(x - z)/1000$	-0.0359 (0.1217)	-0.0012 (0.1012)	0.0371 (0.0853)
N	631	108	68
<i>B. Parameters</i>			
Discount factor ( $\delta$ )	-0.0433** (0.0172)	0.0294** (0.0125)	0.0139 (0.0131)
Present bias ( $\beta$ )	-0.0146* (0.0085)	0.0107 (0.0070)	0.0039 (0.0072)
Utility curvature ( $\gamma$ )	0.0345 (0.0385)	-0.0334 (0.0265)	-0.0011 (0.0262)
Probability sensitivity ( $\alpha$ )	-0.0268 (0.0192)	0.0163 (0.0157)	0.0105 (0.0137)
N	574	97	59

*Notes:* Table gives average partial effects from multinomial logit models of being i) uninsured, ii) insured as a program member, and iii) insured as a dependent of a program member. Effects on the three probabilities sum to zero. Covariate specification as for Table 4 column (2). Strata indicators are not included because doing so resulted in a highly singular covariance matrix for the panel A model that is likely due to small cell sizes. Robust standard errors adjusted for clustering at the municipality level in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Erasmus University Rotterdam**

**Erasmus Centre for Health Economics Rotterdam**

Burgemeester Oudlaan 50

3062 PA Rotterdam, The Netherlands

T +31 10 408 8555

E [escher@eur.nl](mailto:escher@eur.nl)

W [www.eur.nl/escher](http://www.eur.nl/escher)