BELIEFS, PREFERENCES AND HEALTH INSURANCE BEHAVIOR

ISBN: 9789036105118

Cover illustration: Alex Krottje

This book is no. 714 of the Tinbergen Institute Research Series, established through cooperation between Rozenberg Publishers and the Tinbergen Institute. A list of books which already appeared in the series can be found in the back.

Beliefs, Preferences and Health Insurance Behavior

Verwachtingen, voorkeuren en gedrag in relatie tot een zorgverzekering

Proefschrift

ter verkrijging van de graad van doctor aan de
Erasmus Universiteit Rotterdam
op gezag van de
rector magnificus

Prof. dr. H.A.P. Pols

en volgens besluit van het College voor Promoties.

De openbare verdediging zal plaatsvinden op
donderdag 26 april 2018 om 11:30 uur

door
Kim Joanne van Wilgenburg
geboren te Heemstede

Erasmus University Rotterdam

Promotiecommissie

Promotoren:	Prof. dr. O.A. O'Donnell
	Prof. dr. A. Baillon
Overige leden:	Prof. dr. E.K.A. van Doorslaer
	Dr. D. Wiesen
	Dr. A.E. Attema

Contents

Chapter 1 Introduction 1

Chapter 2 Do (non-standard) risk and time preferences explain health insurance enrollment? 7

2.1 Introduction 8

2.2 Characterization of preferences 11

2.2.1 Risk preferences 12

2.2.2 Time preferences 13

2.3 Health insurance in the Philippines 14

2.4 Data 15

2.4.1 Sample design 15

2.4.2 Sample characteristics 16

2.5 Preference elicitation 18

2.5.1 Risk preferences 18

2.5.2 Time preferences 21

2.6 Results 22

2.6.1 Raw data 22

2.6.2 Bivariate analyses of association between insurance and preferences 24

2.6.3 Multivariate analyses of the association between insurance and preferences .26

2.7 Conclusion 31

Appendices Chapter 2 35

Chapter 3 A behavioral decomposition of the willingness to pay for health insurance 53

3.1 Introduction 54

3.2 Decomposition of willingness to pay 57

3.3 Health insurance in the Philippines 61

3.4 Data and method 62

3.4.1 Sample design 62
3.4.2 Elicitation of beliefs about future medical expenditure 63
3.4.3 Estimation of perceived fair price 64
3.4.4 Estimation of fair price...65
3.4.5 Elicitation and specification of risk preference..66
3.4.6 Elicitation of willingness to pay..67
3.4.7 Sample characteristics 68
3.5 Elicited beliefs and subjective distributions of medical expenditures 69
3.5.1 Raw belief data...70
3.5.2 Estimates of subjective distributions..71
3.5.3 Correlates of moments of subjective distributions..72
3.6 Willingness to pay for insurance and its decomposition 77
3.6.1 WTP for insurance 77
3.6.2 Decomposition of WTP...77
3.7 Conclusion 81
Appendices Chapter 3 85
Chapter 4 Long-term effects of temporary inducements: A nationwide randomized health insurance experiment in the Philippines 93
4.1 Introduction...94
4.2 Study setting..97
4.3 Research design 99
4.3.1 Sampling 99
4.3.2 Interventions...100
4.3.3 Statistical power 102
4.3.4 Follow-up sample..102
4.3.5 Outcomes 102

4.4 Empirical strategy 103
4.5 Results 107
4.5.1 Short-term effects 107
4.5.2 Long-term effects 108
4.6 Conclusion 110
Appendices Chapter 4 112
Chapter 5 Debiasing expectations 115
5.1 Introduction 116
5.2 A simple model of reported probabilities 118
5.3 Method 120
5.3.1 Elicitation of probabilities 120
5.3.2 Sample 122
5.3.3 Analysis 123
5.4 Results 125
5.4.1 Raw data 125
5.4.2 Fitting data 129
5.4.3 Individual-specific estimates of subadditvity and beliefs 130
5.4.4 Predicting behavior 133
5.5 Conclusion 135
Appendices Chapter 5 137
Chapter 6 Conclusion 143
References 149
Summary 161
Acknowledgements 163
About the author 167

Chapter 1 Introduction

Beliefs, preferences and constraints are the three fundamental determinants of decision making. Empirical economics has generally tried to explain behavior by collecting data on constraints and decision outcomes, and then analyzing these within the structure of a model that makes assumptions about beliefs and preferences. For a long time, economists were skeptical of attempts to collect data on beliefs and preferences. The costs of avoiding elicitation of these inherently subjective concepts are twofold. First, heavy reliance on assumptions that, at best, provide only a very crude approximation to the beliefs and motivations of many humans. Second, variation in behavior that is attributable to heterogeneity in beliefs and preferences is left unexplained. Growing recognition of these costs has convinced at least some economists that there is much to be gained from eliciting beliefs and preferences (DellaVigna, 2009; Manski 2004). In the last few decades, it has become much more common to collect data on beliefs and preferences in the context of surveys conducted in the field, and not only in the environment of lab experiments. Doing so throws up research challenges concerning the design of survey instruments that can deliver valid data that represent true beliefs and preferences.

This thesis contributes to the burgeoning research concerned with the elicitation and analysis of survey data on beliefs and preferences. It makes a few methodological contributions to elicitation methods for both beliefs and preferences. Most important among these is the introduction of a new survey method that corrects a common bias in reported probabilities (chapter 5). However, the main contribution of the thesis is to demonstrate the insight into economic behavior that can be gained through the elicitation of beliefs and preferences. Specifically, a unique collection of data on beliefs about households' future spending on healthcare, alongside risk attitudes and time preferences, which was done purposefully for this thesis in the context of a nationwide survey in the Philippines, is used to explain a paradoxical, and yet common, phenomenon in low- and middle-income countries: low take-up of health insurance despite households facing substantial (objective) medical expenditure risk. One chapter (4) of the thesis does not use data on elicited beliefs and preferences. But it still examines the substantive issue of health insurance enrollment through a behavioral lens. It uses a nationwide, randomized field experiment in the Philippines to identify whether temporary inducements to insure continue to have an effect even after they have been withdrawn.

In this chapter, I will first motivate interest in the topic of health insurance enrollment. Then, I will briefly outline the behavioral economics approach I take to this issue before introducing each chapter and explaining how they are related.

In low- and middle-income countries (LMIC), where health insurance is often lacking, populations are at risk of facing medical expenses that can exhaust or even exceed their income (WHO, 2010; Wagstaff et al. 2017). Treating sickness might require selling productive assets or accumulating debt. If such coping strategies are not available, healthcare will have to be forgone and health will further deteriorate. Either way, the long-term consequences for welfare can be grave.

Attempts to provide affordable voluntary health insurance to those not covered through either mandatory employment-based insurance or means-tested fully subsidized insurance has usually been unsuccessful due to low take-up (Acharya et al. 2013; Bredenkamp et al. 2015; Pettigrew & Mathauer 2016). This is inconsistent with estimates of large potential demand for, and gains from, health insurance (Limwattananon et al 2015; Pauly et al. 2009). In chapters 2-4, I examine the extent to which insights from behavioral economics can explain this discrepancy.

Estimates of the potential demand for insurance are typically based on normative models built on the neoclassical paradigm, including human rationality. This assumes people are risk averse expected utility maximizers who base their perceptions of risk on the level and variability of medical expenses observed in a sample of similar individuals. Besides this, it assumes they process and use all available information in making their decisions. Evidence from studies in psychology and behavioral economics raises serious questions about these assumptions (Manski 2004). Behavioral economics posits that people deviate from the rational ideal assumed in the standard model in three respects: non-standard preferences, non-standard beliefs and non-standard decision making (DellaVigna, 2009). I collect data that allow the role of the first two of these in explaining health insurance (and stockholding) behavior to be examined.

Preferences in relation to both risk and time are relevant to the decision to insure. In each domain, preferences can be non-standard. The standard assumption about time preferences is that they are consistent. If a smaller-immediate reward is preferred over a larger-later reward, then the ordering will be preserved when both rewards are equally delayed. In fact, evidence shows that the preferences tend to be reversed when the rewards are pushed back equally (Halevy 2015). Present bias induces this time inconsistency. Both standard exponential discounting and present bias are expected to reduce the demand for health insurance that requires paying an upfront premium to protect against the risk of future medical expenses after the passing of a period during which the newly insured is not permitted to make a claim.

The standard assumption about risk preferences is that people maximize expected utility (EU). That is, utility is a function of final wealth and is weighted linearly by the probability of each potential wealth outcome. In contrast, Prospect Theory (PT) assumes that utility is defined over changes in wealth with respect to a reference point. The same person can be risk averse with respect to gains in wealth but risk seeking over losses (Kahneman and Tversky 1979; Tversky and Kahneman 1992). PT also deviates from EU by assuming that the utility of each prospect is weighted non-linearly by the probability that it occurs (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). Both risk seeking in the domain of losses and nonlinear weighting of probabilities potentially contribute to low demand for insurance.

For this thesis, I elicited non-standard preferences related to risk and time, and used them to explain enrollment in (chapter 2) and (for risk preferences) the valuation of (chapter 3) health insurance in the Philippines. The elicitation was done by designing and fielding modules that required respondents of a nationwide, representative household survey to make hypothetical choices between lotteries and time-contingent payments. This contrasts with much of the existing evidence on these preferences in developing countries that is obtained from samples of students, farmers or households in small communities interviewed in an experimental context with ample time for delivery of instructions and completion of the task (e.g. Vieider et al. 2015a). It required the design of tasks that were sufficiently rich to identify the non-standard preference parameters, and yet were also feasible for mostly low-educated respondents to complete within a short response time.

Chapter 2 uses the elicited (non-standard) risk and time preferences to explain health insurance enrollment in the Philippines. Individuals who discount future returns more aggressively are less likely to enroll. Insurance take-up is only related to present bias among individuals with some knowledge of how health insurance operates. Consistent with PT, the majority of respondents are risk seeking for losses. Those who exhibit more risk seeking in the loss domain are more likely to insure. This is counterintuitive, although it is consistent with evidence on risk preferences and demand for other forms of insurance. Respondents who overweight moderate and large probability losses are more likely to purchase health insurance, which is consistent with the relatively high average probability of medical expenditure in our sample.

Beliefs are fundamental to economic decisions, not least those concerning insurance. An individual deciding whether or not to insure must consider the extent to which they are exposed to risk of medical expenses without insurance, and form beliefs about the degree to which insurance will cover this risk. The standard model assumes that this is done rationally using all available information. Even if an analyst follows this approach, elicited beliefs about future spending are useful since they potentially incorporate private information about own health that would not be available to an econometrician predicting an individual's future medical expenditure on the basis of observable characteristics that will not fully capture health issues known to the individual. Beyond that, subjective beliefs can reflect proneness to optimism or pessimism that potentially affects the decision to purchase health insurance. A large body of evidence shows that, on average, people are optimistic, leading to irrational expectations (Sharot, 2011; Tversky and Kahneman, 1974; Weinstein, 1980).

I designed a visual aid to elicit beliefs about medical expenditures and used this to derive a household-specific subjective distribution of those expenditures without asking the respondent to report probabilities, or even chances, which they may not have had a conceptual understanding of. These distributions provide, along with the elicited risk preferences, the information basis for a new behavioral decomposition of the willingness to pay (WTP) for insurance that is introduced in chapter 3. WTP is decomposed into its fair price and four behavioral deviations from that price that arise from subjective beliefs about the distribution of medical expenses, the two dimensions of risk attitudes consistent with prospect theory (utility curvature and probability weighting) and a residual term representing determinants not captured by the behavioral model. The purpose of this decomposition is to gain further insight into the low valuation, and so low take up, of health insurance. Findings show low WTP is not explained by downwardly biased expectations of medical expenditures. Both convex utility in the domain of losses and the transformation of probabilities into decision weights push the WTP below the fair price, reducing the demand for insurance. WTP is further reduced by other factors not included in our model. The decomposition could be adopted by other researchers aiming to understand the demand for insurance products.

As mentioned above, understanding of preferences and beliefs regarding medical expenditure risk can be used to (better) design policy interventions that aim to raise health insurance take up. Increasingly, randomized field experiments are being conducted to test the effectiveness of inducements to enroll. There is some evidence of a positive immediate effect (Asuming et al 2017; Capuno et al., 2016; Chemin 2018; Thornton et al 2010). But this may be insufficient to establish cost-effectiveness if the effects last only as long as the interventions are offered. In Chapter 4, I use a randomized experiment to establish whether a one-off premium subsidy of up to 50% and another intervention that reduced the indirect costs of enrollment by providing one-time assistance with the insurance application had sustained effects on enrollment up to four years after the inducements were withdrawn. Although the second intervention had the stronger impact in the short term, only the effect of the premium subsidy was maintained in the long run. This shows that the short-term effects of interventions may not be indicative of their long-term impacts.

Elicitation of preferences and beliefs often involves respondents undertaking tasks that requires them to make decisions. If they do so using heuristics (Tversky and Kahneman 1974), then the design of the task could affect the results. Careful thought needs to be given to how to elicit preferences and beliefs, and how to interpret the data obtained. A common bias in the reporting of probabilities is subadditivity: the reported probability of the union of two disjoint events is smaller than the sum of the reported probabilities of those events (Fischhoff et al. 1978; Tversky and Kahneman 1983; Johnson et al. 1993; Tversky and Koehler 1994; Tversky and Fox 1995). Chapter 5 introduces a new method that can easily be used in survey research to correct this common bias. The method is simple. It requires the addition of only one question to the standard module used to elicit subjective probabilities. Using it avoids the common practice of dropping a substantial fraction of respondents who display the bias, so preserving sample power and representativeness. An application demonstrates that reported probabilities of stock market returns that are purged of subadditivity explain stockholding better than the biased reported probabilities. This chapter makes a methodological contribution to survey research.

The roadmap of the thesis is as follows. Chapter 2 explains the methods of eliciting risk and time preference parameters before using these explain health insurance enrollment. Chapter 3 introduces the new behavioral decomposition of WTP for insurance and uses this to explain the valuation of health insurance in the Philippines based on the elicited data on households' subjective distributions of medical expenditures. Chapter 4 presents the evaluation of the long-term impact of temporary inducements for health insurance in the Philippines. Chapter 5 introduces the new method of identifying and purging subadditivity bias in reported probabilities and applies it using data from a purposefully collected survey of the stock holding behavior of Erasmus School of Economics alumni. Finally, chapter 6 concludes with potential implications of the findings of this thesis and suggested avenues for future research.

Chapter 2

Do (non-standard) risk and time preferences explain health insurance enrollment?

Joint work with Baillon, A., O'Donnell, O. and Quimbo, S.

2.1 Introduction

Voluntary health insurance enrollment is typically low in developing countries (Acharya et al. 2013; Bredenkamp et al. 2015; Pettigrew and Mathauer 2016). Premium subsidies, information on insurance and assistance with enrollment often have only limited, if any, effects on take-up (Capuno et al., 2016; Chemin 2018; Das and Leino 2011; Thornton et al 2010; Wagstaff et al. 2016).[1] Take-up of highly subsidized health insurance available to low-income households in the US has also been remarkably low (Bundorf and Pauly 2005; Chernew et al 1997; Currie and Gruber 1996; Levy and DeLiere 2008). Given widespread exposure to risks of substantial out-of-pocket medical expenses in low-income populations, the lack of demand for insurance appears inconsistent with standard economic theory.

Insurance demand is usually analyzed using a single-period expected utility (EU) model under the assumption that people are risk averse, typically characterized by a concave utility function defined over final wealth. With this set up, low take-up of health insurance is puzzling (Baicker et al 2008). Even stranger is evidence that *more* risk averse individuals are *less* likely to purchase insurance for medical expenses (Dercon et al 2015) and other risks (Cole et al., 2013; Giesbert et al., 2011; Giné et al., 2008) in low-income settings. To explain this inconsistency with the standard model of insurance, recent papers have argued that insurance itself is a risky product for individuals who lack experience of it and trust in it (Chemin 2018; Cole et al 2013; Dercon et al 2015). In these circumstances, the risk averse will be leery of insurance. Instead of assuming individuals perceive a fundamentally different product that exacerbates rather than ameliorates uncertainty, this chapter considers whether the low take-up of health insurance can be explained by suitably specified preferences related to risk and time. First, concavity of utility over final wealth may be an inadequate characterization of the risk preferences that govern the insurance decision. More pertinent may be preferences in the domain of losses and nonlinear weighting of the probabilities of losses. Second, health insurance involves a trade-off between paying a premium now and possibly receiving benefits in the future. Yet, the role of time preferences in the uptake of health insurance is underexplored. This may miss an important dimension

[1] There is some experiment-based evidence of strong impacts of insurance inducements on enrollment. Large premium subsidies of at least 30 percent have been found to raise enrollment substantially in Ghana (Asuming et al 2017), Kenya (Chemin 2018) and Nicaragua (Thornton et al 2010). More modest subsidies of 10-20 percent had proportionately marked impacts in another study in Kenya (Dercon et al 2015). Information on the operation and benefits of insurance raised take-up to a lesser extent in Ghana (Asuming et al 2017) and Nicaragua (Thornton 2010).

of the decision problem for households on the margins of dire poverty that are focused on making ends meet from day to day (Schilbach et al 2016).

The study presented in this chapter elicits (non-standard) preferences concerning both risk and time and examines their associations with voluntary health insurance enrollment in the Philippines. Growing literatures use elicited risk and time preferences to explain persistent poverty in low- and middle-income countries (LMIC) (Binswanger, 1980; Cardenas and Carpenter, 2008 and 2013; Tanaka et al, 2010; Vieider et al., 2015b) and unhealthy behavior in high-income countries (Anderson and Mellor 2008; Barsky et al. 1997; Cutler and Glaeser, 2005; Fuchs, 1982; Khawaja et al, 2007; Komlos et al, 2004; Sutter et al., 2013). To the best of our knowledge, there has been no empirical examination of the roles played by *both* risk and time preferences in explaining the low demand for health insurance in low- and middle-income, or indeed in high-income, countries. We elicit four dimensions of risk and time preferences that go beyond utility curvature and standard constant discounting.

Prospect theory (PT) is known to provide the best description of decision making under risk (Barberis 2013; Kahneman and Tversky 1979; Tversky and Kahneman, 1992). It characterizes risk attitudes by three non-standard features. First, utility is not defined over final wealth but with respect to deviations from a reference point, with losses looming larger than gains. Second, if utility is concave for gains, implying risk aversion in that range, it can be convex for losses, implying risk seeking in that domain. Third, probabilities are transformed by a weighting function that captures limited discrimination between likelihood levels (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). Application of PT to the explanation of behavior outside of the laboratory is not straightforward. The theory's predictions have been tested in the field only recently (Barberis, 2013; Schmidt, 2016; Tanaka et al, 2010). The few studies applying PT to insurance find that probability weighting plays a role in home and automobile insurance decisions in the US (Barseghyan et al., 2013; Sydnor, 2010). We investigate whether this finding holds with respect to the demand for health insurance in a middle-income country.

Evidence from low-income settings that insurance demand is low among predominantly risk averse individuals (Chemin 2018) and that demand is decreasing with risk aversion (Cole et al 2013; Dercon et al 2015; Giesbert et al., 2011; Giné et al., 2008) is based on preferences elicited through Holt and Laury (2002) lotteries with positive payoffs.[2] This delivers risk attitudes in the domain of gains, which may be less relevant to the insurance decision than risk preferences over losses. At least some low income individuals with little or no experience of insurance appear to perceive it as a risky proposition (Chemin 2018). If they do not fall sick, then they get nothing back for the money spent on insurance. If they do get sick, then they may be unsure whether the insurance will deliver on the promise to cover their medical expenses. Their choice is between a certain loss (the premium) with an uncertain benefit (reimbursed medical expenses) and an uncertain loss (uninsured medical expenses). Consistent with this perspective, we elicit risk preferences in the domain of losses.

To examine the role of time preferences, we elicit the parameters of a quasi-hyperbolic discounting model, which has been repeatedly shown to describe behavior better than constant exponential discounting (Anderson et al. 2008; Burks et al., 2012; Dupas 2011; Frederick et al., 2002; Laibson, 1997; Wang et al., 2016). This model allows for present bias: preference for a smaller-immediate reward over a larger-later reward is reversed when both rewards are equally delayed (Halevy 2015). This trait motivates the design of commitment devices, which have been demonstrated to encourage savings, investment and healthy behavior in developing countries (Ashraf et al., 2006; Brune et al., 2016; Duflo et al., 2011; Giné et al., 2010). Its relevance in such settings plausibly derives from the cognitive load of coping with life on the breadline, which can result in dominance of intuitive, reactive and error-prone decision making over deliberative, consistent and unbiased decision making (Mullainathan and Shafir 2014; Schilbach et al 2016). If present bias is an important influence on health insurance decisions, then offering the possibility to commit to enrollment at a later date could be successful in raising take-up.

We elicit risk and time preferences in a large, nationwide household survey in the Philippines. This contrasts with much of the existing evidence on these preferences in developing countries that is obtained from samples of students, farmers or households in small communities interviewed in an experimental context with ample time for delivery of instructions and completion of the task (e.g. Vieider et al. 2015a). We design and implement

[2] Dercon et al (2015) elicit preferences from choices between lotteries in the loss, as well as the gain, domain. Inconsistent with the findings of many experiments, they find risk aversion in the loss domain. In fact, the point estimates suggest greater risk aversion in the loss domain, although the difference is not significant. The paper shows a positive association between insurance enrollment and risk aversion in the gain domain.

a method that aims to identify sophisticated preference parameters and yet be comprehensible for less educated respondents in a survey conducted with limited time and budget.

We find a positive association between insurance enrollment and the constant discount factor, indicating that those who choose not to purchase insurance discount the future more. While the analysis does not support causal inference, this is at least consistent with aggressive discounting of benefits that are enjoyed, if at all, at some time in the future being one reason many Filipinos do not take out health insurance. In the full sample, there is no evidence that enrollment is significantly related to the degree of present bias. In fact, the majority of respondents do not display present bias. However, when attention is restricted to respondents with some knowledge of how health insurance operates, there is clear evidence that those with more present biased preferences are less likely to take out insurance.

In line with PT, we find that respondents generally exhibit risk seeking behavior for losses, which is represented by strong convex curvature of the utility function in that domain. Respondents who are more risk seeking with respect to losses, along with those who overweight moderate and large probabilities, are more likely to purchase health insurance. However, after controlling for socio-economic factors, there is no significant association between risk preference parameters and insurance enrollment.

Section 2.2 defines the risk and time preference parameters we elicit. Section 2.3 provides background on health insurance in the Philippines. Section 2.4 describes the survey data and our sample. Section 2.5 outlines the preference elicitation method. Section 2.6 presents the results on the associations between preferences and insurance enrollment. Section 2.7 discusses the findings and relates them to the literature.

2.2 Characterization of preferences

We consider the preferences of an individual facing risky or delayed *outcomes*, which are real numbers denoted x, y or z. Let $x_p y$ denote a *prospect* yielding x with probability p and y otherwise. We denote x_t for an *outcome obtained at time* $t \geq 0$ ($t = 0$ indicates the present).

2.2.1 Risk preferences

In PT, risk attitudes are represented through an S-shaped *utility function* $u(x)$ and a probability *weighting function* $w(p)$ (Kahneman and Tversky 1979; Tversky and Kahneman, 1992). The utility function is concave for gains but convex for losses, capturing diminishing sensitivity to both gains and losses. It is steeper for losses than for gains, capturing loss aversion (Tversky and Kahneman, 1992). The weighting function maps cumulative probabilities into decision weights. It is increasing, and satisfies $w(0) = 0$ and $w(1) = 1$. Under PT, the status quo is typically taken as the reference point (Sydnor 2010; Wakker et al., 1997). In an insurance setting, this is initial wealth –the state in which medical expenses are not incurred. We are then only concerned with utility in the loss domain because the choice is between a small certain loss (the insurance premium) and a larger uncertain loss (medical expenses). The loss prospects are valued as:

$$PT\left(x_p y\right) = w(p)u(x) + \left(1 - w(p)\right)u(y), \tag{2.1}$$

where $x \leq y \leq 0$.

To make preference elicitation tractable, we select the one-parameter functional forms for u and w that have been demonstrated to perform best among (combinations of) the most popular specifications (Scott 2006). For utility, we use a power function

$$u(x) = -(-x)^r, \tag{2.2}$$

where r indicates the curvature of the value function for losses. Utility is convex if $r \leq 1$. Loss aversion is omitted because it can be determined only in the presence of both gains and losses, and we are concerned only with the latter.

We use the one-parameter form of the probability weighting function introduced by Prelec (1998),

$$w(p) = \exp(-(-\ln p\,)^{\alpha}), \tag{2.3}$$

Where α captures likelihood insensitivity. If $\alpha < 1$, the weighting function has an inverse S-shape, overweighting small probabilities and underweighting large probabilities. If $\alpha > 1$, the weighting function has an S-shape overweighting moderate and large probabilities and underweighting small probabilities (Tversky and Kahneman, 1992). With $\alpha = 1$ the probability weighting function is linear and the model reduces to Expected Utility (EU).

Prospect theory predicts convex utility curvature for losses, generally resulting in risk seeking behavior. Within this framework, the weighting of probabilities can explain the demand for insurance in addition to utility curvature. In the literature, inverse-S weighting ($\alpha < 1$) is typically associated with a high demand for insurance (Wakker 2010). Indeed, in the case of a binary outcome with a small probability of a loss (typically below 1/3) and no expenditure otherwise, take-up of insurance can be explained by overweighting the small probability. The prediction is reversed if the probability of the loss is moderate or high, which is the case for the chance of incurring any medical expenditures. In our sample, about 80% incur medical expenditures in a year (see Chapter 3 for more details). With such a risk, overweighting large probabilities of losses ($\alpha > 1$) would increase the demand for health insurance, whereas underweighting them ($\alpha < 1$) would decrease the demand. However, this is a crude prediction because medical expenditure risks are not binary and perceptions of the risks may deviate from the objective probabilities. In Chapter 3, I will explore how probability weighting interacts with beliefs about the distribution of medical expenditures and utility to influence the valuation of health insurance at the individual level. For a given weighting function, less convex utility (expressed by a larger value of r) indicates less risk seeking and would be expected to increase the likelihood of taking up health insurance.

2.2.2 Time preferences

We consider time preferences in the gain domain because pretesting indicated this decreased the cognitive burden on respondents. Normative economic theories prescribe no differences in discount factors for gains and losses. However, gains are generally discounted more than losses (Benzion et al., 1989; Thaler, 1981; Yates and Watts, 1975). Caution should therefore be exercised in interpreting absolute values of the discount factor. Since we are interested in the relative difference in discount factors between people with and without health insurance, this should be less of a concern.

We model time preferences using the *quasi-hyperbolic* (QH) discounting model (Laibson, 1997), defined as:

$$QHD(x_t) = \begin{cases} u(x) & \text{if} \quad t = 0 \\ \beta \cdot \delta^t u(x) & \text{if} \quad t > 0 \end{cases} \tag{2.4}$$

with $x \geq 0$. The parameter δ ($0 < \delta < 1$) captures conventional time discounting with a smaller value indicating greater discounting of the future. The parameter $\beta < 1$ captures preferences for the present relative to all future periods. When offered a choice between monetary amounts in the present or in the future, the discount factor is $\beta\delta^t$. When offered a choice between prospects at different dates in the future, the impact of β cancels out and the discount factor is δ^t. If $\beta = 1$, then there is no present bias and discounting is exponential.

Both greater discounting of the future (smaller δ) and more present bias (smaller β) could reduce the likelihood of purchasing health insurance. Insurance involves transferring resources from the present to (some possible) future states. Decreases in both parameters increase the weight on the present and decrease that on the future.

2.3 Health insurance in the Philippines

The Philippines National Health Insurance Program (NHIP) initially (1995) covered civil servants and required that formal sector salaried workers enroll (Bredenkamp and Buisman, 2016; Capuno et al., 2016). Soon after its creation, an indigent program was launched to provide fully subsidized health insurance for the poor. This program was extended to provide the near-poor with fully subsidized cover in 2014, the year before our data were collected (2013 Amendment to the National Health Insurance Act of 1995 (RA 10606)). Since January 2015, all senior citizens (>= 60 years) are covered through a fully tax-financed program (PHIC 2014). Those not covered through these program nor some others that provide fully subsidized insurance to certain groups can insure through the NHIP voluntarily. We seek to explain voluntary enrollment among those not eligible for cover through some other NHIP program. The premium for voluntary enrollment cover is PHP 2,400 per year ($50) for those with an average monthly individual income up to PHP 25,000 ($540). At higher incomes, the annual premium is PHP 3,600. Coverage through all programs extends automatically to the legal spouse, children (<21 years old) and parents (>= 65 years) of the person qualifying or paying the premium for voluntary enrollment.

As of 2014, NHIP programs covered 86 million beneficiaries, which is around 85 percent of the population, according to the national insurance agency's database (PHIC 2014). However, survey estimates based on the number of respondents reporting they are covered put population coverage at only 61 percent (Bredenkamp and Buisman, 2016). These estimates reveal that coverage is lowest in the middle of the income distribution. That is, among informal workers and the self-employed who do not get mandatory cover through employment and are insufficiently poor to qualify for fully subsidized cover. Voluntarily enrolled members from these groups account for only about 10 percent of all those covered by NHIP programs, which is very little considering they account for more than 50 percent of the labor force (Bredenkamp and Buisman, 2016; Manasan, 2011).

2.4 Data

2.4.1 Sample design

Data on risk and time preferences were collected in a nationwide survey of Filipino households conducted in July-August 2015. The survey was a follow-up of a baseline carried out in 2011 in the context of a randomized experiment to evaluate the effectiveness of interventions designed to raise insurance enrollment (Capuno et al., 2016). The baseline survey used multi-stage cluster sampling to randomly select 2,950 households that were nationally representative (excluding the Autonomous Region of Muslim Mindanao).[3]

The follow-up survey aimed to include all households from the baseline that were not covered by the NHIP at baseline, plus those that had cover either through the fully subsidized program for the poor or by voluntary enrollment. Follow-up interviews were conducted with 1513 households in these groups. The attrition rate was about 24 percent (Bredenkamp et al 2017)[4]. The remainder of the follow-up sample consists of a random sample of 267 households with NHIP cover at baseline through formal sector employment or via programs for overseas workers and retired formal sector workers. These households were included in order to obtain a nationally representative sample (after application of weights) that could be used in analysis of smoking behavior, which was one purpose of the follow-up survey. In order to reach the target sample size, any selected household that could not be traced or interviewed was replaced with another random draw from the initially mandatorily insured households.[5]

[3] See Chapter 4 and Capuno et al. (2016) for a detailed description of the sampling method.

[4] Maintaining a nationally representative sample is not critical to the validity of our analysis. Nonetheless, Appendix Table A2.1 presents balancing tests. There are some differences between households that were interviewed at follow-up and those that were not. In particular, households lost to follow-up were more likely to be urban, located in the capital region, richer, better educated and have fewer children. Generally, these are characteristics of more mobile households.

[5] There are only a few significant differences between the sample of households from this group that was interviewed at follow-up and those that were not. Those not followed-up were less likely to be located in an urban setting and the capital region.

2.4.2 Sample characteristics

For each of the 1780 households interviewed at follow-up, we define its insurance status according to the cover of the respondent from whom we elicited the risk and time preferences[6]. Our analysis of the association between preferences and insurance cover is restricted to 774 households that either had voluntarily purchased health insurance (n=172) or were without health insurance (n=602). Out of the 172 with voluntary insurance, 151 were enrolled in the NHIP, 17 obtained cover through a private insurance plan and 4 reported both types of insurance. The remaining 1006 households that are not used in the analysis report having mandatory cover, fully subsidized cover or not knowing if they are covered.

Enumerators were instructed to interview the person who was the original household respondent in the baseline survey or, if that person was unavailable, their spouse. In the baseline survey, the enumerator was instructed to interview the head of the household or spouse if the head was unavailable. Only if it was impossible to interview either of them was another household member above 21 years old interviewed. The majority of respondents are either the household head (277/774) or the spouse of the head (400/774). Table 2.1 reports means of covariates for the analytical sample separately by voluntary insurance cover. The majority of respondents are married and female. Households are roughly evenly divided between urban and rural locations, with a higher share of urban among the insured (not significant). A little less than a quarter of respondents have at least some college education, and the proportion is higher among the insured. The education distribution in the sample is in line with national figures, although the sample does have a slightly higher proportion of respondents that completed high school (PSA, 2015).

Out-of-pocket (OOP) medical expenditure does not differ significantly between the insured and uninsured[7]. This may seem surprising. It could be that the coverage of medical expenses by insurance is offset by higher gross expenses of the insured due to adverse selection. In the whole sample, 34 percent of respondents believe the risk their household will spend more than 8000 pesos out-of-pocket on healthcare in the next year is smaller than the risk of similar households spending that above that amount. The fraction that puts their

---

[6] Any cases in which the respondent was not involved in the decision to obtain their insurance cover will add noise to the analysis.

[7] Neither does income. This is not shown. We do not include income in our regressions because of the large number of missing variables. As a robustness check we run all regressions with a control for income in a smaller sample. This makes no difference to our results.

risk above that of similar households is only 19 percent. This suggests that, on average, the respondents are optimistic, and is consistent with a very large body of evidence that documents optimism bias (Weinstein, 1980; Sharot, 2011). Despite their lack of protection, the uninsured are more likely than the insured to report a smaller than average chance of incurring OOP spending of at least 8000 pesos. This is consistent with optimism bias contributing to the decision not to purchase insurance, but it could also be attributable to selection out of insurance on the basis of good health.

Table 2.1 Means of covariates by insurance cover

Variable takes value of 1 (0 otherwise) if:	All	Uninsured	Voluntarily Insured
Demographics (respondent)			
Male	0.284	0.301	0.227
Married	0.725	0.721	0.738
Age	45.46	45.32	45.94
Demographics (household)			
Urban	0.484	0.468	0.541
Number of household members	4.990	4.993	4.977
Number of household members aged <15	1.491	1.528	1.360
Number of household members aged >=65	0.209	0.203	0.233
Socioeconomic status			
Highest attained education of respondent			
No education	0.173	0.185	0.129
Completed elementary school	0.233	0.245	0.193
Completed high school	0.493	0.495	0.485
College graduate +	0.101	**0.075**	**0.193**
Health care, expenditure and insurance			
At least one hospital inpatient stay in past year (household)	0.072	0.073	0.070
Household OOP medical expenditure (OOP) last year			
0 pesos	0.234	0.231	0.244
1-4000 pesos	0.519	0.530	0.483
4001-8000 pesos	0.125	0.126	0.122
> 8000 pesos	0.121	0.113	0.151
Perceive risk of spending > 8000 pesos on healthcare compared with similar household to be:			
smaller (optimistic)	0.341	**0.364**	**0.262**
same (neutral)	0.468	0.457	0.506
larger (pessimistic)	0.191	0.179	0.233
Health insurance literacy (respondent)			
Low	0.304	0.311	0.279
Medium	0.526	0.523	0.535
High	0.171	0.166	0.186
Knowledge of NHIP benefits			
Low	0.296	0.302	0.273
Medium	0.342	0.349	0.320
High	0.362	0.349	0.407
Treatment site of health insurance experiment	0.786	**0.762**	**0.866**
N	774	602	172

Note: Significant differences between insured and uninsured in bold (5%). There are 771 observations with education information in the sample; 600 uninsured and 171 insured. For other variables, sample sizes are as in bottom row. Precise definitions of the variables related to risks of medical spending, health insurance literacy and knowledge of NHIP benefits are given in Appendix table A2.2.

Those with insurance are ten percentage points more likely to be located in randomly selected municipalities where households eligible for the voluntary enrollment program at baseline were offered a premium subsidy of up to 50%, information on the program and, in some cases, assistance with enrollment. Not all of the households in these municipalities at follow-up were offered the inducements at baseline. Some were ineligible for the voluntary enrollment program at that time[8]. Still, the marked difference between voluntarily insured and uninsured households at follow-up in the proportion resident in the original treatment sites suggests that the inducements may have had lasting effects on insurance enrollment. I test this in Chapter 4.

2.5 Preference elicitation

2.5.1 Risk preferences

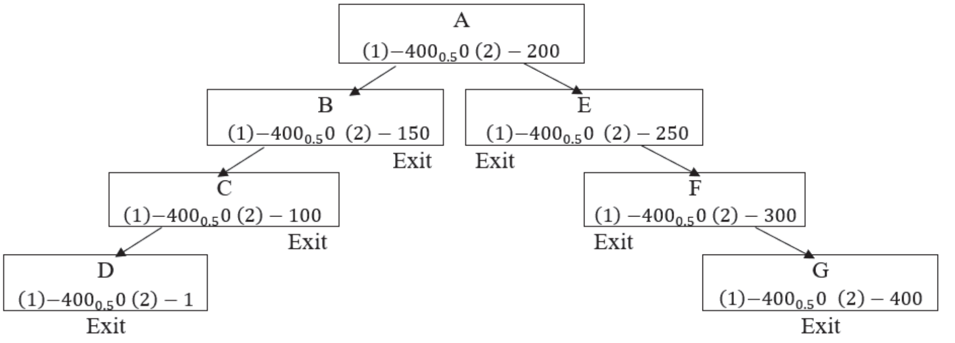
Elicitation of risk preferences is known to produce data containing a large amount of noise (Wakker, 2010; Chuang and Schechter, 2015). Estimation of prospect theory parameters demands some sophistication on the part of respondents (Charness et al., 2013). This poses a challenge in the context of low- and middle-income countries. Visual supports can make the task more feasible, although this is usually done in an experimental context in which there is time for elaborate instructions. We aimed to develop a method that is sufficiently comprehensible to be applicable in a time constrained survey administered to low educated respondents.

To elicit the risk parameters of utility curvature (r) and probability weighting (α), we designed two independent sets of hypothetical lottery choices in the domain of losses summarized in Figure 2.1. The survey respondent of each household was asked to choose between two jars, from which a ball would be drawn randomly. The jar representation avoided making reference in the questions to probabilities, which respondents may not have understood. The exact protocol used and an example of the visual support can be found in appendices A2 and A3 respectively.

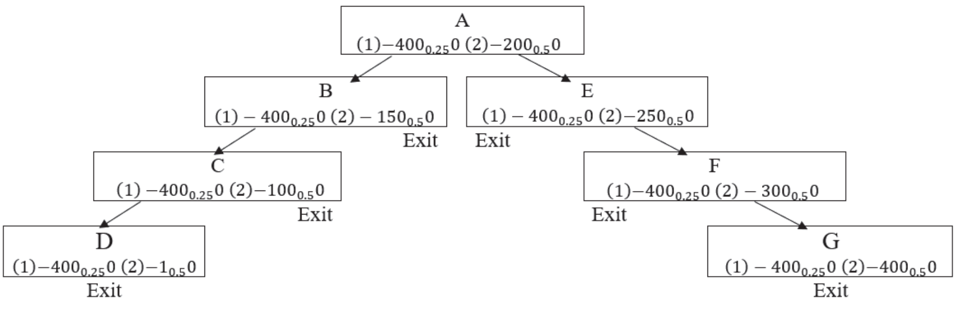
[8] In fact, 50% of those insured through voluntary insurance at follow-up and located in the treatment sites did not receive any health insurance inducements at baseline since they were not considered eligible for the voluntary program at that time.

Figure 2.1 Summary of lottery choices to elicit risk preferences

Lottery 1



Lottery 2



There were two sets of choices, each corresponding to a pair of jars. In the first set, we elicited a loss x that the respondent was indifferent between incurring with certainty and facing a 50% chance of losing 400 pesos.

$$\text{Lottery 1:} \qquad x \sim -400_{0.5}0$$

In the second set, we elicited the loss z such that the respondent was indifferent between facing a 50% chance of incurring that loss and facing a 25% chance of losing 400.

$$\text{Lottery 2:} \qquad z_{0.5}0 \sim -400_{0.25}0$$

Under expected utility, $x = z$. A difference between the two amounts identifies probability weighting.

We started each elicitation process with a choice between two options with the same expected value[9]. Depending on the answer, we then either increased or decreased the expected value of the second option while keeping the first option constant until the respondent switched from one to the other. If there was no switching, then the procedure ended after offering four choices. Figure 2.1 depicts the process.

In the first set of questions, 14 respondents reached question G and did not switch. These respondents make a dominated choice, preferring a loss of 400 pesos for sure over a 50% chance to lose 400 pesos or nothing otherwise. In the second set, more respondents (71) make a dominated choice. This is not surprising since the second set of questions demands more understanding. We exclude respondents who make a dominated choice in either set of questions (76 respondents) from the analysis. In Appendix table A2.7.1, we compare these respondents with those used in the analysis on observable characteristics. Most importantly, the proportion voluntarily insured is similar in the two groups. On most other characteristics they do not differ either. We do not exclude respondents who exhibit what appear to be extreme risk seeking preferences implied by reaching question D and not switching at that point. Around 40 percent of respondents give this sequence of responses in set 1, and 35 percent do so in set 2. Pretesting revealed that respondents making this sequence of choices did appear to understand the task, while this was not true of those who reached question G and did not switch. Those not switching at D explained their choices by an attraction to gambling. While one may doubt that the degree of risk seeking implied by not switching at D is a true reflection of preferences, this does not undermine our purpose. We are interested in the association between risk preferences and insurance uptake, and not in the estimate of the magnitude of utility curvature. However, we do test robustness of the preference-insurance correlation to excluding respondents who do not switch at D.

From the switching point we infer a range of possible values containing the point of indifference between the two options.[10] We chose the midpoint of this range as a respondent's point of indifference. For each combination of points of indifference x and z

[9] The expected value of this choice, 200 pesos, coincides with the monthly premium for those with an average monthly income of no more than PHP 25,000 ($540)

[10] For those who do not switch in Question D we infer a switching point of -0.5.

we can determine the parameters r and α, indicating the curvature of the utility function and probabilistic sensitivity respectively.[11] These are shown in Appendix table A2.7.2.

2.5.2 Time preferences

To elicit time preferences we offered two independent sets of hypothetical choices between monetary amounts to be received at different points in time.[12] The first set of choices is designed to elicit the amount x_0 that if received now ($t = 0$) would leave the respondent indifferent with respect to receiving 200 pesos in half a year from now ($t = 1/2$).

$$\text{Choice 1:} \qquad x_0 \sim 200_{1/2}.$$

The second question elicits the amount y that if received in half a year from now ($t = 1/2$) would leave the respondent indifferent with respect to receiving 200 pesos in one year from now ($t = 1$).

$$\text{Choice 2:} \qquad y_{1/2} \sim 200_1.$$

We use a bisection method depicted in Figure 2.2 to infer a range of possible values containing the points of indifference x_0 and y from the choices at which the respondent switched between options. We use the midpoint of this range as the respondent's point of indifference.[13] Appendix A2.3 contains the exact protocol used.

Having elicited two points of indifference x_0 and y, the parameters β and δ can be determined using the model for quasi-hyperbolic time preferences.[14] It can be done directly if utility is linear ($r = 1$). Appendix table 2.7.3 gives the values for the parameters β and δ for $r = 1$ which we will refer to as β_l and δ_l. Although linear utility is typically assumed when identifying time preferences, utility curvature might have a confounding effect (Anderson et al. 2008; Andreoni et al. 2015). We therefore estimate the parameters over utility as opposed to income assuming the power utility function $u(x_t) = x_t^r$, in, inferring r from the simultaneously elicited data on risk preferences using prospect theory as described in section 2.5.1.

---

[11] The derivations can be found in Appendix A2.5

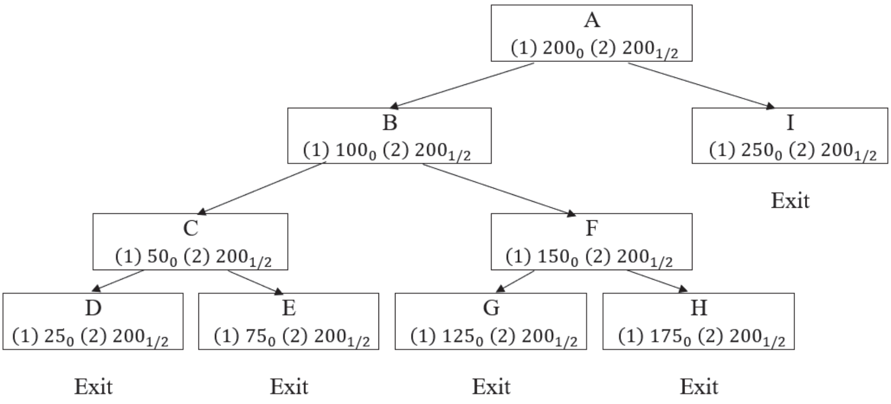
[12] Eliciting time preferences tends to be simpler than that of risk preferences (Chuang and Schechter, 2015) and we therefore didn't include any dominated choices to test for inconsistencies

[13] For respondents that prefer 250 now (in half a year) from 200 in half a year (in a year) we infer a switching point of 275.

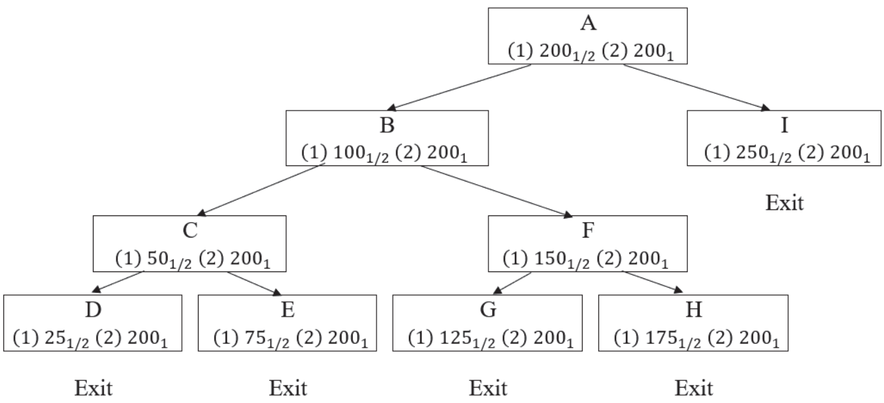
[14] The derivations can be found in Appendix A2.6

Figure 2.2 Summary of the two sets of choices used to elicit time preferences

Choice 1



Choice 2



2.6 Results

2.6.1 Raw data

The median point of indifference is -50 for lottery 1 and -125 for lottery 2. Hence, for both lotteries, a majority prefers a riskier choice indicated by a point of indifference greater than -200. Many respondents choose the same point of indifference for both lotteries (Table 2.2), which implies linear probability weighting. However, on average, the point of indifference is somewhat larger in the first (x) than in the second lottery (z), which indicates non-linear probability weighting. The mean difference between the two lotteries is -22 and statistically significant (p<0.01) while the median difference is 0.

Table 2.2 Frequencies of points of indifference derived from risk questions

	Lottery 2 $z_{0.5}0 \sim -400_{0.25}0$							N
Lottery 1 $x \sim -400_{0.5}0$	-350	-275	-225	-175	-125	-50	-0.5	
-350	1	3	4	2	0	0	1	11
-275	0	3	11	6	5	3	2	30
-225	1	9	49	17	6	4	10	96
-175	1	8	21	22	12	7	5	76
-125	3	5	22	14	32	8	9	93
-50	5	8	15	16	12	39	20	115
-0.5	2	12	20	9	22	18	194	277
N	13	48	142	86	89	79	241	698

	Lottery 1	Lottery 2
Median	-50	-125
Mean	-92.4	-114.5
Standard Deviation	97.2	103.6

Table 2.3 presents the points of indifference from the two choices used to elicit time preferences.

Table 2.3 Frequencies of points of indifference for time preference questions

	Choice 2 $y_{1/2} \sim 200_1$										N
Choice 1 $x_0 \sim 200_{1/2}$	12.5	37.5	62.5	87.5	112.5	137.5	162.5	187.5	225	275	
12.5	174	18	4	13	7	2	1	0	13	6	238
37.5	14	42	4	27	7	4	1	4	6	1	110
62.5	5	4	8	17	3	1	2	1	2	0	43
87.5	5	11	5	57	10	5	5	6	3	3	110
112.5	0	1	0	6	1	0	2	1	1	0	12
137.5	0	1	0	2	2	0	2	1	2	0	10
162.5	0	1	1	1	3	0	2	0	1	0	9
187.5	2	1	1	5	0	1	1	8	1	6	26
225	6	4	1	6	1	1	6	7	25	7	64
275	4	6	1	2	1	3	1	7	13	38	76
N	210	89	25	136	35	17	23	35	67	61	698

	Choice 1	Choice 2
Median	62.5	87.5
Mean	91.4	97.2
Standard Deviation	91.7	87.3

On average, respondents are indifferent between receiving 91 pesos now and 200 pesos in half a year, indicating very high discounting of future rewards. The average respondent is indifferent between 97 pesos to be received in half a year and 200 pesos to be received in one year. The fact that preferences for sooner gratification are only slightly more intense when the earlier period is the present (compare 91 with 97), indicates that, on average, there is only a small degree of present bias, which is, however, significant[15]. The medians differ more, indicating stronger present bias. However, the median difference is 0.

2.6.2 Bivariate analyses of association between insurance and preferences

Figure 2.3 presents cumulative distributions of the utility curvature (r) and probability weighting (α) parameters for respondents with and without health insurance. Parameters of the respective distributions are given in Table 2.4. The utility curvature distributions are very similar at the extremes (i.e. high degrees of convexity and concavity). They appear to diverge elsewhere, although the null of equality of the distributions is not rejected[16]. The sample mean of the utility curvature parameter is smaller for those with insurance, which indicates more risk seeking for a given the probability weighting function (Table 2.4). However, this difference it not significant (p=0.361).

From the right-hand figure and from Table 2.4, it can be observed that the proportion of sample respondents with $\alpha>1$ is higher among those who purchase insurance (24.2%) than it is among those without insurance (18.0%). However, there is no significant difference in the distribution of observations over the categories of alpha (<1, =1, >1) and in the distribution of alpha by insurance status (Pearson $\chi^2(2) = 2.945$, p=0.229). The mean alpha is slightly larger among the insured, indicating less of a tendency to overweight small probabilities, and this difference is marginally statistically significant (p=0.067). The steps in the functions at $\alpha=1$ indicates that a large proportion of respondents do not weight probabilities. For both the insured and uninsured, the median and mean α is close to 1 indicating that, on average, there is no deviation from Expected Utility.

[15] The mean difference between the two points of indifference of 5.84 pesos is significantly different from 0 (p<0.05)

[16] A two-sided Kolmogorov-Smirnov (KS) test fails to reject the null of equality against the alternative of inequality at a 5% level of significance (Bennett, 2013).

Figure 2.3 Cumulative distributions of risk preference parameters[17]

3a Utility curvature: *r*　　3b Probability weighting: *α*

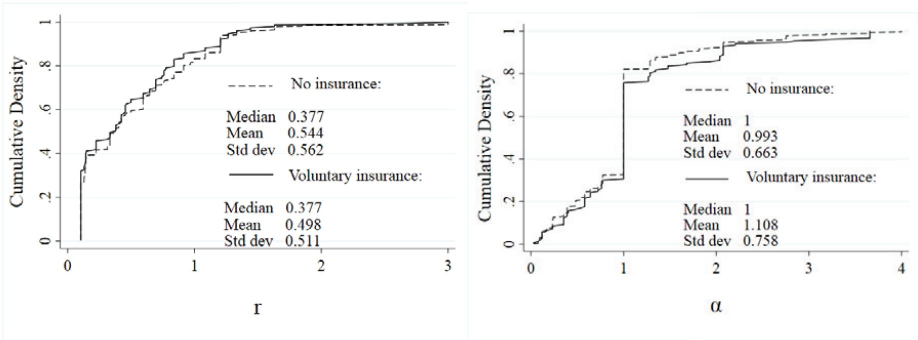


Figure 2.4. Cumulative distributions of time preference parameters[18]

4a Discount factor: δ　　4b Present bias: *β*

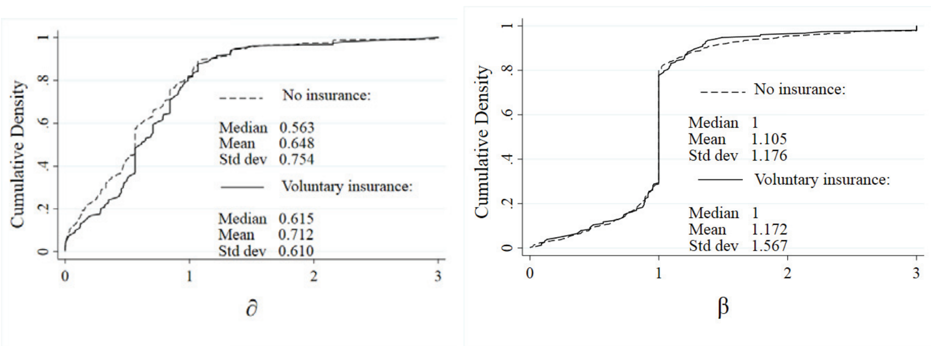


Figure 2.4 shows the cumulative distributions of the time preference parameters split by insurance status, and parameters of the distributions are again shown in Table 2.4. The empirical distribution of the discount factor (left-hand) for those without insurance lies below that for those with insurance at the bottom of the distributions, although the null of equality is not rejected at the 5% level of significance[19]. The sample mean and median of this parameter are both smaller for those with no insurance, indicating they discount the future more, however this difference is not significant. The distributions of the present bias

[17] The distribution for *r* is truncated at 3 (7 observations total). The distribution for α is truncated at 4 (2 observations total). The median, mean and standard deviation are computed before truncation.

[18] The distributions for δ are truncated at 3 (3 observations total). The distributions for *β* are truncated at 3 (15 observations total). The median, mean and standard deviation are computed before truncation.

[19] A two-sided Kolmogorov-Smirnov (KS) test does reject the null of equality against the alternative of inequality at a 10% level of significance (Bennett, 2013).

parameter β are very similar for the insured and uninsured. Equality of the distributions is not rejected at the 5% level. The step in the functions at β=1 indicates that a large fraction of respondents discount exponentially (Table 2.4). The proportion of respondents exhibiting present bias (β<1) (29%) is only slightly larger than those that are future biased (β>1) (20% and 22% for the uninsured and insured respectively).

Table 2.4 Risk and time preferences by insurance status

	(1) Uninsured	(2) Insured	(1) = (2) p-value
Risk preferences			
Utility curvature (r)			
Mean	0.544	0.498	0.361
Std. Dev.	0.562	0.511	
Median	0.377	0.377	
Probability weighting (α)			
Mean	0.993	1.108	0.067
Std. Dev.	0.663	0.758	
Median	1	1	
< 1 (%)	32.48	30.07	
= 1 (%)	49.54	45.75	0.229+
> 1 (%)	17.98	24.18	
Time preferences			
Discount factor (δ)			
Mean	0.648	0.712	0.332
Std. Dev.	0.754	0.610	
Median	0.563	0.615	0.164
Present bias (β)			
Mean	1.105	1.172	0.563
Std. Dev.	1.176	1.567	
Median	1	1	
< 1 (%)	28.62	28.76	
= 1 (%)	51.38	49.02	0.811++
>1 (%)	20.00	22.22	
N	545	153	

+ Pearson $\chi2(2) = 2.945$, ++ Pearson $\chi2(2) = 0.4191$

2.6.3 Multivariate analyses of the association between insurance and preferences

To investigate further whether insurance is associated with preferences, we regress voluntary health insurance status on all four parameters simultaneously. We enter all the parameters, except the probability weighting α, as continuous variables. According to theory, insurance demand does not increase or decrease monotonically with α. As explained in section 2.2.1, overweighting large probabilities of losses (α>1) will increase the demand for health insurance of respondents who perceive themselves to face a high probability of incurring medical expenses. Underweighting large probabilities (α<1) will decrease the demand of those who perceive their risk to be high and increase the demand of those who perceive their risk to be low. We include $\alpha < 1$ and $\alpha > 1$ as separate categories with linear probability weighting ($\alpha = 1$) as reference.

The first column of Table 2.5 gives estimates with control only for demographics and an indicator of whether the household is located in a randomly selected municipality where households eligible for the voluntary insurance program received inducements to enroll in it four years previously. The second column adds controls for socioeconomic characteristics and indicators of past health care use and expenditure, beliefs about comparative risk of incurring high medical expenditure in the future, health insurance literacy and knowledge of the NHIP. This specification potentially eliminates correlation that derives from an impact of preferences on insurance through socioeconomic factors, such as education, as well as the medical expenditure related variables. On the other hand, without controlling for these potential determinants of insurance demand there is risk that any association between insurance and preferences is spurious.

The estimates obtained conditioning only on demographics and the treatment site indicator reveal that respondents with a higher value for the utility curvature parameter, r, are less likely to purchase voluntary health insurance. Counterintuitively, this means that respondents with more convex utility for losses are more likely to take up health insurance. This is similar to the puzzling result found by others that individuals who are more risk averse in the domain of gains are less likely to insure (Cole et al 2013; Dercon et al 2015; Giesbert et al., 2011; Giné et al., 2008). A potential explanation for both results is that insurance is viewed as a risky prospect among those with little experience of it. Only those prepared to gamble on receiving compensation promised by the insurer should they incur medical expenses enroll (Dercon et al 2015). Respondents with a value for α larger than 1, overweighting large probabilities of losses are more likely to insure than those who weight probabilities linearly. The effect sizes for the risk preference parameters drop and they lose significance when additional controls are included. This might be interpreted as indicative of a spurious relationship between insurance and risk preferences arising from correlation of each with socioeconomic factors, such as education. However, it could also be that risk preferences influence insurance partly through socioeconomic characteristics. Most studies on correlates of risk preferences are cross-sectional and it is therefore hard to determine whether socioeconomic characteristics antecede risk preferences or vice versa.

Table 2.5 Variation in probability of health insurance enrollment with risk preference, time preferences and covariates (Probit marginal effects)

	(1)	(2)
r (utility curvature)	-0.076**	-0.059
	(0.037)	(0.037)
α < 1 (Probability weighting)	0.014	0.010
	(0.034)	(0.033)
α > 1 (Probability weighting)	0.107**	0.083*
	(0.047)	(0.046)
δ (discount factor)	0.043**	0.041**
	(0.022)	(0.020)
β (present bias)	0.009	0.010
	(0.012)	(0.011)
Treatment site of health insurance experiment	0.122***	0.140***
	(0.040)	(0.039)
Male	-0.064*	-0.067*
	(0.036)	(0.035)
Married	0.029	0.026
	(0.035)	(0.035)
Age	0.000	0.002
	(0.001)	(0.001)
Urban	0.039	0.019
	(0.031)	(0.031)
Number of household members	0.005	0.004
	(0.008)	(0.008)
Number of household members aged <15	-0.017	-0.011
	(0.015)	(0.015)
Number of household members aged >=65	0.001	-0.004
	(0.034)	(0.032)
Completed elementary school		0.038
		(0.053)
Completed high school		0.070
		(0.047)
College graduate +		0.258***
		(0.057)
At least one hospital inpatient stay in past year		-0.031
		(0.061)
1-4000 pesos OOP past year		-0.052
		(0.040)
4001-8000 pesos OOP past year		-0.095*
		(0.056)
>8000 pesos OOP past year		-0.048
		(0.058)
Optimistic		-0.110***
		(0.037)
Pessimistic		0.026
		(0.041)
Low health insurance literacy		-0.008
		(0.036)
High health insurance literacy		0.007
		(0.042)
Aware of NHIP		0.085
		(0.058)
Low knowledge of NHIP benefits		0.042
		(0.047)
High knowledge of NHIP benefits		0.034
		(0.036)
Observations	695	695

Notes: (1) Estimates are marginal effects averaged over sample. Robust std. err.in parentheses *** p<0.01, ** p<0.05, * p<0.1. (2) Three observations are excluded in both specifications due to missing educ. variable.

We find a positive association between insurance enrollment and the discount factor that is robust in size and significance to controlling for other preference parameters and both sets of covariates. The present bias parameter β is not associated with health insurance in either specification.

In Table 2.6 we examine robustness of the associations between insurance and preferences to excluding respondents who a) give responses that imply extreme risk seeking behavior, and b) have poor knowledge of the operation of health insurance. Respondents are categorized as a) if they arrive at D in lottery 1 and/or lottery 2 and do not switch at that point. After excluding these respondents, utility curvature is no longer significantly associated with health insurance take up. This is mainly due to a loss of power as the sample size falls by almost half. The magnitude of the association decreases only modestly. Hence, it does not appear to be only the extreme risk seekers that generate the association between insurance and convex utility in the full sample. After dropping the extreme risk seekers, the effect of probability weighting for those with an S-shaped probability weighting function ($\alpha > 1$) increases in size and remains significant when including additional controls. In addition, respondents with an inverse S shaped probability weighting function ($\alpha < 1$) appear more likely to buy insurance. The association between insurance and the discount factor is robust in size and significance to this exclusion.

The estimates presented in the middle panel of Table 2.6 are obtained excluding respondents who could not answer at least two out of five questions about basic characteristics of health insurance correctly (see Appendix Table A2.2 for precise definitions). The right-hand panel gives estimates obtained with both extreme risk seekers and the health insurance illiterate excluded. Dropping those with poor health insurance literacy again results in the loss of significance of the negative association between insurance and utility curvature. Clearly, this is the least robust relationship. And the positive association between insurance and the discount rate is the most robust. With both exclusions applied, those who weigh probabilities are significantly more likely to insure than those who behave as assumed in EU and do not. Perhaps the most interesting result to emerge when those with poor health insurance literacy are dropped is that the present bias parameter is significantly negatively associated with insurance.

Table 2.6 Variation in probability of health insurance enrollment with extreme risk seekers and/or health insurance illiterate excluded (Probit marginal effects)

	Extreme risk seekers excluded		Health insurance illiterate excluded		Both extreme risk seekers and health insurance illiterate excluded	
	(1)	(2)	(3)	(4)	(5)	(6)
r (utility curvature)	-0.064	-0.055	-0.069	-0.056	-0.042	-0.033
	(0.058)	(0.058)	(0.047)	(0.046)	(0.062)	(0.058)
$\alpha < 1$ (Probability weighting)	0.074*	0.074*	0.025	0.015	0.099*	0.105**
	(0.044)	(0.042)	(0.041)	(0.039)	(0.052)	(0.048)
$\alpha > 1$ (Probability weighting)	0.128**	0.126**	0.108*	0.099*	0.131*	0.150**
	(0.057)	(0.057)	(0.056)	(0.055)	(0.068)	(0.067)
δ (discount factor)	0.045*	0.045*	0.048*	0.042*	0.053*	0.049*
	(0.025)	(0.024)	(0.026)	(0.024)	(0.028)	(0.025)
β (present bias)	0.010	0.012	0.042**	0.043**	0.045***	0.043***
	(0.011)	(0.010)	(0.017)	(0.018)	(0.017)	(0.017)
Control for:						
Demographics and location	Yes	Yes	Yes	Yes	Yes	Yes
All covariates	No	Yes	No	Yes	No	Yes
N	372	372	481	481	248	248

Notes: See appendix Table A2.7.5 for full results. Estimates are marginal effects averaged over the sample. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Extreme risk seekers are those who arrived at D in lottery 1 and/or 2 and did not switch. Health insurance illiterate are those who could not answer at least two out of five questions about basic characteristics of health insurance correctly. 'Demographics and location' correspond to the controls in column (1) of Table 2.5. 'All covariates' are those in column (2) and Table 2.6.

This holds irrespective of the covariates controlled for and whether or not extreme risk seekers are also excluded. Once we restrict attention to respondents who have minimal knowledge of how health insurance operates, it is clear that health insurance enrollment varies with both dimensions of time preferences. Those who discount delayed rewards more aggressively are less likely to insure. On top of this, those who have a greater tendency toward present bias are less likely to insure. The positive association between the propensity to insure and the present bias parameter does not necessarily imply that those with present biased preferences insure less than those who do not. Around 18 percent of respondents who have some health insurance literacy display future bias. To determine whether insurance demand varies with present bias, future bias or both we re-estimate with indicators of $\beta<1$ and $\beta>1$ (reference: $\beta=1$) replacing the β entered as a continuous variable. We do this in the sample that includes only observations with some health insurance literacy. This reveals that the signs of the effects are as expected: present biased respondents are less likely to insure voluntarily while future biased respondents are more likely to (see Appendix Table A2.7.6). The effects are, however, not significant, which may simply be due to loss of power.

2.7 Conclusion

We elicited risk and time preferences in a nationwide household survey in the Philippines and investigated their associations with health insurance enrollment. We consistently find that individuals who discount the future more are less likely to insure. This suggests that one reason many Filipinos do not take out health insurance is because they value the premium they must pay when enrolling above the highly discounted benefit they will only enjoy, if at all, at some time over the course of the following year. Note that in the Philippines' NHIP, as with most health insurance, new enrollees must wait for a period (3 months) after paying the premium before any claim can be made.

Evidence on the role of present bias in the insurance decision is mixed. In the full sample, about 20% of respondents are future biased: they are more impatient in the future than in the present.[20] This is consistent with several studies that allow for future bias (Attema et al 2010; Bleichrodt et al. 2016; Delaney and Lades, 2015; Loewenstein 1987; Sayman and Öncüler, 2009; Scholten and Read, 2006; Takeuchi, 2011). Insurance does not vary with the present bias parameter in the full sample. This suggests that a financial device that facilitates commitment to enrollment at a later date would not necessarily raise take-up. People would refuse to commit for the same reason that they decline to purchase insurance at a point in time; the future benefits are not considered to be worth the costs incurred at the time that insurance must be paid for. This conclusion appears contrary to evidence that commitment devices are effective in raising saving and the propensity to quit smoking, including in the Philippines (Ashraf et al, 2006; Brune et al., 2016; Duflo et al., 2011; Giné et al., 2010). The difference between this chapter and these other studies is that we measure time preferences directly and use these to draw inferences about the potential effectiveness of policies. The other studies infer in the opposite direction. They estimate the effectiveness of policy interventions and draw conclusions about preferences consistent with this effectiveness. A potential problem with this line of argument is that the commitment devices may work for reasons other than present bias (Delaney and Lades, 2015; Giné et al., 2018). However, we do find that being more present biased is associated with not taking out health insurance among individuals who have some knowledge of how the product operates. This suggests

[20] A bias toward the present or future is often interpreted as time inconsistency while it could also follow from time invariant preferences resulting from e.g. fluctuations of cash flows (Halevy, 2015; Janssens et al., 2017). Our design did not allow testing for this.

that the order in which health insurance inducements are introduced may be important to their effectiveness. First, make people aware of how insurance operates. Then offer devices that commit them to enrolling.

Our findings are in line with evidence from randomized experiments demonstrating that reducing the indirect costs of insurance (application) at enrollment can be highly effective in increasing take-up (Thornton et al., 2010; Capuno et al., 2016).[21] Households on the margins of poverty may be expected to discount the future aggressively and to weigh heavily any costs, including time costs of applying for insurance through bureaucratic procedures that divert resources and energy from fending off destitution (Mullainathan and Shafir 2014; Schilbach et al 2016)).

Consistent with prospect theory, the majority of respondents have a strong convex curvature of the utility function in the domain of losses. Given this, insurance can only be explained by the non-linear weighting of probabilities. We find that respondents who overweight moderate and large probabilities, as well as those with more convex utility, are more likely to purchase insurance. This is can be consistent with theory if these individuals perceive a moderate to large chance of incurring medical expenditures in excess of the insurance premium. It is also in line with the finding that individuals have a greater demand for insurance for high probability-low consequence events (e.g. bicycle theft) than for low probability-high consequence events (e.g. floods) (Browne, 2015). However, after controlling for socioeconomic factors, insurance is not associated with either risk preference parameter in our full sample. The associations that exist in the absence of these controls could be spurious arising from the joint association of both insurance and risk preferences with socioeconomic characteristics. Alternatively, it may be that those characteristics, as well as insurance, are (in part) determined by risk preferences. Restricting attention to respondents with some understanding of how insurance operates and who do not exhibit extreme risk seeking preferences reveals a stronger role for probability weighting. In this restricted sample, those who overweight moderate to large probabilities of losses are more likely to insure than those who weight probabilities linearly. This is consistent with our prediction since the probability of having medical expenditures is relatively high with about 80% of people reporting out of pocket medical expenditures in the past year (see Chapter 3

[21] Asuming et al (2017) find that assistance with enrollment has no impact on insurance uptake in Ghana, while price subsidies and information do.

for more details). In some of our restricted estimations, we also find the probability of having voluntary insurance is higher among those who overweight small probabilities. Insurance demand does not appear to be monotonic in the probability weighting parameter. Understanding this better would require developing a model of insurance against a non-binary loss that allows the subjective distribution of those losses to deviate from the objective distribution, which the individual cannot observe. Chapter 3 partially addresses this research challenge.

The role for utility curvature and probability weighting in explaining health insurance choices certainly deserves further research, but attention should also be given to other explanations relating to risk preferences. We follow the common approach of taking initial wealth –the state in which medical expenses are not incurred- as the reference point (Sydnor 2010; Wakker et al 1997). As such, we are only concerned with utility in the loss domain; the choice is between a small certain loss (the insurance premium) and a larger uncertain loss (medical expenses). However, we cannot be sure about the reference point that people actually use. This is one of the main reasons that application of prospect theory is challenging (Barbaris, 2013).

Elicitation of risk and time preferences in large household surveys in low- and middle- income countries is still very rare. We introduced a method that is applicable in a time constrained survey administered to low educated respondents. There is scope to further improve the methodology. We found that a large proportion of respondents have a preference for extremely risky choices. Our measure could be refined to allow for more discrimination in this part of the distribution of preferences. We used hypothetical lottery choices which are sometimes found to increase risk seeking (e.g. Holt and Laury 2002). This is less of a concern because we are not interested in the absolute value of the risk parameters but rather how they differ between individuals with and without insurance. However, hypothetical questions could also increase noise. Incentivizing the respondents would be preferable, but is seldom feasible in the context of a large survey (Harrison and Rutstrom, 2008; Murphy et al. 2005). We elicited time preferences in the gain domain, as opposed to the loss domain, to reduce the cognitive burden for the respondents. Although normative economic theories prescribe no differences in discount factors for gains and losses, losses are generally discounted less than gains (Benzion et al., 1989; Thaler, 1981; Yates and Watts, 1975). Again, this is not a major concern because we are interested in differences in discount factors as opposed to the absolute values, but it would be interesting to see whether our results replicate with time preferences elicited in the loss domain.

Appendices Chapter 2

Appendix A2.1 Balancing tests of attrition

Balancing tests of attrition on baseline characteristics

	Followed up	Not Followed up	p-value
Informal sector/poor at baseline			
Urban	0.424	0.617	0.000
Head is working	0.876	0.844	0.079
Head has poor health	0.028	0.039	0.220
Head had at least college education	0.077	0.130	0.000
Has available health facility within 15 min	0.721	0.749	0.240
Has other insurance	0.026	0.043	0.065
Number of children under 21	1.851	1.517	0.000
Experienced adverse health outcome in the last year	0.264	0.268	0.864
National Capital Region	0.112	0.245	0.000
Rest of Luzon	0.440	0.483	0.103
Visayas	0.226	0.087	0.000
Mindanao	0.223	0.186	0.093
N	1513	462	
Formal sector at baseline			
Urban	0.652	0.523	0.000
Head is working	0.891	0.912	0.314
Head has poor health	0.026	0.023	0.740
Head had at least college education	0.202	0.254	0.090
Has available health facility within 15 min	0.772	0.733	0.220
Has other insurance	0.127	0.093	0.118
Number of children under 21	1.843	1.952	0.355
Experienced adverse health outcome in the last year	0.255	0.270	0.635
National Capital Region	0.213	0.100	0.000
Rest of Luzon	0.554	0.436	0.001
Visayas	0.090	0.260	0.000
Mindanao	0.142	0.203	0.029
N	267	708	

Appendix A2.2 Definitions of measures of perceived risk of medical spending, health insurance literacy and knowledge of national health insurance program benefits

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

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, medium or high health insurance literacy if s/he correctly answers 0-2, 3-4 or 5 questions respectively. The restricted sample of those with a minimal level of health insurance literacy consistent with those in the medium and high categories.

Knowledge of national health insurance program benefits

Respondents were asked whether the NHIP (fully or partially) covers 18 medical treatments/services. Answers could be "yes", "no" or "don't know". A respondent is categorized as having low, medium or high knowledge of NHIP benefits if s/he correctly answers 0-6, 7-12 or 13-18 questions respectively.

Appendix A2.3 Protocol for elicitation of time and risk preferences

<u>TIME PREFERENCE (1)</u>
<u>SHOWCARD</u>

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?

A.		
Receive 200 pesos now	1	**CONTINUE TO B**
Receive 200 pesos half a year from now	2	**SKIP TO I**

B.		
Receive 100 pesos now	1	**CONTINUE TO C**
Receive 200 pesos half a year from now	2	**SKIP TO F**

C.		
Receive 50 pesos now	1	**CONTINUE TO D**
Receive 200 pesos half a year from now	2	**SKIP TO E**

D.		
Receive 25 pesos now	1	**PROCEED TO NEXT SET**
Receive 200 pesos half a year from now	2	**PROCEED TO NEXT SET**

E.		
Receive 75 pesos now	1	**PROCEED TO NEXT SET**
Receive 200 pesos half a year from now	2	**PROCEED TO NEXT SET**

F.		
Receive 150 pesos now	1	**CONTINUE TO G**
Receive 200 pesos half a year from now	2	**SKIP TO H**

G.		
Receive 125 pesos now	1	**PROCEED TO NEXT SET**
Receive 200 pesos half a year from now	2	**PROCEED TO NEXT SET**

H.		
Receive 175 pesos now	1	**PROCEED TO NEXT SET**
Receive 200 pesos half a year from now	2	**PROCEED TO NEXT SET**

I.		
Receive 250 pesos now	1	**PROCEED TO NEXT SET**
Receive 200 pesos half a year from now	2	**PROCEED TO NEXT SET**

TIME PREFERENCE (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?

A.		
Receive 200 pesos half a year from now	1	**CONTINUE TO B**
Receive 200 pesos one year from now	2	**SKIP TO I**

B.		
Receive 100 pesos half a year from now	1	**CONTINUE TO C**
Receive 200 pesos one year from now	2	**SKIP TO F**

C.		
Receive 50 pesos half a year from now	1	**CONTINUE TO D**
Receive 200 pesos one year from now	2	**SKIP TO E**

D.		
Receive 25 pesos half a year from now	1	**PROCEED TO NEXT SET**
Receive 200 pesos one year from now	2	**PROCEED TO NEXT SET**

E.		
Receive 75 pesos half a year from now	1	**PROCEED TO NEXT SET**
Receive 200 pesos one year from now	2	**PROCEED TO NEXT SET**

F.		
Receive 150 pesos half a year from now	1	**CONTINUE TO G**
Receive 200 pesos one year from now	2	**SKIP TO H**

G.		
Receive 125 pesos half a year from now	1	**PROCEED TO NEXT SET**
Receive 200 pesos one year from now	2	**PROCEED TO NEXT SET**

H.		
Receive 175 pesos half a year from now	1	**PROCEED TO NEXT SET**
Receive 200 pesos one year from now	2	**PROCEED TO NEXT SET**

I.		
Receive 250 pesos half a year from now	1	**PROCEED TO NEXT SET**
Receive 200 pesos one year from now	2	**PROCEED TO NEXT SET**

RISK AVERSION (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.

A.		
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 losing 400 pesos and losing nothing	1	**CONTINUE TO B**
Lose 200 pesos for sure	2	**SKIP TO E**
B.		
NOTE TO THE INTERVIEWER: Change the visual support for only the second option 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 losing 400 pesos and losing nothing	1	**CONTINUE TO C**

Lose 150 pesos for sure	2	**PROCEED TO NEXT SET**

C.		
NOTE TO THE INTERVIEWER: Change the visual support for only the second option 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 losing 400 pesos and losing nothing	1	**CONTINUE TO D**
Lose 100 pesos for sure	2	**PROCEED TO NEXT SET**

D.		
NOTE TO THE INTERVIEWER: Change the visual support for only the second option What if the first jar stays the same, but if you choose the second jaryou 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 losing 400 pesos and losing nothing	1	**PROCEED TO NEXT SET**
Lose 1 peso for sure	2	**PROCEED TO NEXT SET**

E.		
NOTE TO THE INTERVIEWER: Change the visual support for only the second option What if the first jar stays the same, but if you choose the second jaryou 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 losing 400 pesos and losing nothing	1	**PROCEED TO NEXT SET**
Lose 250 pesos for sure	2	**CONTINUE TO F**

F.		
NOTE TO THE INTERVIEWER: Change the visual support for only the second option What if the first jar stays the same, but if you choose the second jaryou 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 losing 400 pesos and losing nothing	1	**PROCEED TO NEXT SET**
Lose 300 pesos for sure	2	**CONTINUE TO G**

G.

NOTE TO THE INTERVIEWER: Change the visual support for only the second option What if the first jar stays the same, but if you choose the second jaryou 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	**PROCEED TO NEXT SET**
Lose 400 pesos for sure	2	**PROCEED TO NEXT SET**

<u>RISK AVERSION(2)</u>

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.

A.		
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?		
A chance of 1 out of 4 (25%) of losing 400 pesos and 3 out of 4 (75%) losing nothing	1	**CONTINUE TO B**
An equal chance (fifty-fifty) of losing 200 pesos and losing nothing	2	**SKIP TO E**
B.		
NOTE TO THE INTERVIEWER: Change the visual support for only the second option 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?		
Again, a chance of 1 out of 4 (25%) of losing 400 pesos and 3 out of 4 (75%) losing nothing	1	**CONTINUE TO C**
An equal chance (fifty-fifty) of losing 150 pesos and losing nothing	2	**PROCEED TO NEXT SET**

C.		
NOTE TO THE INTERVIEWER: Change the visual support for only the second option 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?		
Again, a chance of 1 out of 4 (25%) of losing 400 pesos and 3 out of 4 (75%) losing nothing	1	**CONTINUE TO D**

An equal chance (fifty-fifty) of losing 100 pesos and losing nothing	2	**PROCEED TO NEXT SET**

D.		
NOTE TO THE INTERVIEWER: Change the visual support for only the second option 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	**PROCEED TO NEXT SET**
An equal chance (fifty-fifty) of losing 1 peso and losing nothing	2	**PROCEED TO NEXT SET**

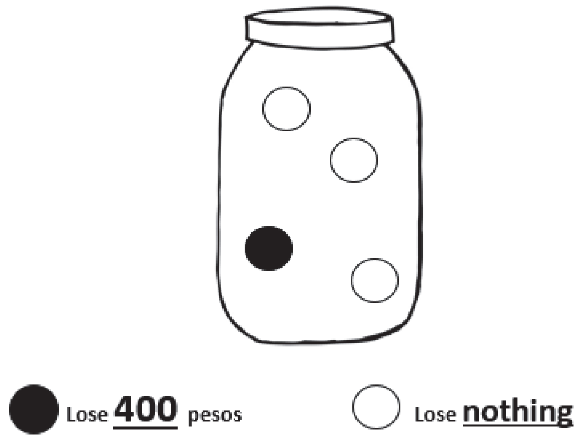
E.		
NOTE TO THE INTERVIEWER: Change the visual support for only the second option What if the first jar stays the same but the second jar changes? If a black ball is drawn from the second jar it now means you lose 250 pesos. If you were to choose between these two jars, which one will you choose?		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

F.		
NOTE TO THE INTERVIEWER: Change the visual support for only the second option 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	**PROCEED TO NEXT SET**
An equal chance (fifty-fifty) of losing 300 pesos and losing nothing	2	**CONTINUE TO G**

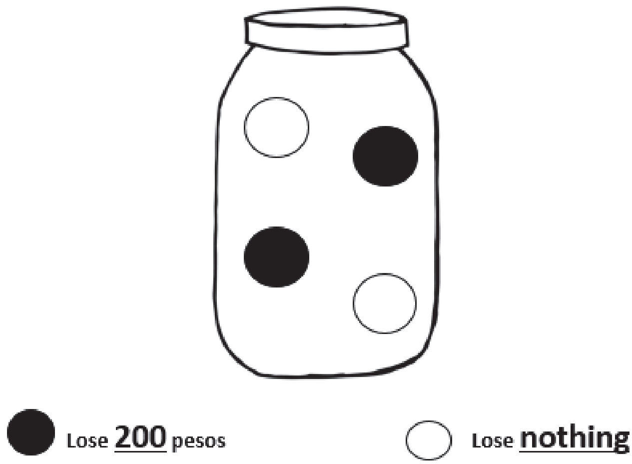
G.		
NOTE TO THE INTERVIEWER: Change the visual support for only the second option What if the first jar stays the same but the second jar changes? If a black ball is drawn from the second jar it now means you lose 400 pesos. If you were to choose between these two jars, which one will you choose?		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

Appendix A2.4 Example of visual support risk elicitation

1



2



Appendix A2.5 Derivations risk parameters

First, note that $x, z < 0$. Under PT, $u(0) = 0$ and we can fix its value at another point. We fix $u(-400) = -1$.

(1) First indifference

$$x \sim -400_{0.5}0$$

$$u(x) = -w\ (0.5)$$

(2) Indifference choice question 2

$$z_{0.5}0 \sim -400_{0.25}0$$

$$w\ (0.5)u\ (z) = -w\ (0.25)$$

$$u(z) = -\frac{w(0.25)}{w\ 0.5)}$$

Applying power utility and Prelec's weighting function, the first indifference implies:

$$(-x)^r = \exp(-(-\ln 0.5\ )^{\propto})$$

$$r \ln(-x) = -(-\ln 0.5\ )^{\propto}$$

The second indifference implies :

$$(-z)^r = \frac{\exp(-(-\ln 0.25\ )^{\propto})}{\exp(-(-\ln 0.5\ )^{\propto})}$$

$$r \ln(-z) = (-\ln 0.5\ )^{\propto} - (-\ln 0.25\ )^{\propto}$$

Combining these results gives:

$$r\ (\ln(-x) + \ln(-z)) = -(-\ln 0.25\ )^{\propto}$$

$$\frac{\ln(-x)}{\ln(-x) + \ln(-z)} = \frac{(\ln 0.5\ )^{\propto}}{(\ln 0.25\ )^{\propto}}$$

Hence,

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

and

$$r = \frac{-(-\ln 0.5\ )^{\propto}}{\ln(-x)}.$$

Appendix A2.6 Derivations time parameters

First indifference:

$$x_0 \sim 200_1$$

Second indifference

$$y_1 \sim 200_2$$

Applying the quasi-hyperbolic discounting model:

$$x^r = 200\, \beta \delta^{1/2}$$

$$y^r \beta \delta^{1/2} = 200 \beta \delta^1 \Leftrightarrow y^r = 200\, \delta^{1/2}$$

Hence,

$$\delta = \left(\frac{y^r}{200}\right)^2$$

and

$$\beta = \frac{x^r}{y^r}$$

Assuming linear utility

$$\delta_l = \left(\frac{y}{200}\right)^2$$

and

$$\beta_l = \frac{x}{y}$$

Appendix A2.7 Additional Tables

Table A2.7.1 Comparisons by item response on elicitation of risk parameters

	Risk parameters elicited		
	No	Yes	p-value
Enrolled in voluntary health insurance	0.250	0.219	0.540
Treatment site in health insurance experiment	0.737	0.791	0.277
Demographics (respondent)			
Male	0.303	0.282	0.709
Married	0.724	0.725	0.982
Age	44.46	45.56	0.467
Demographics (household)			
Urban	0.500	0.483	0.776
Number of household members	5.105	4.977	0.624
Number of household members aged <15	1.382	1.503	0.461
Number of household members aged >=65	0.197	0.211	0.822
Socioeconomic status			
Highest attained education of respondent			
No education	0.224	0.167	0.214
Completed elementary school	0.263	0.230	0.520
Completed high school	0.447	0.498	0.404
College graduate +	0.066	0.105	0.282
Health care, expenditure and insurance			
At least one hospital inpatient stay in past year (household)	0.053	0.074	0.485
Household OOP medical expenditure (OOP) last year			
0 pesos	0.276	0.229	0.358
1-4000 pesos	0.513	0.520	0.909
4001-8000 pesos	0.079	0.130	0.199
> 8000 pesos	0.132	0.120	0.776
Perceive risk of spending > 8000 pesos on healthcare compared with similar household to be:			
smaller (optimistic)	0.408	0.334	0.196
same (neutral)	0.382	0.477	0.113
larger (pessimistic)	0.211	0.189	0.653
Health insurance literacy (respondent)			
Low	0.263	0.308	0.420
Medium	0.526	0.526	0.993
High	0.211	0.166	0.330
Aware of national health insurance program (NHIP)	0.737	0.858	0.005
Knowledge of NHIP benefits			
Low			
Medium	0.382	0.287	0.085
High	0.276	0.350	0.202
N	76	698	

Note: For education there are 695 observations for those with parameters for risk.

Table A2.7.2 Utility curvature (r) and probability weighting (α) for all combinations of answers

r

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

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

	-0.5	-50	-125	-175	-225	-275	-350
-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

α

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

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

	-0.5	-50	-125	-175	-225	-275	-350
-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

Table A2.7.3 Parameters δ_l and β_l for all combinations of answers to the choice questions with r=1 (linear utility)

∂_l

Set 2
$y_{1/2} \sim 200_1.$

	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

β_l

Set 2
$y_{1/2} \sim 200_1.$

Set 1
$x_0 \sim 200_{1/2}.$

	12.5	37.5	62.5	87.5	112.5	137.5	162.5	187.5	225	275
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

Table A2.7.4 Regressions of risk and time parameters

	Utility curvature r	Probability weighting α	Discount factor δ	Present bias β
Treatment site of health insurance experiment	-0.013	0.009	-0.146	0.048
	(0.058)	(0.063)	(0.096)	(0.102)
Male	-0.053	-0.055	0.010	0.037
	(0.044)	(0.057)	(0.062)	(0.134)
Married	-0.091*	-0.047	-0.041	-0.045
	(0.054)	(0.060)	(0.065)	(0.114)
Age	-0.004*	0.000	-0.002	-0.006
	(0.002)	(0.002)	(0.002)	(0.004)
Urban	0.009	0.070	-0.038	0.022
	(0.044)	(0.054)	(0.055)	(0.104)
Number of household members	0.005	-0.012	-0.011	0.019
	(0.016)	(0.015)	(0.021)	(0.024)
Number of household members aged <15	-0.014	-0.025	-0.010	-0.039
	(0.020)	(0.025)	(0.024)	(0.028)
Number of household members aged >=65	-0.017	0.035	-0.042	0.082
	(0.039)	(0.065)	(0.047)	(0.087)
Completed elementary school	-0.203***	-0.029	-0.120	0.223
	(0.068)	(0.089)	(0.085)	(0.147)
Completed high school	-0.132**	-0.079	-0.036	0.092
	(0.067)	(0.066)	(0.086)	(0.091)
College graduate +	-0.177**	0.103	-0.076	0.122
	(0.089)	(0.105)	(0.110)	(0.151)
At least one hospital inpatient stay in past year	0.012	0.076	0.171	0.160
	(0.115)	(0.114)	(0.146)	(0.201)
1-4000 pesos OOP past year	-0.076	0.005	-0.132*	-0.239
	(0.053)	(0.058)	(0.075)	(0.192)
4001-8000 pesos OOP past year	-0.060	-0.043	-0.152	-0.093
	(0.067)	(0.089)	(0.095)	(0.257)
>8000 pesos OOP past year	-0.031	-0.084	-0.059	-0.309
	(0.080)	(0.102)	(0.099)	(0.246)
Optimistic	0.023	0.018	0.053	0.028
	(0.050)	(0.066)	(0.064)	(0.119)
Pessimistic	0.084	0.040	0.067	0.001
	(0.062)	(0.078)	(0.078)	(0.154)
Low health insurance literacy	0.036	-0.025	0.010	0.185
	(0.048)	(0.055)	(0.074)	(0.125)
High health insurance literacy	-0.045	0.060	-0.138**	0.187
	(0.051)	(0.092)	(0.055)	(0.178)
Aware of NHIP	-0.227***	-0.144*	0.070	-0.110
	(0.081)	(0.086)	(0.121)	(0.161)
Low knowledge of NHIP benefits	-0.016	-0.155**	-0.036	-0.134
	(0.058)	(0.075)	(0.069)	(0.151)
High knowledge of NHIP benefits	-0.016	-0.029	-0.033	-0.119
	(0.051)	(0.070)	(0.065)	(0.135)
Constant	1.149***	1.324***	1.087***	1.461***
	(0.182)	(0.178)	(0.287)	(0.408)
Observations	695	695	695	695
R-squared	0.062	0.028	0.035	0.024

Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A2.7.5 Variation in probability of health insurance enrollment – extreme risk seeking respondents and health insurance illiterate excluded (Probit marginal effects)

	A		B		C	
	(1)	(2)	(3)	(4)	(5)	(6)
r (utility curvature)	-0.064	-0.055	-0.069	-0.056	-0.042	-0.033
	(0.058)	(0.058)	(0.047)	(0.046)	(0.062)	(0.058)
α < 1 (probability weighting)	0.074*	0.074*	0.025	0.015	0.099*	0.105**
	(0.044)	(0.042)	(0.041)	(0.039)	(0.052)	(0.048)
α > 1 (probability weighting)	0.128**	0.126**	0.108*	0.099*	0.131*	0.150**
	(0.057)	(0.057)	(0.056)	(0.055)	(0.068)	(0.067)
δ (discount factor)	0.045*	0.045*	0.048*	0.042*	0.053*	0.049*
	(0.025)	(0.024)	(0.026)	(0.024)	(0.028)	(0.025)
β (present bias)	0.010	0.012	0.042**	0.043**	0.045***	0.043***
	(0.011)	(0.010)	(0.017)	(0.018)	(0.017)	(0.017)
Treatment site of health insurance experiment	0.209***	0.244***	0.100**	0.120**	0.180**	0.227***
	(0.058)	(0.055)	(0.048)	(0.047)	(0.070)	(0.065)
Male	-0.032	-0.024	-0.071	-0.055	-0.061	-0.017
	(0.048)	(0.045)	(0.044)	(0.042)	(0.061)	(0.056)
Married	0.056	0.062	0.071	0.058	0.131**	0.144**
	(0.045)	(0.045)	(0.046)	(0.044)	(0.061)	(0.058)
Age	0.001	0.002	-0.001	0.001	0.000	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Urban	-0.010	-0.039	0.063*	0.046	0.035	0.009
	(0.040)	(0.040)	(0.037)	(0.037)	(0.049)	(0.049)
Number of household members	-0.001	-0.001	0.003	-0.002	-0.005	-0.011
	(0.011)	(0.011)	(0.010)	(0.010)	(0.013)	(0.013)
Number of household members aged <15	0.003	0.010	-0.010	-0.000	0.011	0.020
	(0.019)	(0.019)	(0.016)	(0.017)	(0.022)	(0.021)
Number of household members aged >=65	-0.000	-0.007	0.014	0.021	-0.017	0.003
	(0.044)	(0.041)	(0.042)	(0.039)	(0.056)	(0.052)
Completed elementary school		0.050		0.063		0.121
		(0.067)		(0.063)		(0.078)
Completed high school		0.089		0.062		0.112
		(0.057)		(0.057)		(0.070)
College graduate +		0.254***		0.241***		0.267***
		(0.075)		(0.069)		(0.093)
At least one hospital inpatient stay in past year		-0.046		-0.046		-0.027
		(0.082)		(0.067)		(0.089)
1-4000 pesos OOP past year		0.025		-0.053		-0.009
		(0.053)		(0.048)		(0.063)
4001-8000 pesos OOP past year		0.032		-0.105		-0.021
		(0.071)		(0.064)		(0.086)
>8000 pesos OOP past year		0.105		-0.033		0.079
		(0.074)		(0.069)		(0.091)
Optimistic		-0.078		-0.118***		-0.133**
		(0.049)		(0.043)		(0.055)
Pessimistic		0.010		0.054		0.045
		(0.053)		(0.050)		(0.065)
Low health insurance literacy		0.006				
		(0.046)				
High health insurance literacy		0.018		-0.002		0.011
		(0.053)		(0.043)		(0.053)
Aware of NHIP		0.072		0.135*		0.064
		(0.066)		(0.076)		(0.081)
Low knowledge of NHIP benefits		0.080		0.088		0.116*
		(0.058)		(0.054)		(0.065)
High knowledge of NHIP benefits		-0.006		0.073*		0.033
		(0.050)		(0.042)		(0.058)
Observations	372	372	481	481	248	248

Notes: Estimates are marginal effects averaged over the sample. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Panel a) Extreme risk seekers excluded. Panel b) health insurance illiterate excluded. Panel c) Both extreme risk seekers and health insurance illiterate excluded

Table A2.7.6 Variation in probability of health insurance enrollment - β as categorical variable, health insurance illiterate excluded (Probit marginal effects)

	(1)	(2)
r (utility curvature)	-0.058	-0.044
	(0.044)	(0.042)
α < 1 (probability weighting)	0.028	0.015
	(0.041)	(0.039)
α > 1 (probability weighting)	0.111**	0.098*
	(0.056)	(0.054)
δ (discount factor)	0.042*	0.036
	(0.025)	(0.023)
β <1 (present bias)	-0.034	-0.026
	(0.041)	(0.040)
β >1 (future bias)	0.075	0.080
	(0.056)	(0.054)
Treatment site of health insurance experiment	0.102**	0.120**
	(0.048)	(0.048)
Male	-0.067	-0.052
	(0.044)	(0.042)
Married	0.067	0.054
	(0.045)	(0.044)
Age	-0.001	0.000
	(0.002)	(0.002)
Urban	0.061*	0.044
	(0.037)	(0.037)
Number of household members	0.003	-0.002
	(0.010)	(0.010)
Number of household members aged <15	-0.011	-0.002
	(0.017)	(0.017)
Number of household members aged >=65	0.014	0.023
	(0.042)	(0.039)
Completed elementary school		0.064
		(0.064)
Completed high school		0.067
		(0.058)
College graduate +		0.241***
		(0.070)
At least one hospital inpatient stay in past year		-0.039
		(0.067)
1-4000 pesos OOP past year		-0.056
		(0.048)
4001-8000 pesos OOP past year		-0.105*
		(0.064)
>8000 pesos OOP past year		-0.043
		(0.070)
Optimistic		-0.115***
		(0.043)
Pessimistic		0.060
		(0.049)
High health insurance literacy		0.013
		(0.043)
Aware of NHIP		0.151*
		(0.077)
Low knowledge of NHIP benefits		0.099*
		(0.055)
High knowledge of NHIP benefits		0.072*
		(0.042)
Observations	481	481

Notes: Estimates are marginal effects averaged over the sample. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Chapter 3

A behavioral decomposition of the willingness to pay for health insurance

Joint work with Baillon, A., O'Donnell, O. and Kraft, A.

3.1 Introduction

Despite widespread exposure to risks of substantial medical expenses in low- and middle-income countries (LMIC), revealed willingness to pay (WTP) for health insurance has been low. Those not covered through either mandatory employment-based insurance or means-tested fully subsidized insurance usually do not take up voluntary health insurance (Acharya et al. 2013; Bredenkamp et al. 2015; Pettigrew and Mathauer 2016). Inconsistent with this observation are estimates of large potential demand for, and gains from, health insurance of individuals assumed to be risk averse expected utility maximizers who rationally base their perceptions of risk on the level and variability of medical expenses observed in a sample of similar individuals (Limwattananon et al 2015; Pauly et al. 2009). This chapter aims to explain the discrepancy between the high WTP for health insurance derived from this normative model and the low WTP reported by individuals. We do this by introducing a new decomposition of the WTP for insurance into its fair price and four behavioral deviations from that price that arise from subjective beliefs about the distribution of medical expenses, two dimensions of risk attitudes consistent with prospect theory and a residual term representing all determinants of WTP not captured by our behavioral model. The fair price of insurance – the expected medical expenditure – is estimated by the mean spending across a group of individuals with common observable characteristics. The contribution of beliefs to the WTP is given by the deviation of the perceived fair price from the fair price. The former is derived from elicited beliefs about future spending that are used to estimate an individual's subjective distribution of medical expenditures. Any discrepancy between the mean perceived fair price and the fair price indicates systematically biased beliefs, which can be in either an optimistic or a pessimistic direction. At the individual level, the perceived fair price can differ from the group level fair price because of within group heterogeneity in healthcare needs that is recognized by the individual: private information. The contributions of the two dimensions of risk preferences – utility curvature and probability weighting – are identified using elicitations of those parameters obtained for each individual from their choices in hypothetical lotteries in combination with their estimated subjective distribution of medical expenditures. Finally, the residual term is equal to the difference between the directly elicited WTP and that derived indirectly from the behavioral model. We obtain all the data required for the decomposition -- actual medical expenditures, elicited beliefs about future medical expenditures, risk preferences and the directly elicited WTP – from a nationwide household survey conducted in the Philippines. Comparing WTP and its decomposition for insured and uninsured households allows us to identify some factors that may contribute to the low take-up of voluntary insurance in that country, and to rule out other potential explanations for this phenomenon.

Our approach to deriving WTP indirectly from a model differs in a number of respects from that usually followed. First, an individual's exposure to medical expenditure risk is commonly based on the cross-sectional distribution of that expenditure. But only under strong assumptions is the cross-section distribution indicative of the risk of volatile medical expenses faced by any individual. And even if these assumptions did hold, additional assumptions are required: people must have access to statistical information on the cross-sectional distribution and they must use it to form rational expectations about the medical risks they face. These assumptions are unlikely to hold (Manski 2004). Elicited beliefs about future medical expenditures can potentially yield additional predictive power regarding the value of insurance.

Second, behavior might deviate from that characterized by the expected utility (EU) model. Prospect theory (PT), the most descriptively valid model of choice under risk, assumes that people maximize utility defined over changes in wealth with respect to a reference point, which is typically assumed to be the status quo (Kahneman and Tversky 1979; Tversky and Kahneman 1992). If this is the state in which medical expenses are not incurred, then we are only concerned with utility in the loss domain, where PT predicts convex utility, implying risk seeking. A demand for insurance can still arise in this model through the transformation of probabilities by a weighting function that captures limited discrimination between likelihood levels and could, for example, involve overweighting of low probability, high medical expense scenarios.

We show that the difference between the directly reported WTP for insurance and the fair price is equal to the sum of four components, which we call premiums. First, we estimate the *belief premium* as the difference between the perceived fair price based on subjective beliefs of medical expenditure risk and the fair price based on the empirical distribution of expenditures across households. Second, we incorporate utility for losses, estimated under PT, and compute the WTP for insurance based on each individual's elicited utility curvature and their beliefs about the distribution of expenses faced. We call the difference between this computed WTP and the perceived fair price the *u-premium;* it captures the impact of utility. Then we add probability weighting to the model and re-compute WTP. The change in value, which is due only to the additional of probability weighting, gives us what we call the *w-premium*. Finally, we take the difference of the WTP computed with our complete model and the WTP reported directly by the respondent to get the *ε-premium*. This captures what we cannot explain by our model, such as time preferences, self-insurance and any influence of the budget constraint that is taken into account by the respondent in the reported WTP but not in the beliefs about future spending.

We elicit subjective beliefs by following a common approach using visual aids (Delavande et al. 2011b) but adapt this to the context of medical expenditure and the Philippines. Respondents were given 10 sticks and were asked to distribute these across four cups representing different intervals of medical expenditures in accordance with how likely they were to spend in each interval. The responses along with a distributional assumption allows us to estimate the first two moments of the subjective distribution of medical expenditures for each household. To elicit risk preferences, we design and implement a method that aims to identify sophisticated preference parameters under PT and yet be comprehensible for less educated respondents.

We establish the validity of the belief elicitation method by showing that the subjective beliefs of medical expenditures correlate with various factors, including past medical spending. The WTP decomposition reveals three main findings. First, low reported WTP cannot be explained by the belief premium, which is positive. That is, the subjective expectation of medical expenses exceeds the objective expectation, on average, and yet reported WTP falls short of the fair price. The belief premium is close to zero for the uninsured indicating that distorted beliefs is not the reason that they choose not to insure. Any strategy to communicate to this group the risks they face is unlikely to be effective in raising their enrollment. It is something other than biased beliefs that causes them not to insure. Second, negative u- and w- premiums explain a large part of shortfall of reported WTP from the fair price. A large negative u-premium, which comes from risk seeking in the domain of losses, calls for framing insurance in terms of gains as opposed to losses, focusing more on the reimbursements received if insured, as opposed to the expenditures one may incur if uninsured. Finally, we find a negative ε-premium, which is especially large for the poor. A likely explanation for this finding is that self-insurance options reduce the WTP. In addition, the poor may pay more attention to their tight budget when reporting WTP than when reporting beliefs about future spending. And they may feel entitled to subsidized insurance and therefore report low willingness to pay for insurance.

Section 3.2 explains how we decompose WTP. Section 3.3 provides background on the Philippines health insurance setting. Section 3.4 presents the data and methods we use to obtain the parameters needed to estimate the premiums in the decomposition. Section 3.5 assesses the validity of the elicited beliefs and section 3.6 presents the results of the decomposition. The final section concludes with a summary and interpretation of the main results, plus acknowledgement of limitations.

3.2 Decomposition of willingness to pay

Assume we use an individual's observable characteristics to estimate their medical expenditure risk, which is given by a probability mass at 0 and a density for non-zero expenditures. Let p_0 be the probability of zero expenditure and f be the density conditional on facing any expenditure, with max being the maximum possible value. Both p_0 and f vary with the observable characteristics. Working with negative values of expenditure to highlight similarity with the computation of WTP to come, the actuarially fair price for health insurance (μ) based on the individual's observable characteristics is given by:

$$-\mu = (1 - p_0) \int_{-max}^{0} xf(x)dx, \tag{3.1}$$

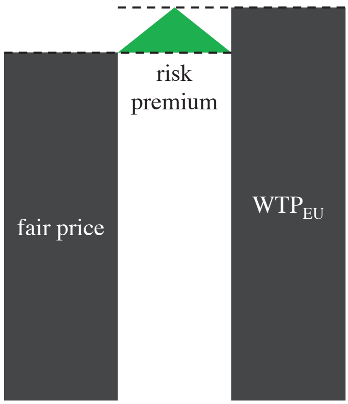
with x a generic integration variable. Under EU, the WTP for health insurance of an individual with wealth W and utility over final wealth is determined by:

$$U(W - WTP_{EU}) = p_0 \times U(W) + (1 - p_0) \int_{-max}^{0} U(W + x)f(x)dx. \tag{3.2}$$

The difference between WTP_{EU} and the fair price is the standard risk premium, which is positive if and only if U is concave. This model, represented in Figure 3.1, would predict a relatively high WTP of a risk averse (U concave) individual facing sizeable and variable medical expenditures. This is difficult to reconcile with the low enrollment rates in (low cost) voluntary health insurance programs (Acharya et al. 2013; Bredenkamp et al. 2015; Pettigrew and Mathauer 2016).

There are several reasons why an individual's WTP may differ from that predicted by the EU model applied to their medical expenditure risk estimated from the observed distribution of expenditures over individuals with similar characteristics. First, private information about their health, as well as their proneness to optimism or pessimism, may cause their beliefs to deviate from the risk estimated on the basis of their observable characteristics. Assume we can model beliefs by probabilities and let p_0^s and f^s be the subjective equivalent of p_0 and f respectively. Substituting p_0^s and f^s for their objective counterparts in Eq. 3.1 gives the perceived fair price of insurance (μ^s). We call the difference between this and the fair price based on observable characteristics the *belief premium* ($\pi^b = \mu^s - \mu$). It can be positive or negative, depending on the agent's private information and degree of optimism.

Figure 3.1 Traditional model of WTP



Second, behavior may deviate from EU. Under PT (Kahneman and Tversky, 1979), the most compelling descriptive model of choice under risk, people do not maximize utility over final wealth but over changes in wealth with respect to a reference point. Let u be PT utility, with $u(0) = 0$. It is concave for gains but convex for losses (implying risk seeking for losses), and it is steeper for losses than for gains (loss aversion). The reference point is typically assumed to be the status quo (Sydnor 2010; Wakker et al., 1997), which in an insurance setting can be defined as initial wealth – the state in which medical expenses are not incurred. We are then only concerned with utility in the loss domain. With this representation of utility, WTP is determined by.

$$\begin{aligned} u(-WTP_u) &= p_0^s \times u(0) + (1 - p_0^s) \int_{-max}^{0} u(x) f^s(x) dx \\ &= (1 - p_0^s) \int_{-max}^{0} u(x) f^s(x) dx . \end{aligned} \tag{3.3}$$

We call the difference between WTP_u and the perceived fair price the *u-premium* ($\pi^u = WTP_u - \mu^s$). This is negative for people with convex utility in the loss domain, as predicted by PT. Hence, it can potentially contribute to low WTP.

According to PT (Kahneman and Tversky 1979), the second way in which behavior can deviate from EU, and so WTP differ from WTP_{EU}, is through the transformation of probabilities into decision weights. Here we use Tversky and Kahneman's (1992) cumulative PT, in which cumulative probabilities are transformed, because the 1979 version could lead to inconsistent predictions.[22] Let F^s be the cumulative distribution function associated with f^s. The subjective probability of incurring expenditure greater than $-x$ is $(1-p_0^s)F^s(x)$.[23] In cumulative PT, this (cumulative) probability is transformed through a weighting function w. Therefore, its derivative, the density $(1-p_0^s)f^s(x)$ in Eq. 3.3, must be replaced by the derivative of $w\big((1-p_0^s)F^s(x)\big)$, that is $(1-p_0^s)f^s(x)w'\big((1-p_0^s)F^s(x)\big)$. We obtain

$$u(-WTP_{u\&w}) = (1-p_0^s)\int_{-max}^{0} u(x)f^s(x)w'\big((1-p_0^s)F^s(x)\big)dx. \qquad (3.4)$$

We call the difference between $WTP_{u\&w}$ and WTP_u, which captures the impact of probability weighting, the *w-premium* $(\pi^w = WTP_{u\&w} - WTP_u)$.

The sign of *w-premium* depends on a combination of factors. The function w has been found to be typically inverse-S, i.e., overweighting small probabilities (typically, below 1/3) and underweighting large ones. Then, in the case of a binary prospect, with a probability smaller than 1/3 to bear a fixed amount of expenditure as opposed to incurring no expenditure, w will increase the WTP and the *w-premium* will be positive. For distributions that are not binary, the implication of w is less obvious as shown by the role of w' in Eq.3.4. The derivative of an inverse-S weighting function is larger than 1 for low and high values of the cumulative distribution and is smaller than 1 for intermediary values. Hence, the probability of extreme outcomes in both directions (expenses of *max* but also 0) will be overweighted, while the intermediary expenses will be underweighted. The global impact of w thus depends on the whole distribution of expenses perceived by the individual.

Finally, the WTP given by Eq. 3.4 can be compared with the WTP reported by the individual through a direct elicitation task (WTP_r). We call this difference the *ε-premium* $(\pi^\varepsilon = WTP_r - WTP_{u\&w})$. It includes everything that influences the individual's reported valuation of insurance that is not captured by our model. For instance, a budget constraint

[22] The original version of PT can lead to violations of stochastic dominance. See Wakker (2010, Appendix 9.8) for a discussion of the issue.

[23] Keep in mind that x is the negative valued loss corresponding to expenditure of $-x$.

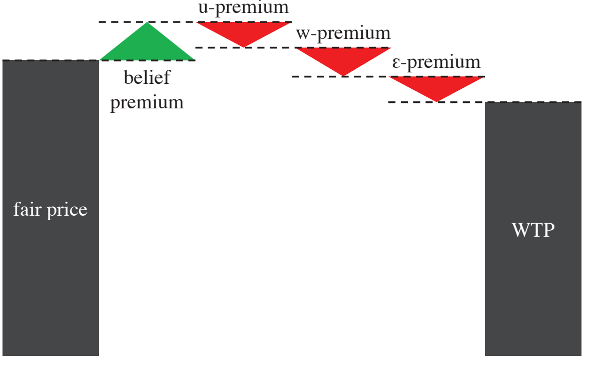
the individual does not fully take account of when stating subjective probabilities of future medical expenditure but which is respected when reporting WTP_r for health insurance (decreasing WTP), savings, assets and credit opportunities that can be used to self-insure medical expenditure risks (decreasing WTP), ambiguity aversion (increasing WTP) and time discounting (decreasing WTP).

An alternative risk premium equal to the difference between an individual's reported WTP and the fair price of insurance based on their observable characteristics can be written, after sequential substitution, as the sum of the four premiums defined by the behavioral model.

$$WTP_r - \mu = \pi^b + \pi^u + \pi^w + \pi^\varepsilon \qquad (3.5)$$

This decomposition of the WTP into the fair price and the various premiums is illustrated in Figure 3.2. It is worth noting that the signs of the premiums are difficult to predict because they depend on beliefs and private information. An exception is the u-premium π^u, which is likely to be negative according to PT. Figure 3.2 displays the case of an individual expecting to spend more than is predicted on the basis of their observable characteristics ($\pi^b>0$), which may be due to pessimism and/or private information about the likelihood of illness, who has convex PT utility for losses ($\pi^u<0$), who has a lower WTP because of reduced sensitivity to the probability of higher medical expenditures resulting in a negative w-premium ($\pi^w<0$) and who also has a negative ε-premium ($\pi^\varepsilon<0$).

Figure 3.2. Behavioral decomposition of WTP



Determining the relative importance of the four sources of difference between the reported WTP and the fair price can potentially help identify broad strategies that could increase health insurance uptake. For instance, a positive average *belief premium* would suggest that communicating information on the medical expenditures that can be incurred would not raise the demand for insurance. It may well do the opposite. A large negative *u-premium* would suggest that framing insurance in terms of gains instead of losses by informing of reimbursement to be received if insured instead of expenditures that would be incurred if uninsured may be an effective strategy to raise demand. A negative *w-premium* would suggest that in spite of expecting high expenditures on average, there is overweighting of the chance of having no expenditures. Finally, a negative *ε-premium* for low-income groups may suggest that their demand for insurance is limited by a tight budget constraint, possibly reinforced by preference for self-insurance that offer protection against multiple risks and not only medical expenses (Gollier 2003).

3.3 Health insurance in the Philippines

Most Filipino households are covered by the National Health Insurance Program (NHIP) through an employed-based program that is mandatory for formal sector employees, fully subsidized indigent and sponsored programs that cover the poor and near poor respectively, a senior citizens program, an overseas workers program and a voluntary program that offers cover to informal sector workers and the self-employed. Coverage through all programs extends automatically to the legal spouse, children (<21 years old) and parents (>= 65 years) of the person qualifying. According to the NHIP database, by 2015, 89.4 million individuals were covered in a population of around 100 million (Bredenkamp et al 2017). However, survey data consistently show a coverage rate that is lower by about 20 percentage points (Bredenkamp and Buisman 2016; Bredenkamp et al 2017)[24]. The remaining gap in coverage is mainly because of low take-up of the voluntary program among those engaged in the informal sector of the economy. For those with an average monthly individual income of no more than 25,000 pesos ($540), the premium for voluntary enrollment is 2,400 pesos per year ($50). At earnings above 25,000 pesos, the premium is 3,600 pesos per year.

[24] The discrepancy partly arises because fully subsidized members, such as the poor and senior citizens, who are automatically enrolled are not be aware of their insurance cover.

The NHIP benefit package includes a wide range of inpatient treatments at accredited public and private sector providers. Coverage of outpatient services and primary care is more limited. Despite the breadth of population coverage, the NHIP appears to provide only limited financial protection (Bredenkamp and Buisman 2016). This results from the limited coverage of ambulatory care and medication, and also from the latitude of providers to charge in excess of the reimbursement ceilings set by NHIP. Patients must pay out-of-pocket (OOP) to cover the difference. In principle, providers are prevented from charging indigent and sponsored program members (i.e., the poor and near poor) in excess of the reimbursement ceiling. However, this prohibition does not appear to be well enforced (Bredenkamp and Buisman 2016). In sum, in addition to the medical expenditure risk faced by the uninsured in the informal sector, those insured through the NHIP are also likely to be exposed to considerable medical expenditure risk.

3.4 Data and method

3.4.1 Sample design

Data were collected through a nationwide survey of 1780 Filipino households conducted in 2015. This was a follow-up to a baseline survey carried out in 2011 as part of a randomized health insurance experiment (Capuno et al., 2016). The baseline had a multi-stage cluster sampling design to randomly select 2,950 households that were nationally representative (excluding the Autonomous Region of Muslim Mindanao). The follow-up targeted all households that, at baseline, were not covered by any NHIP program, plus those that were covered either by the programs for the poor and near poor or through voluntary enrollment. Interviews were conducted with 1513 households from these three groups. The attrition rate was about 24 percent (Bredenkamp et al 2017).[25] In addition, a random sample of 267 households with mandatory, employment-based NHIP cover at baseline was selected for follow-up in order to increase the sample size. In order to reach the target sample size, any

[25] Maintaining a nationally representative sample is not critical to the validity of our analysis. Nonetheless, Appendix Table A3.5.1 presents balancing tests. There are some differences between households that were interviewed at follow-up and those that were not. In particular, households lost to follow-up were more likely to be urban, located in the capital region, richer, better educated and have fewer children. Generally, these are characteristics of more mobile households.

selected household that could not be traced or interviewed was replaced with another random draw from the initially mandatorily insured households.[26]

In the follow-up, the intention was to interview the person who was the original household respondent in the baseline survey or, if that person was unavailable, their spouse. In the baseline survey, the enumerator was instructed to interview the head of the household or spouse if the head was unavailable. Only if it was impossible to interview either of them was another household member above 21 years old to be interviewed.

We restrict the sample to respondents who answer all the questions needed to construct all components of the WTP decomposition (Eq. 3.5). We are left with 1565 observations out of the total of 1780. The 215 who are excluded are all dropped due to missing data on risk preferences.[27]

3.4.2 Elicitation of beliefs about future medical expenditure

Accumulating evidence demonstrates the feasibility and value of eliciting subjective expectations about various prospects in low- and middle-income countries (LMIC) (Attanasio, 2009; Delavande et al. 2011b; Delavande 2014). This is only the second study to elicit subjective probabilities of future spending on medical care (Yilma et al 2018). We follow a common approach of using a visual aid to reduce the cognitive effort required to complete the task (Delavande et al. 2011b). Respondents were asked to think of all expenditures on medical care and medicines that their household could incur in the next 12 months, excluding expenditures that would be reimbursed from health insurance. They were then presented with four cups labelled to represent ranges in which their household's total out-of-pocket (OOP) expenditure on healthcare over the next twelve months could fall: 0, 1-4000 pesos, 4001-8000 pesos and > 8000 pesos. They were given ten sticks and asked to distribute them by placing more sticks in a cup if they thought it more likely that their household's healthcare spending would lie in the range indicated by that cup.[28] This procedure, which is similar to one that has been used to elicit the subjective probability

---

[26] There are only a few significant differences between the households from this group that were interviewed at follow-up and those that were not. Those not followed-up were less likely to be located in an urban setting and the capital region.

[27] See Chapter 2 section 2.2.5 for characteristics of these observations.

[28] To elicit a subjective probability distribution of a continuous variable, survey respondents have typically been asked to distribute 10 or 20 items (Delavande 2011a). One experiment finds similar distributions irrespective of whether 10 or 20 beans are allocated (Delavande et al. 2011b).

distribution of a continuous variable in other LMIC settings (Delevande et al. 2011a; Delevande et al. 2011b), avoids making reference to the concept of probability, or even chance, that is unlikely to be understood by many of the respondents. The exact protocol followed is set out in Appendix A3.1.

The intervals of expenditure offered to respondents were selected on the basis of the cross-section distribution of expenditures in the baseline survey. Despite the right-skewed nature of the cross-section distribution, the middle two intervals were intentionally made of equal size to facilitate comprehension and to test for random distribution of the sticks. If beliefs are at least partly based on realized expenditures, then the sticks should not be distributed equally over the middle two intervals. We allow respondents to indicate a perception of a right-skewed distribution but do not impose this shape on the subjective distribution. The last interval was left open to capture perceptions of the probability of extremely high expenditures.

After completing the task designed to elicit their subjective probability distribution of medical expenditures, the respondent was asked to make a comparative assessment of their household's medical expenditure risk. Specifically, they were asked whether they thought the chance that their household would spend more than 8000 pesos on healthcare in the next year was smaller, the same or larger than the risk for households similar to them (see Appendix A3.2).

3.4.3 Estimation of perceived fair price

We use each household's subjective distribution of medical expenditures to estimate its perceived fair price for health insurance that fully covers the risk it faces. We interpret a respondent's allocation of sticks to each of the four cups as corresponding to their perception of the likelihood that their household's medical expenditure over the next twelve months will fall in the respective interval.

Let c_i denote the number of sticks placed in cup i, where i=0, 1, 2 and 3 for the cups indicating 0, 1-4000 pesos, 4001-8000 pesos and >8000 pesos respectively. As explained in section 3.2, we model each respondent's beliefs as a probability of not incurring any medical expenses p_0^s and a conditional distribution f^s of non-zero expenditures. The value p_0^s is given by $\frac{c_0}{10}$. We allow for the possibility that the respondent is entirely certain of having no medical spending, i.e. $p_0^s = 1$. If $p_0^s \neq 1$, we use nonlinear least squares to fit a lognormal distribution (adapted to negative values[29]) on the conditional cumulative probabilities defined by

$$F^s(-4000 \times i) = 1 - \frac{\sum_{j=1}^{i} c_j}{10 - c_0} \tag{3.6}$$

We choose a lognormal distribution since this allows for a long tail without having to fix the maximum. Advantages of the lognormal relative to two other distributions we considered (piecewise uniform and beta) are set out in Appendix A3.4.

We did not ask respondents to report their maximum possible expenditure. Even if we had, the reported amount could not be interpreted literally as the maximum (Delavande et al 2011a; Manski 2004). Besides, medical expenditures are known to have a long right tail. Note that Eq. 3.6 implies $F^s(-12000) = 0$ for *i*=3. Using this point in the fitting helped prevent the distribution being too fat at extremely high values given that the lognormal has a long tail. We report checks of the sensitivity of our estimates to fixing the point $F^s(x) = 0$ at other values of *x* in Appendix A3.4.

We enter the estimates of p_0^s and f^s into Eq.3.1 to obtain the perceived fair price of insurance. This is also the subjective expectation of medical expenditures and we will denote it μ^s. The square root of the second moment of the subjective distribution of expenditures, σ^s , is given by:

$$\sigma^s = \left((1 - p_0) \int_{-max}^{0} x^2 f(x) dx - (\mu^s)^2\right)^{\frac{1}{2}} \tag{3.7}$$

In all computations, we set $max = 500{,}000$, truncating the lognormal at that value. This was large enough to have negligible impact on our results.

3.4.4 Estimation of fair price

After reporting their expectations of future spending on healthcare, respondents were asked how much they spent OOP over the past 12 months. Specifically, they were asked in which of the same four intervals (0, 1-4000, 4001-8000, >8000) was their household's total spending on healthcare net of any insurance reimbursements (see Appendix A3.2). This allows us to directly compare the sample empirical distribution of past expenditures with the subjective probability distributions of future expenditures averaged over the sample. It also

[29] Let G be the cumulative distribution of the lognormal. We used $F^s(x) = 1 - G(-x)$.

makes it possible to estimate a fair price for insurance based on expenditure in the past year averaged over all households with the same observable characteristics. We use the sample means for groups characterized by their insurance cover.[30] Each mean is obtained by fitting a lognormal distribution to the cumulative frequencies of households within a group who report spending in the last year in each of the four intervals.

3.4.5 Elicitation and specification of risk preference

Risk preferences were elicited using an instrument designed to identify utility curvature separately from the weighting of probabilities and yet be comprehensible for less educated respondents, as well as feasible in the limited time available in a field survey (see Chapter 2). Respondents were offered two independent sets of hypothetical lottery choices in the loss domain. Each choice was visualized using two jars from which respondents were told a ball would be drawn randomly. The task is described in Chapter 2, section 2.5.1.

One set of lotteries identified the sure loss that the respondent found equivalent to facing a 50% chance of another loss. This was used to identify utility curvature. The second set identified the loss faced with a 50% probability that the respondent was prepared to accept rather than take a lottery over two losses with unequal probabilities. The losses and probabilities were fixed such that an EU maximizer would have the same point of indifference in both sets of lotteries. Hence, the difference between the selected points of indifference identifies probability weighting. See Chapter 2, Appendix A2.5 for details of the derivation.

We assume power utility $u(x) = -\lambda(-x)^r$, with λ the loss aversion parameter. The latter drops out of the equation for WTP because loss aversion is only identified in the presence of both gains and losses. Indeed:

$$WTP_u = \left(\frac{(1-p_0^s)\int_{-max}^{0} -\lambda(-x)^r f^s(x)dx}{-\lambda}\right)^{\frac{1}{r}} = \left((1-p_0^s)\int_{-max}^{0}(-x)^r f^s(x)dx\right)^{\frac{1}{r}} \quad (3.8)$$

We used the one-parameter weighting function $w(p) = \exp(-(-\ln(p))^\alpha)$ introduced and axiomatized by Prelec (1998), which gives $w'(p) =$

[30] It would be possible to allow for further heterogeneity by estimating a conditional mean function over other covariates, including age composition of the household, health status, income, etc. However, but for income, the premiums charged by the NHIP do not vary with such characteristics.

$\frac{\alpha}{p}(-\ln(p))^{\alpha-1}\exp(-(-\ln(p))^{\alpha})$. Substitution of this and the power utility function into Eq. 3.4 and inverting gives $WTP_{u\&w}$.

3.4.6 Elicitation of willingness to pay

WTP for health insurance was elicited in two ways that were randomized between respondents. One used an iterative bidding approach. It started by asking the respondent whether they would pay 500 pesos per month for health insurance that would cover all medical expenses for their entire household. Depending on whether the hypothetical offer was accepted or rejected, it was subsequently raised or lowered and the bidding continued until the respondent changed their response to the offer. If the respondent claimed to be willing to pay (WTP) more than 900 pesos, they were asked to state the amount they would pay.

The other method involved listing a number of WTP intervals each with a range of 100 pesos and asking the respondents to pick the one closest to their WTP. The intervals listed amounts up to 900 pesos, with a final option to indicate the WTP amount if it exceeded that value. The protocol for the WTP questions is set out in Appendix A3.3.

The respondent is asked how much they would be willing to pay for insurance that would cover all the medical expenses their household will incur. The question is not explicit about whether it is referring to expenses gross or net of those that would be reimbursed through any insurance the household currently has. If the respondent interprets the question as asking about gross expenses, then for households with insurance there is an inconsistency between this directly elicited WTP and both the estimated fair price and the perceived fair price of insurance, each of which is derived from a distribution (empirical and subjective) of OOP expenditures net of insurance reimbursement. It is impossible to know how each respondent interprets the WTP question. Since they are asked to state WTP for insurance covering expenses they will incur, it may be reasonable to assume that they will factor out expenses that will be covered by their current insurance. In that case, there is no problem. Otherwise, for insured households, the reported WTP will be inflated relative to the estimated fair price and this upward bias will be captured by a larger (positive) ε-premium (π^{ε}) in the decomposition given by Eq. 3.5. However, this bias would not affect the other three components of the decomposition. And it is not present for uninsured households.

3.4.7 Sample characteristics

The vast majority of respondents are either the household head (545/1565) or their spouse (839/1565). Table 3.1 reports means of other characteristics. The majority of respondents are female. Their average age is about 45 years. They are approximately evenly divided between urban and rural locations. About one tenth have at least some college education

Table 3.1. Sample characteristics

	Mean	Std. Dev.
Demographics		
Male (respondent)	0.276	
Age (respondent - years)	46.8	13.0
Urban	0.454	
Number of household members	5.14	2.27
Number of household members aged <15 or >=65	1.82	1.51
Socioeconomic status		
Highest education (respondent)		
No education completed	0.201	
Elementary school completed	0.255	
High school completed	0.440	
College completed or more	0.104	
Log of per capita household income (continuous)	10.230	1.06
Healthcare behaviors, knowledge, beliefs and preferences		
At least one hospital inpatient stay in past year (household)	0.100	
OOP healthcare expenditure in the past year (household)		
None	0.211	
1-4000 pesos	0.534	
4001-8000 pesos	0.141	
> 8000 pesos	0.114	
Health insurance (respondent)		
No insurance	0.348	
Voluntary	0.086	
Employment-based(mandatory)	0.194	
Sponsored (near-poor, 100% subsidized)	0.113	
Indigent (poor, 100% subsidized)	0.147	
Other insurance	0.079	
Don't know if insured	0.033	
Perceived risk of spending > 8000 pesos on healthcare compared with similar households (respondent),		
Smaller	0.339	
Same	0.484	
Larger	0.177	
Risk preference: Utility power (ρ, continuous)	0.487	0.491
Risk preference: Prelec alpha (α, continuous)	1.029	0.739
WTP for insurance(pesos per month)	171	149
N	1565	

Notes: Unless otherwise stated variable takes value of 1 if characteristic is present and is 0 otherwise. For education there are 1558 observations. For Log of average per capita household income there are 1462 observations. For other variables, sample sizes are as in bottom row. Other insurance includes those with more than one type of insurance.

A majority of respondents reported that their household spent 1-4000 pesos on healthcare in the past year. A little more than a fifth reported spending nothing and 11 percent spent more than 8000 pesos. Consistent with an optimistic bias (Weinstein 1980; Weinstein and Klein 1996), the fraction (33.9%) perceiving their risk of incurring medical expenses in excess of 8000 pesos to be smaller than that for similar households is approximately double the fraction (17.7%) that perceives their risk to be greater.

Respondents were asked whether each member of the household was covered by health insurance. We use the insurance status of the respondent to categorize households as insured or uninsured. Two thirds are insured. Since NHIP cover is extended to the spouse, children and parents of a member, there is little intra-household variation in insurance. When the respondent is insured, on average, 90% of other individuals in their household also have cover. When the respondent is not insured, on average, 89% of those in their household are also without cover. We further separate the insured by the type of program through which they obtain cover: employment, poverty (indigent program), near poverty (sponsored program) and voluntary. One fifth of the sample is covered through employment, about 15% is covered by the indigent program, 11% obtain cover through the sponsored program for the near poor and 9% is enrolled voluntarily.

Consistent with PT, on average, respondents are risk seeking for losses as characterized by utility curvature ($r<1$). The mean of Prelec's alpha is close to 1 indicating that, on average, there is no deviation from EU. Finally, the average WTP for health insurance coverage is 171 pesos per month, which is about 30 pesos less than the premium for low income households joining the NHIP voluntarily. This is also far below both the 500 pesos starting point in the iterative bidding elicitation of WTP and the midpoint (450 pesos) with the showcard approach. This suggests there was little anchoring on the starting value in the first case and no strong tendency to gravitate to the middle value in the second.

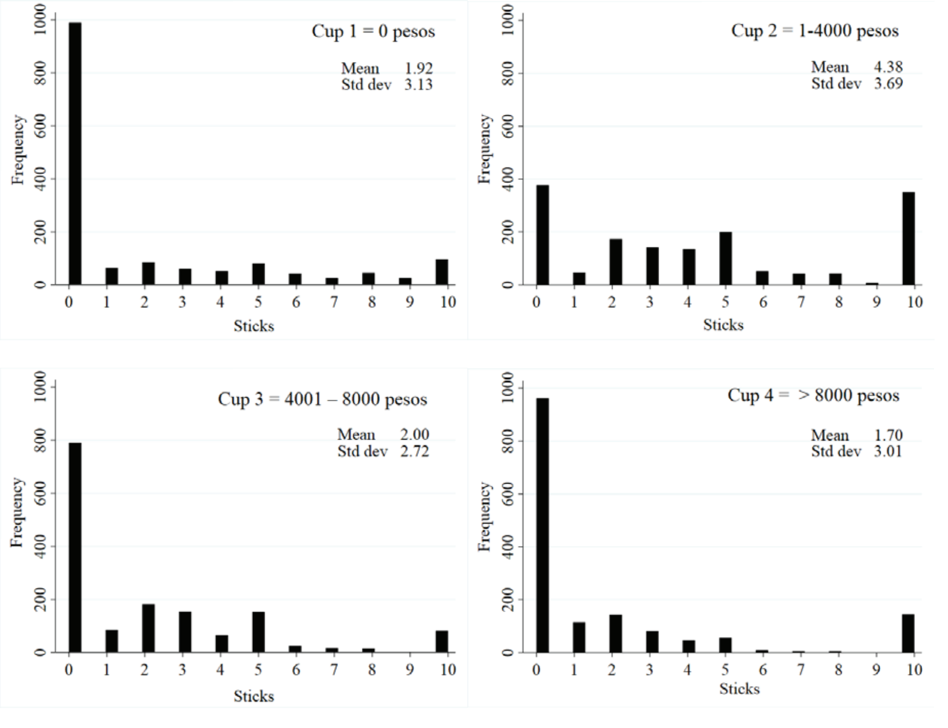
3.5 Elicited beliefs and subjective distributions of medical expenditures

Before presenting the behavioral decomposition of WTP for insurance, we first examine the elicited beliefs about future medical expenditures that are critical to the decomposition. We start by presenting the raw data on the elicited beliefs and then show estimates of the perceived fair price of insurance and moments of the subjective probability distributions of medical expenditures derived from them. We then assess whether and how these moments correlate with past medical spending and other covariates in order to establish the information respondents appear to use in forming the beliefs they report. The raw data and estimates of the risk preference parameters that are used to calculate the *u-premium* and *w-premium* components of the WTP decomposition are presented in Chapter 2, section 2.6.

3.5.1 Raw belief data

All respondents answered the questions designed to elicit their subjective distributions of spending on medical care. On average, respondents put most sticks (4.4/10) in the cup indicating spending of 1-4000 pesos (Figure 3.3). This implies that, on average, the respondents perceived a 44 percent chance of incurring medical expenses in that range. This is 10 percentage points less that the fraction of households that did spend in that interval in the previous year (Table 3.1). Nonetheless, the fact that the respondents, on average, attribute the greatest likelihood to spending in the range that has that greatest density in the empirical distribution of actual spending suggests that there is a degree of correspondence between the subjective and objective distributions.

Figure 3.3. Distribution of sticks allocated to each cup representing a range of medical expenditure



On the basis of the allocation of the sticks, spending between 4001 and 8000 pesos has the next highest average perceived likelihood (2/10), followed by no spending whatsoever (1.9/10). The fact that sticks were not divided evenly over the four cups provides further indication that respondents did not allocate them randomly. The data may well contain information on beliefs held with respect to future medical spending.

In total, 671 out of 1565 respondents put all 10 sticks in one cup, which, according to the instructions they were given, indicates certainty that their spending would fall in that range. About half (350) of these respondents put all sticks in the cup indicating spending between 1 and 4000 pesos. The propensity to allocate all the sticks to one cup may result from the relatively broad intervals of spending represented by each.

Many respondents do not place any sticks at all in at least one of the cups, which indicates that they rule out the possibility of that level of spending. This tendency is most common at the two extremes. Nearly a thousand of the respondents indicate that there is no chance that they will incur no medical expenses whatsoever, and nearly a thousand rule out spending more than 8000 pesos. There are 587 respondents who do not place any sticks in either of the cups representing the two extremes. These respondents appear to perceive limited exposure to medical expenditure risk defined in terms of the volatility of expenses.

3.5.2 Estimates of subjective distributions

Table 3.2 shows statistics from the sample distribution of the estimates of the first moment (μ^s) and square root of the second moment (σ^s) of the subjective distribution of medical expenditures for each household.[31,32]

Table 3.2. Estimates of first two moments of subjective probability distribution of household medical expenditure – sample statistics

	Mean	Std. Dev.	Percentiles				
			p25	p50	p75	p90	N
First moment (μ^s)	3,341	3,291	78	3,217	5,670	8,171	1,565
Second moment (σ^s)	1,323	1,868	51	274	2,891	4,409	1,565

Notes: Columns give summary statistics of the sample distribution of household-specific estimates of the first two moments of the subjective distribution of healthcare expenditures. The square root of the second moment (standard deviation) is given.

[31] To enhance readability, we will refer to the 'second moment' rather than the 'square root of the second moment'.

[32] See Appendix Table A3.4.1 for the sensitivity of our estimates obtained to assuming beta and the piecewise uniform distributions and bounds of 20,000 pesos and 50,000 pesos on the upper interval presented to respondents.

The sample mean of the estimates of the first moment of the household-specific subjective distribution of OOP healthcare expenditures (i.e. the mean of subjectively expected expenditure) is 3,341 pesos. This is reasonably close to the sample mean of actual spending, 3,146 pesos. The mean of actual spending is lower because 330 respondents reported having spent nothing on healthcare in the previous year, while only 96 were certain that they would spend nothing in the coming year. At the other extremity of the distribution, there is not such a large discrepancy between actual and expected spending. Specifically, 178 reported spending more than 8,000 pesos in the previous year compared with 144 who claimed being certain that they would spend above this threshold.

The sample mean of the square root of the second moment of the subjective probability distribution is less than half the sample mean of the first moment. Yilma et al. (2017) – the only other study we know that has collected data on perceptions of future medical spending – also find that the standard deviation of the subjective distribution tends to be less than its expected value. In contrast, it is common to find that the standard deviation in OOP spending across households is substantially larger than the cross-section mean (e.g. Van Doorslaer et al, 2007). Indeed, we find that the standard deviation across the sample of spending incurred in the previous year is greater than the sample mean. The standard deviation is estimated to be 4114 pesos – 1.3 times the estimated sample mean (3,146 pesos). These findings indicate that attempts to approximate risk exposure from measures based on the cross-sectional variance of medical spending lead to substantial overestimation. Household-specific risk is confounded by predictable heterogeneity in spending across households. Separation of the two is a major advantage of collecting data on households' perceptions of future spending prospects.

3.5.3 Correlates of moments of subjective distributions

We first assess whether and how the subjective probability distributions of medical expenditures correlate with past medical spending. Then we look at the correlation with the comparative measure of medical expenditure risk. Finally in this sub-section, we turn to multivariate analysis of relationships between the first two moments of the subjective distributions and the covariates described in Table 3.1.

3.5.2.1 Association with past medical expenditure

The rows of Table 3.3 split the sample into four categories according to spending in the previous year. The cells show the subjective probability of future spending falling in each of the same four categories averaged over the subsample defined by past expenditure. For example, the top left cell indicates that, on average, those with no OOP medical spending in the previous year believe they have a 43 percent chance of not incurring any expenses again in the coming year. As the level of spending in the previous year rises, the subjective probability of incurring no medical expenditure in the next year falls significantly, if not quite monotonically. This is consistent with the respondents believing that spending on healthcare is serially correlated and so using their past experience to forecast future expenses. Moving across the table confirms the positive association between forecast and past spending. In each column, the mean subjective probability of future spending lying in the interval differs significantly across the categories of past expenditure. The mean probability is nearly always largest on the diagonal: the subjective probability of future spending falling in an interval is highest among those who incurred expenses in that interval in the previous year. This indicates beliefs that medical expenditures are positively serially correlated.

Table 3.3 Mean subjective probabilities of future medical expenditure falling in intervals by past medical expenditure

Medical expenditure previous year (pesos)	Medical expenditure next year (pesos) 0	1-4000	4001-8000	> 8000	N
0	0.43	0.35	0.12	0.10	330
1-4000	0.15	0.55	0.19	0.11	836
4001-8000	0.07	0.39	0.36	0.18	221
> 8000	0.08	0.16	0.18	0.59	178
Test equal means: p-value	0.000	0.000	0.000	0.000	

Notes: Each cell shows the subsample mean of the proportion of sticks placed in the cup corresponding to the respective interval of future medical expenditure. The bottom row gives the p-value of a one way ANOVA (F-test) of equality of the means across the four categories of past expenditure

Table 3.4 shows the distribution of households across categories of actual spending in the previous year (rows) and expected spending in the coming year (columns). The column into which a household is placed is determined by the first moment of its subjective probability distribution. The null of independence is strongly rejected. The clustering of observations close to the diagonal indicates that expected medical expenditure is strongly positively correlated with spending in the previous year. One slight deviation from this pattern is that among those with expected spending in the 4001-8000 interval, more had spent 1-4000 pesos than had spent 4001-8000 in the previous year. But the numbers in either of these categories of past expenditure are much greater than the numbers who previously spent nothing or more than 8000 pesos.

Table 3.4 Frequencies of households by categories of expected future and actual past medical expenditure

Medical expenditure previous year (pesos)	Expected medical expenditure next year (pesos) 0	1-4000	4001-8000	> 8000	N
0	69	181	58	22	330
1-4000	19	516	252	49	836
4001-8000	4	57	144	16	221
> 8000	4	25	51	98	178
N	96	779	505	185	1565
Pearson $\chi2(9)$	661.7	p-value	0.000		

Notes: Columns categorize households according to value of estimated first moment of subjective probability distribution of medical expenditure next year.

The correlation coefficient between expected spending and past spending calculated as the mid-point of the reported interval is 0.49.

3.5.2.2 Association with comparative assessment of future medical expenditure

If a respondent holds beliefs about their future spending on healthcare, then there should be consistency across their answers to different types of questions about that spending. Each respondent was asked whether the chance that they would spend more than 8000 pesos on medical care in the next year was smaller, the same or greater than that for similar households. Provided 'similar households' is not interpreted to mean households with the same needs for healthcare and an equal economic capacity to meet those needs, then, if the respondent's beliefs are well-formed and they are able to express them through the answers given to both the subjective probability and comparative questions, we should observe that respondents who report a smaller chance of spending above 8,000 pesos tend also to give subjective probabilities that imply a lower expected level of expenditure. This is precisely what we see in Table 3.5. Both the sample mean and median of expected spending (first moment of subjective distribution) rise monotonically, substantially and significantly on moving from those reporting a smaller chance of spending more than 8000 pesos to those reporting a greater chance. This suggests that respondents do hold reasonably consistent beliefs about future medical spending and that our method of eliciting those beliefs in the form of subjective probabilities is at least partially successful.

Table 3.5 Expected medical expenditure (μ^s) by comparative assessment of future spending

Perceived chance of spending > 8000 pesos on healthcare compared with similar households is	Expected medical expenditure (μ^s)			
	Mean	Std. Dev.	Median	N
Smaller	2014	2730	78	531
Same	3446	3055	3769	757
Larger	5601	3602	6085	277
Test of equality across groups – p-value	0.000		0.000	

Notes: Expected expenditure is the first moment of the subjective distribution. The table shows the mean, standard deviation and median of these expectations across subsamples defined by the three categories of the comparative measure.

3.5.2.3 Multivariate analysis

The OLS regression estimates presented in Table 3.6 show that expected medical expenditure (μ^s) continues to be significantly associated with medical spending in the previous year after controlling for demographics and socioeconomic characteristics, and it is also correlated with insurance status. Expected spending rises monotonically and significantly in moving from those who reporting having spent nothing on medical care in the previous year to those who claim to have spent more than 8,000 pesos. On average, a respondent who reports that their household spent at least 8,000 pesos in the previous year expects to spend almost 5,000 pesos more over the next year than a household that spent nothing in the previous year. Again, it appears the respondents believe there is a high degree of positive serial correlation in medical expenditures.

Rather surprisingly, expected spending on medical care does not seem to vary with income.[33] But it does rise strongly with education. College graduates expect to spend around 900 pesos more than those without any education. Urban dwellers expected to spend 400 pesos less than those living in rural areas. This may be because transport costs are included in the healthcare expenditures.

[33] This may be due to measurement error in the income variable. The variable includes the income from different sources including salary, entrepreneurial activities, remittances and other sources.

Overall, the covariates explain 20 percent of the sample variation in expected medical expenditure. This represents a good deal of systematic variation, indicating that by no means do the elicited subjective probabilities contain only noise.

The second moment of the distribution of subjective beliefs σ^s is also found to be significantly associated with medical spending in the previous year. Compared with households who spent nothing in the previous year, those who spent in any of the other intervals report subjective probabilities that imply a more dispersed distribution and greater medical expenditure risk. Those who spent 4001-8000 pesos in the previous year perceive the highest volatility. Urban dwellers perceive less variation than those living in rural areas.

Table 3.6 OLS regressions of subjective beliefs of medical expenditure - first moment μ^s and second moment σ^s

	μ^s	σ^s
Medical expenditure in the past year (ref. = 0)		
1-4000 pesos	593.7***	384.0***
	(199.6)	(110.2)
4001-8000 pesos	2,506.9***	991.7***
	(254.1)	(170.9)
> 8000 pesos	4,848.6***	312.2*
	(330.2)	(165.9)
At least one hospital inpatient stay in past year	208.1	-188.2
	(305.0)	(192.0)
Log of per capita household income	49.9	2.8
	(73.9)	(49.0)
Urban	-379.5**	-362.1***
	(157.5)	(101.3)
Number of household members	60.3	-7.2
	(46.9)	(27.4)
Number of household members aged <15 or >=65	27.9	17.3
	(68.4)	(40.4)
Highest education (ref. no schooling)		
Elementary school completed	380.0*	83.5
	(222.8)	(150.6)
High school completed	180.5	-159.1
	(206.2)	(136.7)
College completed or more	877.1***	235.8
	(306.9)	(199.9)
Constant	1,088.1	1,111.8**
	(832.4)	(550.7)
Observations	1,456	1,456
R-squared	0.2237	0.0404

Notes: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

3.6 Willingness to pay for insurance and its decomposition

3.6.1 WTP for insurance

Table 3.7 gives estimates of WTP for insurance. The statistics in the top row are obtained from the empirical distribution of the WTP estimates obtained from Eq 3.4 in accordance with PT based on the elicited subjective distributions of medical expenditures and of risk attitudes. The mean estimate of $WTP_{u\&w}$ is about 200 pesos ($4) above the 2,400 pesos premium at which voluntary enrollment in the social health insurance fund is offered to lower income households. However, the median $WTP_{u\&w}$ is only 380 pesos and so the majority would not demand social insurance at the current (reduced) premium even if it could deliver full cover of all medical expenses, which it does not promise.

The bottom row gives WTP estimates obtained from the direct elicitation methods described in section 3.4.4[34]. The amount each respondent reported being willing to pay per month for insurance has been converted to the annual equivalent in order to make the magnitudes comparable with those obtained using our indirectly derived measure. The mean of the directly elicited WTP is lower than the estimate derived from the subjective distribution of medical expenditures while the median is higher.

Table 3.7. Estimates of willingness to pay for insurance

	Mean	Std. Dev.	Median	N
Derived from subjective distribution ($WTP_{u\&w}$)	2,598	3,198	380	1,565
Directly elicited (WTP_r)	2,057	1,789	1,200	1,565

There is positive correlation between the estimates of WTP elicited directly and those derived indirectly, but it is small (ρ=0.06, p=0.015).

3.6.2 Decomposition of WTP

Table 3.8 presents our decomposition of WTP for health insurance (Eq. 3.5). We show means of the behavioral determinants of the WTP and compare these between the insured and the uninsured. We discuss, in turn, findings related to each component of the decomposition – the belief premium, the risk attitude (u- and w-) premiums and the residual (ε-) premium.

[34] WTP was elicited using two different methods. The average WTP using the bidding approach is 2141 pesos while the average of the approach listing intervals is slightly lower at 1966 pesos (p=0.053).

Table 3.8 Decomposition of willingness to pay for health insurance

	Fair price	Premium								WTPr	
		belief		u		w		ε			N
			(r)=(6		(r)=(6		(r)=(6		(r)=(6		
All	3146	196		-386		-358		-540		2057	1565
Insured (1)	3179	309	0.10	-382	0.71	-395	0.21	-669	0.11	2066	1514
Voluntary (2)	3263	803	0.02	-346	0.51	-496	0.25	-405	0.91	2818	135
Employer (3)	3201	56	0.88	-356	0.49	-295	0.99	-455	0.70	2151	304
Sponsored (4)	3944	222	0.48	-266	0.03	-561	0.07	-1372	0.00	1966	177
Indigent (5)	2304	852	0.00	-389	0.87	-372	0.51	-725	0.18	1670	230
Uninsured (6)	3086	21		-400		-294		-359		2054	545

Notes: The column labelled (r)=(6) gives the p-value of a t-test of equality of the mean for the group in row (r) with the mean for the uninsured in row (6). The test allows for unequal variances across groups.

Finding 1: positive belief premium

On average, respondents have a positive belief premium. This was already evident from the comparison of means in section 3.5.2: the amount respondents expect to spend on healthcare over the next year is greater than the sample average of expenses incurred in the past year. The average subjective expectation is greater than the objective expectation. If the respondents were risk neutral, then, motivated only by their expectations, on average, they would purchase insurance that is priced fairly for the average risk. The discrepancy between the perceived fair price and fair price does not result from pessimism about the likelihood of incurring high levels of expenditure. We established in section 3.4.8 that, on average, people are optimistic about avoiding such expenses. As noted in section 3.5.2, the subjective and objective distributions diverge most at the bottom. A substantial proportion of households incur no expenses but few report being certain of avoiding spending on healthcare completely.

The mean belief premium is larger for the insured in the sample than it is for the uninsured. While the difference is not statistically significant, the mean is significantly positive for the insured (p=0.004) but not significantly different from zero for the uninsured (p=0.878). One must keep in mind that the belief premium is obtained from the empirical and subjective distributions of OOP spending. It tells us about the discrepancy between the fair price and the perceived fair price of insurance that is supplementary to any insurance the household currently has. The positive mean belief premium of the insured implies that, based solely expectations, the average of these households would demand fairly priced supplementary insurance, were it available. Their positive belief premium may be because they do not fully appreciate the cover they get from their current insurance. On average, they expect to spend 3488 pesos on healthcare but they spent 309 pesos less than that in the last year.[35]

The expectations of the uninsured, on average, are unbiased.[36] Their decision not to insure does not appear to be due to optimism. They are aware of the average risk of OOP expenditure and so efforts to communicate this risk would not be effective in encouraging them to insure. The mean perceived fair price of insurance for this group is 3107 pesos (=3086+21). This is greater than the 2400 pesos premium at which a low income household can enroll in the NHIP, but it is less than the 3600 pesos premium at which insurance is available to higher income households. Hence, according to these estimates, any low income uninsured household would have decided to insure if it were risk neutral or risk averse. Either risk preferences explain the behavior of these households, or there is some other explanation that is not captured by our model. High income, uninsured households would need to have a risk premium of at least 493 pesos (=3600-3107) in order to be persuaded to join the NHIP. Their revealed preference suggests that they are not so risk averse.

Among the insured, the average belief premiums are largest for the voluntarily insured and for the poor who get fully subsidized insurance through the indigent program. The substantial excess of the subjective expectation of OOP spending over the mean of actual spending suggests that pessimism could possibly contribute to the decision to enroll voluntarily. Even with insurance, this group still expects to be spending more than it did, on average, in the last year. Putting differences in the degree to which beliefs are pessimistic aside, the group that enrolls voluntarily still has more reason to do so than those who choose to not enroll. The fair price of insurance for those who enroll voluntarily is 177 pesos greater than that for those who remain uninsured. Bearing in mind that the former group will have additional medical expenses that are already reimbursed and so not reflected in this fair price for supplementary cover, it does appear to be the higher risk individuals who choose to enroll. The difference in the mean perceived fair prices is even greater (959 pesos). Consistent with adverse selection, the voluntarily insured seem to realize they are high risk, while the uninsured are aware that they are low risk.

---

[35] Insured households pay OOP for healthcare because insurance is incomplete in both the services covered and the expenses reimbursed. In particular, providers can, and do, charge in excess of reimbursement ceilings (Capuno et al 2016).

[36] Strictly, this is true only if there is no change in the mean of actual spending from one year to the next.

The large belief premium of those covered by the indigent program is puzzling. This group does not appear to appreciate the extent of the insurance cover they have. This might be because they do not realize that providers are prohibited from charging them fees on top of the reimbursement ceiling. However, this is not particularly compelling because of low compliance with the no balanced billing policy for the poor (Bredenkamp and Buisman 2016). Another explanation could be that the indigent expect to need and pay for health care but when they fall sick they are constrained from seeking care by their extremely tight budget and possibly also because of procrastination.

Finding 2: negative u- and w- premiums explain low WTP

The means of both risk attitude premiums are negative for all groups indicating risk seeking as opposed to risk aversion, on average. This explains a large part of the shortfall of WTP from the fair price. The sum of the two (mean) negative risk attitude related premiums is larger in magnitude than the positive belief premium. Hence, based on only their perceived fair price and their risk attitudes, the average household would not purchase actuarially fair insurance that fully covered their currently uninsured medical expenses. For those already partially insured, this means that they would not be interested in supplementary cover offered at a premium equal to their expected OOP payments which fully protected them from the residual risk they face because of gaps in their current cover. The risk related premiums do not differ so much between the insured and the uninsured except that the probability weighting premium is less negative, on average, among the uninsured, although only the difference from those covered by the sponsored program for the near poor is significant (at 10%).

Finding 3: ε-premium large for the poor

The difference between the WTP derived indirectly from the model of beliefs and risk attitudes ($WTP_{u\&w}$) and the directly reported WTP_r gives us the residual ε-premium capturing whatever cannot be explained by the model. This is negative and large in magnitude relative to WTP_r for all groups. Besides beliefs and risk attitudes, there are other factors that push the WTP for insurance below the fair price. One contributing factor could be opportunities for self-insurance. In a multi-period model, it is not optimal for a household holding a sufficient buffer stock of wealth and who is not liquidity constrained to purchase full formal insurance offered at an actuarially fair premium (Gollier 2003). Consumption can be maintained while spending on healthcare by drawing down savings and/or borrowing.

Respondents who have these self-insurance options would be expected to report a lower WTP_r for health insurance for any given exposure to medical expenditure risk. Our measure of risk is the subjective distribution of medical expenditures derived from elicited beliefs about future spending. Respondents who have self-insurance options and who take account of them will forecast greater future spending. In our model, this will raise the perceived fair price of insurance (μ^s). Self-insurance financed medical expenditures will also raise the fair price (μ) and so it has no effect on the belief premium (μ^s-μ). The reduction in WTP_r relative to μ generated by self-insurance will therefore push the ε-premium in the negative direction. There is plenty evidence that self-insurance and informal insurance are important sources of financing medical expenses in LMIC (Genoni 2012; Gertler and Gruber 2002; Islam and Maitra 2012; Liu 2016; Mohanan 2013; Townsend 1994,). It is plausible that this contributes to the low value of WTP_r and the large negative value of the ε-premium. However, the larger magnitude of ε-premium among the poor and near-poor households covered by the indigent and sponsored programs respectively suggest that this is not the full story. According to the multi-period model with self-insurance options, the value of formal insurance is highest for those who have a smaller buffer stock of wealth and those who are liquidity constrained. Poorer households have both characteristics. Hence, their WTP relative to the risk they are exposed to should be higher. This would imply a larger, not a smaller, ε-premium. One possible explanation is the poor respondents are cognizant of their tight budget constraint when reporting their *WTP* for insurance but pay less attention to it when forecasting their future spending on healthcare. Another possibility is that the poor feel entitled to the fully subsidized insurance they have and report a low willingness to pay (relative to their forecast expenditure) as a statement of that entitlement, or possibly as a strategy to maintain the subsidy.

3.7 Conclusion

We have presented a new decomposition of the willingness to pay for insurance into its fair price and four behaviorally determined contributions that reflect the individual's beliefs about their exposure to risk, two components of risk attitudes – utility curvature and probability weighting – consistent with prospect theory and a residual term that absorbs all determinants of WTP that are not captured by our single-period PT model, as well as measurement error. The motivation for this decomposition was to explain the discrepancy between low (revealed) WTP for health insurance relative to the substantial medical expenditure risk households are exposed to in LMIC. We confirmed this discrepancy exists in the Philippines and implemented the WTP decomposition using a unique combination of data on elicited beliefs about future spending on healthcare, actual medical expenditure and elicited risk preferences that are obtained from a nationwide survey.

The average WTP in the sample is only about two thirds of the fair price of insurance. This deficit is not explained by downwardly biased expectations of medical expenditures. In fact, expectations are biased in a pessimistic direction. The mean subjective expectation of medical expenditures is 6.2% above the mean expenditure incurred by the households in the previous year. This positive *belief premium* is more than offset by negative premiums related to risk attitudes. Both convex utility in the domain of losses and the transformation of probabilities into decision weights push the WTP below the fair price, reducing the demand for insurance. On average, individuals are not risk averse. Risk seeking characterized as convex utility in the domain of losses is widely observed and is consistent with PT. The perhaps surprising result here is that this is not offset by probability weighting to generate a demand for insurance, on average. WTP is further reduced by other factors not included in our model. We suspect that time is a major missing element. The analysis presented in Chapter 2 found that time preferences were a stronger determinant of the demand for health insurance in the Philippines than risk preferences. Added to this, the self-insurance options that are available when medical expenditure risk is examined in a multi-period context are expected to reduce WTP for formal insurance.

The mean directly elicited WTP is highest among the voluntarily insured and lowest among the poor with fully subsidized insurance. The low WTP of the poor is presumably a direct reflection of their limited purchasing power. After the poor, WTP is lowest among the uninsured. They do not differ from the voluntarily insured so much with respect to the two risk related premiums of the WTP decomposition. It does not appear to be the case that the opportunity to purchase insurance is forgone because of more risk seeking preferences or because there is less volatility in the subjective distributions of medical expenditures. Rather, it is with respect to subjectively expected medical expenditures that the uninsured differ most from the voluntarily insured. Objectively, the average expenses incurred by the uninsured are 5.4% below the average expenses of the voluntarily insured. Allowing for the fact that the latter have additional expenses that are covered by their insurance, this suggests that there is adverse selection in voluntary enrollment. But the larger difference is in the subjective expectations. The voluntarily insured overestimate their medical expenses by 25%, which corresponds to a large positive belief premium. The belief premium of the uninsured is effectively zero. This difference in beliefs should not be used to explain why those who are voluntarily insured decided to take this cover since their beliefs are with respect to OOP medical expenses that are not covered by their insurance. But for the uninsured we can conclude that, on average, their expectations are unbiased. It is not distorted beliefs that are responsible for their decision not to enroll. This suggests that communicating information about exposure to medical expenses is unlikely to stimulate enrollment in health insurance. Preferences, along with the other factors captured by the residual term, appear to be responsible for the decision not to insure. Of course, besides the question of whether it is ethically defensible, it is far from easy to design a policy that influences preferences.

We decompose WTP using beliefs modelled as subjective probabilities and preferences consistent with PT. Compared with relying on the assumptions that the cross-sectional distribution provides an adequate approximation to the perceived distributions used by individuals in decision making and that EU is a descriptively accurate model of decision making, we believe our approach has advantages and that these are evident from partial success in explaining the low WTP for health insurance. However, we do not have any evidence that people are PT maximizers. We also had to assume specific functional forms (power utility and Prelec's weighting function). We are not aware of evidence supporting these specifications in settings similar to that studied here. Most tests of the suitability of these functional forms have been conducted in western countries, and usually with student samples.

Our computed WTP relied on several measurements (beliefs, utility, probability weighting), each possibly subject to noise. It is thus not surprising to obtain relatively low cross-individual correlation between the indirectly derived and directly elicited WTP. However, it is reassuring that comparisons of groups formed on the basis of insurance cover give meaningful findings. Our model, which is purely based on risk perception and risk attitude, does not incorporate important factors, such as a time dimension, self-insurance options and liquidity constraints, that can explain the reported WTP, as well as its discrepancies from both the fair price and the perceived fair price of insurance. These abstractions obviously decrease the correlation that can be expected between the WTP derived from our model and those directly reported by the respondents.

The extent to which we can use the analysis to explain the health insurance choices observed in the data is limited by the fact that beliefs about future spending on healthcare were elicited after the purchase of insurance. Ideally, we would estimate a household's subjective distribution before it had the opportunity to purchase health insurance. We do not know what an insured household's beliefs would have been if it had not been covered. Correcting this weakness is a priority for future research. In a context where there is ex ante elicitation of beliefs and preferences as well as ex post observation of who takes up an offer to insure, our decomposition could be used to explain variation in the observed insurance behavior.

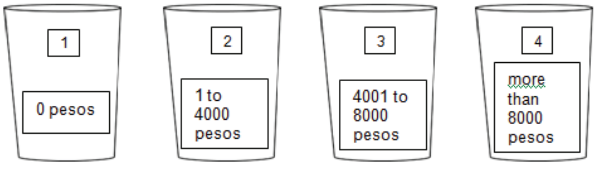
Appendices Chapter 3

Appendix 3.1 Protocol for elicitation of subjective distribution of medical expenditures

I am interested in the amount your household expects to spend out-of-pocket on medical and dental care, medicines and maintenance drugs, including transportation costs to health facilities in the next 12 months (1 year).

Out-of-pocket expenditures include spending from salary/income, loans, savings and donations or charity assistance, but exclude spending that will be reimbursed from any health insurance cover, if you have any. They also exclude the government benefits SSS, GSIS and ECC.

NOTE TO THE INTERVIEWER: PRESENT THE RESPONDENT WITH THE FOUR CUPS



These cups represent four possible amounts of expenditure on medical and dental care, medicines and maintenance drugs your household might face over the next 12 months (1 year) including transportation costs to health facilities, but not including any expenses that will be covered by all health insurance

1. spend nothing at all
2. spend between 1 and 4000 pesos
3. spend between 4001 and 8000 pesos
4. spend more than 8000 pesos

NOTE TO THE INTERVIEWER: GIVE THE RESPONDENT THE 10 STICKS.

I am interested in your beliefs about the chance that your household will incur the different levels of expenditure over the next 12 months (1 year). I would like you to distribute the 10 sticks over the cups to express what you think is the chance of each level of expenditure. One stick represents one chance out of 10. If you do not put any sticks in a cup, it means you think that you will NOT spend that amount. As you add sticks, it means that you think the chance of facing that level of expenditure increases. For example, if you put one or two sticks in a cup, it means you think it is unlikely that you will spend that amount but it is still possible. If you put 5 sticks in a cup, it means that there is an equal chance that you will spend that amount as it is that you will not (fifty-fifty). If you put 6 sticks in a cup, it means that there is slightly more chance that you will spend that amount. If you put 10 sticks in a cup, it means you think that you will spend that amount, and there is no chance that you will spend any of the other amounts. There is not a right or wrong answer, I just want to know what you think.

How would you distribute these 10 sticks now? Please remember that this concerns out-of-pocket expenditures for healthcare, medicines and maintenance drugs your entire household will face in the next 12 months (1 year), including transportation costs.

Appendix 3.2 Protocol for eliciting past expenditures

TOTAL HEALTH CARE EXPENDITURES PAST 12 MONTHS
[SHOWCARD]

How much did your household spend out-of-pocket on medical and dental care, medicines and maintenance drugs including transportation costs to health facilities <u>in the past 12 months (1 year)</u>?

Out-of-pocket expenditures <u>include</u> spending from salary/income, loans, savings and donations or charity assistance, but <u>exclude</u> spending that will be reimbursed from any health insurance cover, if you have any. They also <u>exclude</u> the government benefits SSS, GSIS and ECC.

<u>NOTE TO INTERVIEWER</u>: IF THE RESPONDENT IS HAVING DIFFICULTY ESTIMATING THE TOTAL EXPENDITURES, ASSIST HIM/HER IN ADDING UP THE EXPENSES THAT HE/SHE RECALLS.

NOTE TO THE INTERVIEWER: IN CASE NECESSARY, REPEAT THAT WE ARE ASKING FOR OUT-OF-POCKET EXPENDITURE OF HEALTHCARE, MEDICINES AND MAINTENANCE DRUGS THE ENTIRE HOUSEHOLD FACED IN <u>THE PAST 12 MONTHS (1 YEAR)</u>

Nothing at all	1
Between 0 – 4,000 pesos	2
Between 4,001 – 8,000 pesos	3
More than 8,000 pesos	4

Appendix 3.3 Protocol for eliciting willingness to pay for full health insurance coverage

<u>WILLINGNESS TO PAY FOR FULL HEALTH INSURANCE COVERAGE</u>

NOTE TO INTERVIEWER: WE HAVE TWO QUESTIONS FOR AMOUNT WILLING TO PAY. QUESTION A WILL BE ASKED TO HALF OF THE RESPONDENTS. QUESTION B WILL BE ASKED TO THE OTHER HALF OF THE RESPONDENTS (RANDOMLY SELECTED)

FOLLOW TICKMARK

[ ]	**ASK QUESTION A**
[ ]	**ASK QUESTION B**

A. AMOUNT WILLING TO PAY

Think of the amount you are willing to pay per month for a membership in a health insurance programme which covers all costs your entire household will incur for medical and dental care, medicines and maintenance drugs including transportation costs to health facilities.

For a full membership in this health insurance programme, would you be willing to pay (MENTION AMOUNT)?

NOTE TO THE INTERVIEWER: PLEASE START BY ASKING FOR THE AMOUNT OF 500 PESOS (Q504A). THEN DEPENDING ON THEIR ANSWER ASK IN INCREMENTS AS PROVIDED BY THE INSTRUCTIONS IN THE TABLE

	AMOUNT IN PESOS	**WILLINGNESS**		**FINAL ANSWER WILLINGNESS TO PAY =**
		YES	**NO**	
A	500	1	2	
		SKIP TO F	CONTINUE TO B	
B	400	1	2	
		STOP. RECORD FINAL ANSWER AS PHP400. SKIP TO Q506.	CONTINUE TO C	
C	300	1	2	
		STOP. RECORD FINAL ANSWER AS PHP300. SKIP TO Q506.	CONTINUE TO D	
D	200	1	2	
		STOP. RECORD FINAL ANSWER AS PHP200. SKIP TO Q506.	CONTINUE TO E	
E	100	1	2	
		STOP. RECORD FINAL ANSWER AS PHP100. SKIP TO Q506.	STOP. RECORD FINAL ANSWER AS PHP0. PROCEED TO Q505	
F	600	1	2	
		CONTINUE TO G	STOP. RECORD FINAL ANSWER AS PHP500. SKIP TO Q506.	
		1	2	

G	700	CONTINUE TO H	STOP. RECORD FINAL ANSWER AS PHP600. SKIP TO Q506.	
H	800	1	2	
		CONTINUE TO I	STOP. RECORD FINAL ANSWER AS PHP700. SKIP TO Q506	
I	900	1	2	
		CONTINUE TO J	STOP. RECORD FINAL ANSWER AS PHP800. SKIPTO Q506.	
J	**HIGHER THAN 900?**	1	2	
		ASK MAXIMUM AMOUNT AND RECORD AS FINAL ANSWER.	STOP. RECORD FINAL ANSWER AS PHP900 SKIP TO Q506	

NOTE TO INTERVIEWER: QUESTION B (WITH SHOWCARD) WILL BE ASKED TO SELECTED HOUSEHOLDS (HALF OF THE RESPONDENTS).

B. AMOUNT WILLING TO PAY
SHOWCARD
How much are you willing to pay per month for a membership in a health insurance programme which covers all costs your entire household will incur for medical and dental care, medicines, and maintenance drugs including transportation costs to health facilities?

PhP 0	1	**ASK Q505**
PhP 1-100	2	**SKIP TO Q506**
PhP 101-200	3	
PhP 201-300	4	
PhP 301-400	5	
PhP 401-500	6	
PhP 501-600	7	
PhP 601-700	8	
PhP 701-800	9	
PhP 801-900	10	
If more than PhP 900, specify: ____________	11	

Appendix 3.4 Sensitivity to distributional assumption

To construct a measure for the perceived fair price from the moments of the subjective probability distribution requires us to make a distributional assumption. We choose a lognormal distribution since this allows for a large tail without fixing the maximum. We explain the limitations of other distributional assumptions below.

We considered using a piecewise uniform distribution, however this distribution is relatively sensitive to the value at which the bound for the upper interval for the elicitation of medical expenditures is set. This value has the largest impact on the estimates for respondents that put all the sticks in the cup indicating expenditure of more than 8,000 pesos. This degree of sensitivity to a parameter about which we have little information is a major disadvantage of assuming a piecewise uniform distribution. The sensitivity carries over to estimates of the second moment. Even if we had elicited a bound on the last interval each household contemplated incurring, it would be implausible to assume that the density is flat in the region preceding that value. For these reasons, we did not choose to give consideration to estimates obtained under the assumption of a piecewise uniform distribution.

Another consideration was using the beta distribution. The sample mean of the estimates of the expectation is robust to assuming each household's subjective probability distribution of expenditures has a beta form rather than being lognormal. The main difference between the sample distributions of estimates of expected medical expenditure derived from the assumptions of lognormality and beta is that the latter produces fewer low-valued expectations. For example, the first quartile is 78 with lognormality and 568 with beta. The reason for choosing the lognormal over the beta distribution is because the latter does not allow for a tail and requires setting a maximum on the distribution. Table A3.4.1 below further illustrates the sensitivity of our distributional assumption.

Besides making a distributional assumption we need to assume an upper bound on the last interval for which we elicited likelihood of medical expenditures. The bottom panel of the table shows summaries of estimates of the first two moments of the subjective distributions under the assumption of lognormality with the upper bound of the last interval set at 20,000 pesos and 50,000 pesos. Comparing these with the estimates shown in the top panel using an upper bound of 12,000 pesos reveals that the sample means are somewhat sensitive to the value imposed. Actually, the distribution of estimates of the first moment shifts little with the upper bound value up to the 75th percentile. But there are substantial differences at the top of the sample distribution, which affect the mean. These are generated by respondents who place many sticks in the cup indicating spending in excess of 8,000 pesos. The upper bound assumed for such spending obviously has a large impact on the expected value calculated. As would be expected, the distribution of estimates of the second moment is more sensitive to the upper bound value. The median obtained with a value of 50,000 pesos is 1.9 times that derived using 12,000 pesos. In contrast, the median of the first moment essentially remains the same irrespective of the upper bound value imposed.

Table A3.4.1 Estimates of first two moments of subjective probability distribution of household medical expenditure – sensitivity to distributional assumption and upper bound imposed

	Mean	Std. Dev.	Percentiles			
			p25	p50	p75	p90
Upper bound 12000 pesos						
First moment (μ_s)						
Lognormal	3,341	3,291	78	3,217	5,670	8,171
Beta	3,379	3,140	603	2,979	5,514	8,189
Piecewise uniform	3,779	2,837	2,001	2,801	5,601	8,001
Second moment (σ_s)						
Lognormal	1,323	1,868	51	274	2,891	4,409
Beta	1,351	1,350	302	835	2,569	3,640
Piecewise uniform	1,885	1,089	1,154	1,291	2,921	3,517
Lognormal						
First moment (μ_s)						
Upper bound						
20.000 pesos	3,742	3,962	78	3,277	5,661	9,294
50.000 pesos	4,634	5,883	80	3,461	5,738	14,462
Second moment (σ_s)						
Upper bounds						
20.000 pesos	1,785	2,768	50	409	3,192	6,277
50.000 pesos	2,816	8,050	51	403	3,210	8,138
Sample size	1565					

Notes: Columns give summary statistics of the sample distribution of household-specific estimates of the first two moments of the subjective distribution of healthcare expenditures. The square root of the second moment (standard deviation) is given. When fitting the Beta distribution we assume a uniform distribution for respondents that put all sticks in the last cup.

Appendix 3.5 Balancing tests of attrition

Table A3.5.1 Balancing tests of attrition on baseline characteristics

	Followed up	Not Followed up	p-value
Informal sector/poor at baseline			
Urban	0.424	0.617	0.000
Average per capita household expenditure	22351	29766	0.000
Head is working	0.876	0.844	0.079
Head has poor health	0.028	0.039	0.220
Head had at least college education	0.077	0.130	0.000
Has available health facility within 15 min	0.721	0.749	0.240
Has other insurance	0.026	0.043	0.065
Number of children under 21	1.851	1.517	0.000
Experienced adverse health outcome in the last year	0.264	0.268	0.864
National Capital Region	0.112	0.245	0.000
Rest of Luzon	0.440	0.483	0.103
Visayas	0.226	0.087	0.000
Mindanao	0.223	0.186	0.093
N	1513	462	
Formal sector at baseline			
Urban	0.652	0.523	0.000
Average per capita household expenditure	35592	57223	0.639
Head is working	0.891	0.912	0.314
Head has poor health	0.026	0.023	0.740
Head had at least college education	0.202	0.254	0.090
Has available health facility within 15 min	0.772	0.733	0.220
Has other insurance	0.127	0.093	0.118
Number of children under 21	1.843	1.952	0.355
Experienced adverse health outcome in the last year	0.255	0.270	0.635
National Capital Region	0.213	0.100	0.000
Rest of Luzon	0.554	0.436	0.001
Visayas	0.090	0.260	0.000
Mindanao	0.142	0.203	0.029
N	267	708	

Chapter 4

Long-term effects of temporary inducements: A nationwide randomized health insurance experiment in the Philippines

Joint work with Baillon, A., Capuno, J., O'Donnell, O., Quimbo, S. and R. Tan, C.

4.1 Introduction

The greatest challenge for countries striving to reach universal health coverage is the 'missing middle': informal sector workers who do not benefit from employment-based mandatory insurance and who are not sufficiently poor to qualify for means-tested fully subsidized insurance (Bredenkamp et al. 2015; Tangcharoensathien et al. 2011; Wagstaff et al., 2016). Voluntary insurance enrollment of these workers and their families, which comprise a very large share of the population of most middle-income countries, is typically low (Acharya et al. 2013; Bredenkamp et al. 2015; Pettigrew and Mathauer 2016). This has prompted experimentation with inducements – premium subsidies, information on benefits and assistance with application – that are intended to encourage enrollment. Evidence on the effects on take-up at the time the inducements are offered is mixed (Asuming et al 2017; Capuno et al., 2016; Chemin 2018; Das and Leino 2011; Dercon et al 2015; Thornton et al 2010; Wagstaff et al. 2016). But even when the effect is positive, it would be expected to dissipate once the inducement is withdrawn, unless the experience of being insured changes the valuation of it or the inducement helps the recipient overcome a fixed cost to enrollment that is not faced again at reenrollment. Knowing whether inducements have short- or long-lived impacts on the demand for insurance is critical to determining their cost-effectiveness. And yet, as far as we know, the only evidence on the long-term (> 1 year) effects that exists comes from an experiment conducted in one rural district of northern Ghana (Asuming et al 2017).

This chapter adds to this meagre evidence base on the long-term effects of health insurance inducements by using a nationwide randomized experiment to estimate the impact four years later of two sets of interventions designed to encourage enrollment in the voluntary plan of the National Health Insurance Program (NHIP) of the Philippines (Capuno et al. 2016). The first intervention consisted of a one-off premium subsidy of up to 50%, plus information on the operation and benefits of the insurance program as well as SMS reminders to enroll over a period of eleven months. We will refer to this as the *subsidy+info* intervention. Half of the treated households that did not respond to this intervention were randomly selected to receive a second that reduced the indirect costs of enrollment by providing one-time assistance with completion and submission of the insurance application. We will refer to this as the *handholding* intervention. Households offered the *subsidy+info* intervention, but not the *handholding* intervention, were 4.8 percentage point (ppts) more likely than controls to be voluntarily enrolled in NHIP four years later ($p<0.05$). This is a staggering four fifths of the short-term effect. Attenuation of the effect of the *handholding* intervention, which had a much larger short-term impact, was much greater. In fact, it had no significant long-term effect on enrollment. The non-significant point estimate indicates that sample households randomly offered this inducement after failing to respond to the *subsidy+info* intervention were 3.0 ppts more likely to be voluntarily insured four years later than the sample households not offered *handholding* despite also failing to respond to the *subsidy+info* intervention. This is only 11% of the short-term impact of this intervention. The combined effect of the two interventions is to raise enrollment by 8.5 ppts ($p<0.01$) four years after the inducements were offered. This is 23% of their combined short-term impact.

Our study adds to the scant and mixed evidence on the long-term effects of inducements for health insurance enrollment. The results contradict those of two experiments that find the immediate impact of a premium subsidy on health insurance enrollment already dissipates after one year (Chemin 2018; Thornton 2010), but they are partially consistent with a third experiment that finds the effect of a premium subsidy is sustained to some degree three years after it was offered (Asuming et al 2017). Thornton et al. (2010) report that a substantial premium subsidy offered to informal workers in three markets in Managua (Nicaragua) initially raised enrollment by about 30 ppts, but this diminished after 1 year, with less than 10% of those who enrolled during the experiment still remaining in the program. Similarly, Chemin (2018) finds that a full premium subsidy in combination with information and assistance with application initially raised enrollment by 45 ppts in a rural community in the Central Province of Kenya, but this effect completely vanished after a year when the subsidy was withdrawn. However, the same study finds that another intervention designed to build trust in the insurance product by having a respected community member present it during a regular meeting of an existing informal group increased take-up by 12 ppts, and almost three fifths of this was maintained after one year. This suggests that changing the way in which people who are unfamiliar with the concept of insurance perceive it can be important to achieving permanent changes in demand. But this may not hold universally. In a rural district of Northern Ghana Asuming et al (2017) find that a subsidy of 33-100% raised enrollment by 40 ppts initially and by 15 ppts after three years. But a 17 ppts initial impact of information on enrollment was not sustained at all three years later. Rather strangely, a handholding intervention had no immediate impact but is estimated to have raised enrollment by 20 ppts after three years[37]. The long-term combined effect of all three interventions is an incredible 86% of their combined short-term effect. This study shows that it is possible for temporary inducements to have a lasting impact on health insurance enrollment. But given the location of the experiment in one rural district of one province in Ghana, one may wonder about the extent to which the results generalize.

The present chapter provides evidence from an experiment conducted nationwide in the Philippines in both rural and urban areas. Our results confirm that temporary inducements for voluntary health insurance can indeed have a long-term, sustained impact on enrollment. In addition, we show that the ranking of the effectiveness of the different inducements switches as the follow-up period is stretched. This demonstrates that short-term results may be a poor guide of the long-term relative cost-effectiveness of programs.

One-time interventions, such as a subsidy, could heighten or dampen demand for insurance, health services or, indeed, other products in the long run (Dupas 2014). The effect may be positive if the consumer previously had little or no experience of the product and found it difficult to assess its value. In that case, a temporary inducement may permanently shift preferences by making the consumer aware of what they were previously missing. In the context of insurance, this is most likely to occur for those who make a claim during the initial period of cover. However, given a right-skewed distribution of medical expenses, for insurance to be viable without continued, substantial subsidies, a minority must claim in any period. The experience of purchasing insurance, even at a subsidized price, may disillusion the majority that do not make a claim. Unless this is compensated by the peace of mind from knowing that they would be covered if expenses were incurred, then a temporary period of insurance may discourage many from renewing their cover when the subsidy is withdrawn. A negative learning effect could also arise if those responding to the subsidy are disappointed by the benefits offered when they do make a claim. In the Philippines, providers are permitted to charge prices that exceed the reimbursement ceiling covered by NHIP. Most take advantage of this. Acquiring insurance cover can therefore result in being charged a higher price for the same treatment. The insured may then enjoy little benefit in terms of reduced exposure to medical expenditure risk. Of course, in this case the low demand for insurance should be of less concern since it offers little effective protection.

---

[37]The authors do not have a clear explanation for this finding. They suggest that those treated in the village may have created a personal relationship over time with the government field officers which increased the pressure to enroll in the long run but not in the short run.

Development practitioners and economists are alert to the potential for one-off subsidies for health and other products to impact negatively on demand in the long run, although there is only limited evidence on the extent to which such fears are well founded (Dupas 2014). Demand inducement through a price subsidy runs the risk that the recipients may anchor their willingness to pay (WTP) on the discounted price (Dupas 2014). The one-time subsidy may then reduce take-up in the long run as it reduces the consumer's reservation price below the unsubsidized price (Simonson and Tversky 1992, Koszegi and Rabin 2006, Simonsohn and Loewenstein 2006, Dupas 2014). In addition to the impact of the interventions on insurance enrollment, we also estimate effects on WTP for insurance in the long term. This makes it possible to assess the plausibility of some mechanisms through which the long-term effect on enrollment may operate. We do not find any significant effect of the *subsidy+info* intervention, the *handholding* intervention or the combination of the two on WTP four years later.

The rest of this chapter is organized as follows. Section 4.2 provides background of the health insurance setting in the Philippines. Section 4.3 presents the research design and methods, and section 4.4 presents the empirical strategy. The results are summarized in Section 4.5 and Section 4.6 concludes.

4.2 Study setting

The NHIP, which is administered by and is commonly referred to as PhilHealth, initially (1995) provided mandatory cover for civil servants and formal sector salaried employees only (Bredenkamp and Buisman, 2016; Capuno et al., 2016). It was extended first to provide fully subsidized insurance for the poor and later to make voluntary insurance available to informal sector workers and the self-employed through the Individually Paying Program (IPP). By 2010, the year before our experiment, PhilHealth claimed to cover 75% of the population and have 70 million beneficiaries. Of these, only 16% were enrolled through the IPP program and they accounted for only 33% of those eligible for this program (Manasan 2011; Capuno et al. 2016). Two thirds of those who could enroll chose not to.

All PhilHealth programs extend coverage to the spouse, children (<21 years) and parents (≥ 65 years) of the enrolled member. At the time of the experiment, the annual premium for the IPP was 1,200 pesos (just under $30) for those with an average monthly individual income of no more than 25,000 pesos. It was 2,400 pesos for those with higher incomes.

Between 2011/12 when the experiment took place and the long-term follow-up in 2015, PhilHealth implemented various changes. In 2014, fully subsidized cover was extended to the near poor (2013 Amendment to the National Health insurance Act of 1995 (RA 10606)). About half of the households benefitting this extension of free health insurance were not previously covered by any PhilHealth program, while the other half did have insurance, including some who were enrolled in the IPP program (Bredenkamp et al. 2017). At the start of 2015, a law mandating government-sponsored health insurance for all senior citizens (≥ 60 years) came into effect (PHIC 2014). According to the PhilHealth database, between the end of 2011 and mid 2015 coverage increased from 27.9 million families (78.4 million individuals) to 38.5 million families (89.4 million individuals) (Bredenkamp et al 2017). However, survey data consistently show coverage rates that are lower by about 20 ppts (Bredenkamp and Buisman 2016; Bredenkamp et al 2017)[38]. In any case, coverage undoubtedly did increase markedly in the period from our interventions to the long-term follow-up. This does not invalidate our design provided that the coverage extensions benefited the treatment and control groups equally, which should hold given random allocation of the initial inducements.

By 2015 those with an average monthly individual income of no more than 25,000 pesos ($540), paid a premium of 2,400 pesos per year ($50) to enroll voluntarily in the IPP. At earnings above 25,000 pesos, the premium was 3,600 pesos per year.

The benefit package includes a wide range of inpatient services at accredited Philhealth providers in both the public and private sector. In also includes some specific outpatient interventions and there is a limited primary care benefit package (Bredenkamp and Buisman 2016). There is, however, evidence that PhilHealth coverage provides only limited financial protection (Bredenkamp and Buisman 2016). This most likely results from the fact that providers are allowed to set their own prices while PhilHealth does not cover expenses beyond reimbursement ceilings, leaving patients to pay the excess out-of-pocket. The insured face a high degree of uncertainty over both the amount the provider will charge and the amount PhilHealth will reimburse.

[38] This most likely results from the fact that subsidized members such as the poor and senior citizens are automatically enrolled in PhilHealth by virtue of their status as opposed to having to actively enrol themselves and might therefore not be aware of their insurance status.

4.3 Research design

The sampling strategy, interventions, randomization and data collection are described in Capuno et al. (2016), which presents estimates of the short-term effects of the interventions.

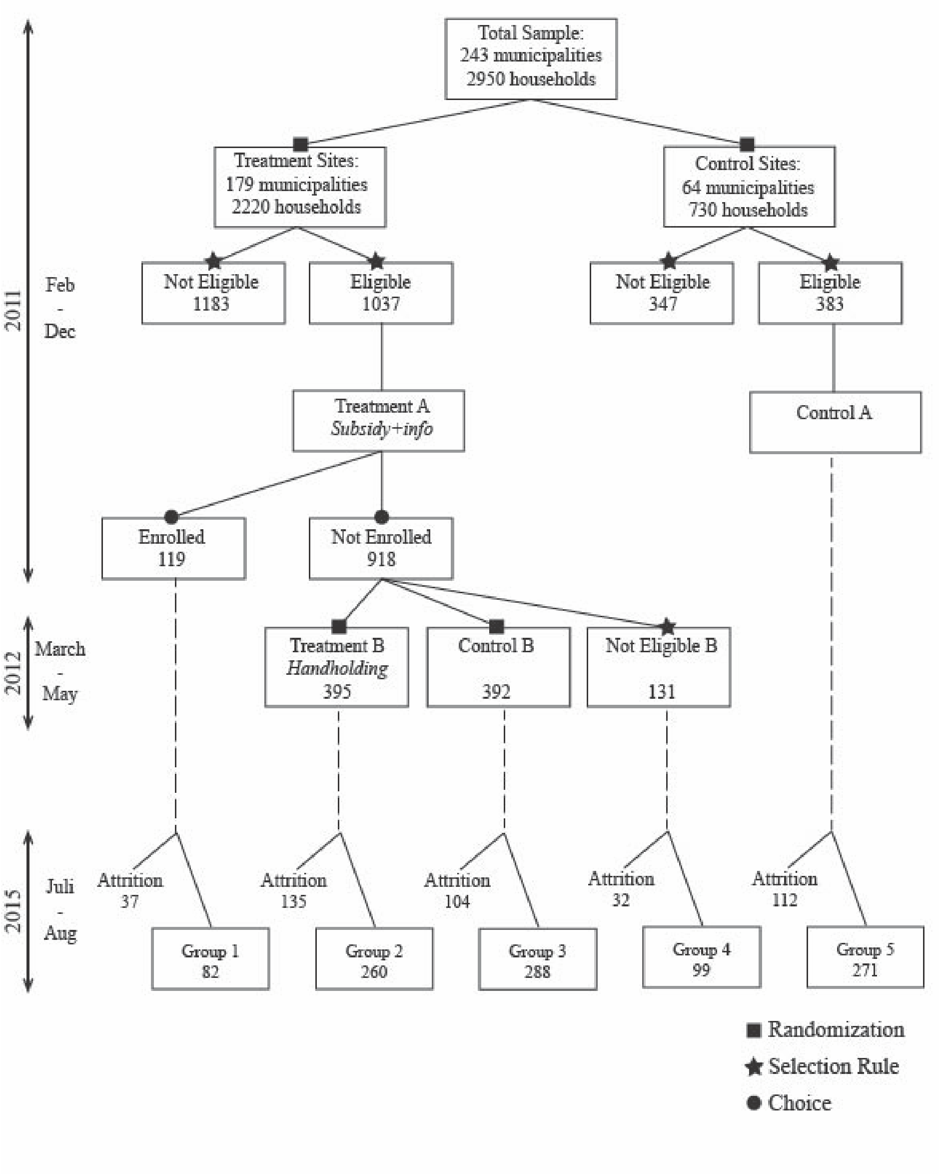
4.3.1 Sampling

A multi-stage cluster randomized design was used to select 2950 households from 243 municipalities that are representative at the national level, excluding the conflict area of Autonomous Region Muslim Mindanao. First, there was stratification by broad regions (National Capital Region, North-Central Luzon, South Luzon, Visayas, and Mindanao) within which provinces were selected using proportionate to population sampling (PPS). Within each sampled province, first municipalities/cities, and then barangays (community/neighborhood), were selected again using PPS. From each barangay, five households were drawn using simple random sampling (Capuno et al. 2016). The baseline survey was fielded February-April 2011.

Randomization of the insurance inducements was done at the municipality level rather than the barangay or household levels to reduce the scope for contamination between treatment and control groups, and to avoid non-compliance that could occur if control households were to see their neighbor benefiting from a subsidy they were denied. Out of 243 municipalities selected by the sampling procedure described in the previous paragraph, 179 were randomly assigned to be intervention sites and the remaining 64 designated as control sites. In the 179 intervention sites, 2200 households were selected for interview to establish eligibility for the IPP. Those found to be eligible (1,037 households) were offered the insurance inducements described in the next sub-section. A household was considered eligible if the survey respondent reported: a) that either the household head or the spouse was not covered by any PhilHealth program; b) being unsure whether the head/spouse were covered by any program; or, c) that they had not paid the IPP premium in the preceding six months (Capuno et al 2016). Hence, households in which both the head and the spouse were paid-up members of the IPP program, or any other PhilHealth program, were not eligible for the interventions. In the 64 control municipalities, 780 households were interviewed and none was offered any inducement.

Figure 4.1 shows the study design and participant flow.

Figure 4.1 Participant flow



4.3.2 Interventions

Households located in the treatment sites that were eligible for the IPP program were offered the *subsidy+info* intervention at the end of the baseline interview that was conducted at some time from February to April 2011. This consisted of a voucher giving entitlement to enroll in the IPP at a reduced premium, an information kit and a series of SMS messages sent intermittently reminding the respondent to use the voucher to enroll. The voucher was initially valid until the end of 2011 (9-11 months depending on the date of interview) and was worth a 600 pesos ($13.66) discount on the annual premium for IPP membership. The amount was equivalent to a 50% reduction in the price for a low income individual (≤ 25,000 pesos monthly income) and a 25% discount for a higher income individual. The recipient could use the voucher at their nearest PhilHealth service office, where they would have to submit the requisite application forms and pay the part of the annual premium not covered by the voucher. The voucher was not transferable. The information kit consisted of leaflets covering enrollment, claims procedure and frequently asked questions, as well as the application form. Until the end of period for which the voucher was valid, a recipient who had not yet redeemed their voucher was sent SMS messages reminding them to use it and how to do so. Those in the control sites eligible for the IPP program were not offered anything, neither were those not eligible in both types of site.

In January 2012, households in the treatment sites who had been issued with a voucher but who had not yet enrolled in the IPP and were still eligible to do so were randomly allocated to one of two groups, with randomization in this case being done at the household level[39]. One half of these households were sent (by mail) a letter containing the same information kit they had been issued with earlier and with notification that the validity of the voucher had been extended up to the end of February 2012. They were also sent SMS messages with the same information. The other half of these non-responding but eligible households were also sent a letter that, in addition to including the same information kit, informed them that the voucher would remain valid until they were visited by a survey enumerator (March-May 2012) who would offer assistance with completion of the application form, deliver it to the PhilHealth office on their behalf and ensure that the PhilHealth ID card was mailed back to them. Essentially, this eliminated the indirect cost of enrollment, which in some cases could be substantial when transport connections, e.g. by boat, were poor. This is what we refer to as the *handholding* intervention.

---

[39] In January 2012, PhilHealth gave the study team a list of households who had used their voucher to purchase IPP cover. Households that had received the voucher but were not on this list became the target group for the sub-experiment. Their IPP eligibility was double checked in the end line survey conducted March-May 2015 (Capuno et al 2016).

Of the 918 households in the treatment sites that had been offered the voucher for IPP enrollment but had not taken it up by the end of 2011, 787 were still eligible for the program at that time. From these households, 392 were randomly assigned to receive the two-month extension to the *subsidy+info* intervention. The other *395* were given the handholding intervention. The remaining 131 non-responding households were no longer eligible for the IPP program. These households received no further inducement.

4.3.3 Statistical power

The experiment was powered to estimate the short-term (approximately one year) effect on IPP enrollment of the *subsidy+info* intervention. No separate power calculations were made for the *handholding* intervention. The sample size was set to detect a short-term increase in the enrollment rate of 7.5 percentage points among IPP eligible households not yet enrolled with power fixed at 0.8 and the significance level set at 0.05. The PhilHealth overall coverage rate was assumed to be 53%, the IPP coverage rate was assumed to be 33% of those eligible for that program, the IPP enrollment rate in the control group at short-term follow-up was assumed to be 10% and the intra-cluster correlation coefficient was assumed to be 0.16. Clustering was at the municipality level, which was the unit of randomization.

4.3.4 Follow-up sample

The long-term effects of the interventions are estimated using a follow-up survey conducted in July-August 2015. The intention was to interview all 1420 households that were IPP-eligible at baseline. It proved possible to trace and interview 1000 of these households. The households that attrited differ from those that were followed up in some baseline characteristics. They are more likely to be urban (/capital city) dwellers, they are better educated, have higher incomes, have fewer children and are willing to pay more for insurance through PhilHealth. (Appendix Table A4.1). We explain in section 4.4 how we reweight the sample to deal with these differences.

The bottom of Figure 4.1 shows how the 1000 households who were followed up are split across the various treatment and control groups.

4.3.5 Outcomes

The main outcome of interest is whether a household that was IPP eligible in 2011 was enrolled in this program in 2015. If either the household head or spouse is reported to be enrolled as an IPP member and was not enrolled in 2011, then we consider that the household is insured through this program given coverage extends to the family of the IPP member. We do not consider insurance through any other program because individuals qualify for these schemes through formal sector employment, poverty or by belonging to a defined population group. They do not voluntarily pay a premium to join these programs.

In addition to evaluating the long-term impact on enrollment, we estimate the impact on the willingness to pay (WTP) for insurance through a PhilHealth program in 2015. WTP was elicited in two ways that were randomized between respondents. The first method was the iterative bidding approach. This started by asking the respondent whether they would pay 100 pesos per month for PhilHealth membership. Depending on whether or not they said they would, the amount was subsequently raised or lowered and the bidding continued until the respondent changed their response. If the respondent claimed to be willing to pay more than 300 pesos, they were asked to state the amount they would pay. The other method involved listing WTP intervals, each with a range of 50 pesos, and asking the respondent to pick the one closest to their WTP. The intervals were given for amounts up to 300 pesos, with a final option to indicate their WTP amount if it exceeded this. Since the elicitation method was randomized, it is orthogonal to the randomly allocated interventions. But to increase power we control for an indicator of the method of elicitation.

4.4 Empirical strategy

Randomized allocation of both interventions is the basic strategy used to identify their long-term effects on enrollment in the IPP program and WTP but there are two potentially confounding factors that need to be dealt with: attrition and eligibility for the *handholding* intervention being partly behaviorally determined. To identify the long-term effect of the *subsidy+info* intervention, households that were also exposed to the *handholding* intervention must be excluded from the treatment group. That leaves three groups that were exposed only to *subsidy+info:* i) those who responded to this inducement by enrolling in the IPP by the end of 2011 (*Group 1*) (see Figure 4.1); ii) those who did not enroll in IPP and were still eligible for it at the end of 2011, and who were randomly assigned not to receive the *handholding* intervention (*Group 3*); and, iii) those who did not enroll in IPP and were no longer eligible for it at the end of 2011 (*Group 4*). Comparing the mean outcome across these three groups in 2015 with the mean outcome of the control group that did not received any intervention (*Group 5*) does not provide an unbiased estimate of the average treatment effect of *subsidy+info* because exclusion of households that were exposed to this intervention, did not respond to it by the end of 2011 and were subsequently randomly allocated to receive the *handholding* intervention (*Group 2*) renders the treatment group potentially compositionally different, in unobservables as well as observables, from the control group. If the insurance demand without inducement of households that did not respond to the *subsidy+info* intervention differs from that of the average household initially eligible for the experiment, then comparing outcomes in a treatment group consisting of *Group 1 + Group 3 + Group 4* with outcomes in *Group 5* will give a biased estimate of the effect. Let Y^0 be the potential outcome in the absence of any intervention. The problem is that, in general,

$E[Y^0|Group\ 1\ \cup Group\ 3\ \cup Group\ 4] \neq E[Y^0|Group\ 5]$, while, due to randomization, $E[Y^0|Group\ 1\ \cup Group\ 2\ \cup Group\ 3\ \cup Group\ 4] = E[Y^0|Group\ 5]$.

We deal with this problem by reweighting the treatment group used to estimate the effect of *subsidy+info* such that the weighted proportion of households that responded to this intervention by the end of 2011 in this treatment group is equal to its unweighted proportion of all households initially exposed to the intervention. Define group membership indicators $D_{ji} = 1(i \in Group\ j\ )$, where 1() is the indicator function. Then the group sizes are $N_j = \sum_{i\in\ Group\ j} D_{ji}$. Define weights,

$$w_i = \begin{cases} \frac{N_3+N_4}{N_2+N_3+N_4} & if\ \ i \in Group\ 1 \\ 1 & otherwise \end{cases}, \tag{4.1}$$

such that, $\frac{\sum_{i\in\ Group\ 1} w_i}{\sum_{j=1,3}^{4}\sum_{i\in\ Group\ j} w_i} = \frac{N_1}{N_1+N_2+N_3+N_4}$. Application of these weights to a treatment group consisting of *Group 1 + Group 3 + Group 4* ensures that households of the type that initially respond to the *subsidy+info* intervention have the same influence on the composition of this group as these types of households have in the full treatment group, which, due to random assignment, is not expected to differ compositionally from the control group. Hence, if there were no attrition, then the average long-term effect of *subsidy+info* could be estimated without bias from the weighted mean outcome across *Groups 1, 3* and *4* less the mean outcome of the control *Group 5*.

We further reweight the sample to correct for the observable baseline differences between the treatment and control groups that arise from attrition (Rosenbaum 1987; Imbens 2004). Inverse probability weights (IPW) are derived from the estimated propensity scores of receiving the *subsidy+info* intervention in a sample consisting of *Groups 1, 3, 4* and *5*. The propensity scores are estimated from a probit model of the treatment indicator on the baseline characteristics $(\mathbf{X}_i)$ that are identified in Appendix Table A4.1. These include the baseline values of one of the outcomes - WTP.[40] The other outcome – enrollment in IPP – is equal to zero for all observations at baseline. The weights defined above are applied in this probit. Let the estimated propensity score for an individual in the control *Group 5* be $\Phi(\mathbf{X}_i\hat{\gamma})$, where $\Phi(\ )$ is the standard normal cumulative density function. Then, that observation is given a weight equal to $w_i = v_i / \bar{v}$, where $v_i = \Phi(\mathbf{X}_i\hat{\gamma}) / 1-\Phi(\mathbf{X}_i\hat{\gamma})$, $\bar{v} = \frac{1}{N_5}\sum_i D_{5i} v_i$. Weights for the treated households continue to be defined as in (1). After reweighting the estimation sample, there are no differences in the means of any of the baseline characteristics between the treatment groups (1, 3 and 4) and the control group (5) (see Appendix Table A4.2).

The average long-term effect of *subsidy+info* is estimated by,

$$\left[\bar{y}\middle|Groups\,1,3\,\&\,4\right]-\left[\bar{y}\middle|Group\,5\right]=\frac{1}{\sum_{j=1,3,4}\sum_i D_{ji}w_i}\sum_{j=1,3,4}\sum_i D_{ji}w_i y_i-\frac{1}{\sum_i D_{5i}w_i}\sum_i D_{5i}w_i y_i \qquad (4.2)$$

where the expressions on the left hand side represent weighted sample means over the respective groups of the outcome (y) in 2015 and these means are written explicitly on the right hand side. We obtain this estimate from a weighted least squares regression of the outcome (enrollment or WTP) on an indicator of being in *Groups 1, 3* or *4* as opposed to *Group 5*. We also present doubly robust estimates obtained by applying the IPW and also conditioning on the baseline covariates listed in Appendix Table A4.1. This estimator is consistent if either the propensity score or the regression, but not necessarily both, is correctly specified (Robins and Rotnitzky 1995). For the enrollment outcome, we present probit in addition to the least squares estimates of this doubly robust estimator.

We estimate the long-term effect of the *handholding* intervention by restricting the estimation sample to the households that had not to enrolled in the IPP by the end of 2011 but that were still eligible at that time and comparing outcomes of those randomly allocated to be offered the handholding inducement (Group 2) with those who were not (Group 3). Reweighting is necessary in this case only to correct for differences in observable baseline

[40] For observations that are missing on WTP at baseline, the mean WTP at baseline is entered and an indicator of being missing on WTP is included. The effects on enrollment are robust to excluding baseline WTP in the estimation of the propensity score.

characteristics that result from attrition. Following the general procedure described above, we estimate a probit model for the probability of being in *Group 2* as opposed to *Group 3*, use the estimated propensity score to construct weights for the control group (3) and then take the weighted mean difference in outcomes between the two groups.

Last we define a combined treatment consisting of being offered *subsidy+info* followed, if necessary, by *handholding* if there is no initial response to the first inducement. To estimate the effect of this treatment combination, we compare the outcomes of a treatment group consisting of those households that had enrolled by the end of 2011 (*Group 1*) plus those that did not and were subsequently randomly assigned to receive handholding (*Group 2*) with the control group that did not receive any intervention (*Group 5*). For the reasons described in relation to estimation of the effect of *subsidy+info*, this also requires reweighting the treatment group to make it representative of the whole initial treatment group and so comparable with the control group. In this case, the appropriate weights are,

$$w_i = \begin{cases} \frac{N_2}{N_2+N_3+N_4} & if \ \ i \in Group\ 1 \\ 1 & otherwise \end{cases}, \quad (4.3)$$

such that, $\frac{\sum_{i \in Group\ 1} w_i}{\sum_{j=1}^{2} \sum_{i \in Group\ j} w_i} = \frac{N_1}{N_1+N_2+N_3+N_4}$. Differences between the treatment group and control group in baseline characteristics due to attrition are corrected by application of IPW constructed from propensity scores analogous to those described above. The difference in the weighted means is obtained from a bivariate regression in the case of the IPW estimator and from a multivariate regression for the doubly robust estimator, as described before.

All standard errors are adjusted for clustering at the municipality level, which was the level of randomization to the *subsidy+info* intervention[41].

In addition to estimating the long-term effect approximately four years after the offer of the insurance inducements, we also estimate short-term effects. To facilitate comparison, we do this using the same sample used to obtain the long-term effects. That is, those attriting by 2015 are not used even if they did participate in the 2012 follow-up. Consequently, all the identification issues discussed above also arise for estimation of the short-term effects in

[41] To be conservative we also used clustered standard errors at this level when estimating the effect of *handholding* although randomization of this treatment was done at the household level.

this sample and we use exactly the same estimation methods. All that changes is that outcomes are measured from the 2012 follow-up rather than the 2015 follow-up.[42]

4.5 Results

After application of the IPW obtained from the estimated propensity scores, the control group and treatment group are balanced on baseline line characteristics for each of the three treatment groups used for the *subsidy+info, handholding* and combined interventions. The corresponding tables are given in Appendix A4.2.

4.5.1 Short-term effects

Before examining the long-term effects, we present the short-term effects in Table 4.1. The *subsidy + info* intervention that provided a premium subsidy, information and SMS reminders is estimated to have raised enrollment in the IPP program by 6 percentage points (ppts) ($p<0.01$) according to the IPW estimator approximately one year after the inducements were first offered and before any household was required to renew their insurance without the subsidy. The doubly robust estimator implemented using least squares gives essentially the same estimate. Using probit to condition on the covariates (in addition to applying the IPW) raises the estimate to 6.8 ppts. In the control group, 6.3 percent of eligible households had enrolled after one year. So, the intervention is estimated to have approximately doubled the rate of enrollment.

Our estimates of the short-term effect of subsidy+info are approximately twice as large as those obtained by Capuno et al (2016). The reason is that we estimate the effect of these inducements being offered initially for a period of around 9 months plus an extension for a further 3 months. Capuno et al. (2016) estimate the effect of the original offer only. They measure enrollment in January 2012. We measure enrollment in March-May 2012.

The handholding intervention is estimated to have raised enrollment by 29 ppts ($p<0.01$) after about one year using either the IPW or doubly robust (least squares) estimators. Using probit in the second step of the doubly robust estimator reduces the

[42] Capuno et al. (2016) estimate the short-term effect of the *subsidy+info* intervention by comparing the enrollment rate in January 2012 (before implementation of the handholding intervention) of the full treatment group with that of the full control group. The estimate the effect of the *handholding* intervention by comparing enrollment in May 2012 of those offered this with that of those not offered it within the treatment group households that had not enrolled by January 2012.

estimate only on 1 ppt. This compares to an enrollment rate of 3.1% amongst those who only received the premium subsidy, information and reminders and who had not enrolled by January 2012. Clearly, the offer to provide assistance with completion and submission of the application form had a very large impact on enrollment in a group that had not been responsive to the premium subsidy. Our estimates are extremely close to those of Capuno et al (2016), which are obtained from enrollment measured, like our short-term effects, in March-May 2012.

Table 4.1 Short-term effects on health insurance enrollment

	Effect	Standard error	*z*-Stat	*N*
subsidy+info				
Inverse probability weights	0.0608***	0.0208	2.92	740
Doubly robust				
Least squares	0.0593***	0.0199	2.99	740
Probit	0.0679***	0.0229	2.97	740
handholding				
Inverse probability weights	0.2877***	0.0311	9.26	548
Doubly robust				
Least squares	0.2870***	0.0307	9.35	548
Probit	0.2787***	0.0283	9.84	548
Combined				
Inverse probability weights	0.3604***	0.0319	11.29	613
Doubly robust				
Least squares	0.3634***	0.0312	11.64	613
Probit	0.3601***	0.0290	12.43	613

Notes: Standard errors are adjusted for clustering at the municipality level. *** $p<0.01$

The combined intervention of initially providing the subsidy, information and reminders and subsequently providing the handholding intervention to those who opted not to enroll after being offered the subsidy+info inducements is estimated to have increased enrollment by 36 ppts ($p<0.01$) after approximately one year. This is a six-fold increase on the enrollment rate of the control group.

4.5.2 Long-term effects

Estimates of the long-term effects of the three sets of interventions after four years are reported in Table 4.2. The *subsidy + info* intervention is estimated to have raised enrollment by 4.5-4.8 ppts ($p<0.05$) four years after the inducements were first offered and three years after they had been withdrawn. Compared to an enrollment of the control group of 5.5

percent, this represents an increase of at least 82%. It is also around three quarters of the short-term effect. This represents a remarkable maintenance of the treatment effect after expiry of the treatment. Apparently, the majority of those induced by the subsidy to enroll continued to do so even when the subsidy was no longer offered.

The point estimates of the long-term effect of the *handholding* intervention on enrollment are around 3 ppts but are not significant. The non-significance likely reflects insufficient power since the experiment was powered to detect an effect of7.5 ppts in the full sample. The point estimate of 3 ppt is reasonably large compared with an enrollment rate of the respective control group of 8.3 percent. However, it is a small fraction of the 28 ppt short-term effect. The effect of the *handholding* inducement appears to have been sustained to a much lesser extent than the *subsidy+info* intervention, although in making this comparison one must bear in mind that the two effects are estimated for different samples.

The estimates of the long-term effect of the combined interventions are approximately equal to the sum of the separate effects of the two interventions. Offering the *subsidy+info* followed up with *handholding* for those who do not initially respond is estimated to have raised enrollment after four years by a significant 8.5-9.1 ppts ($p<0.05$) compared to not offering any intervention whatsoever. This is about a quarter of the respective short-term effect.

Table 4.2 Long-term effects on health insurance enrollment

	Effect	Standard error	*z*-Stat	*N*
subsidy+info				
Inverse probability weights	0.0476**	0.0232	2.05	740
Doubly robust				
Least squares	0.0448**	0.0217	2.07	740
Probit	0.0462*	0.0245	1.89	740
handholding				
Inverse probability weights	0.0303	0.0273	1.11	548
Doubly robust				
Least squares	0.0307	0.0268	1.15	548
Probit	0.0360	0.0254	1.42	548
Combined				
Inverse probability weights	0.0848***	0.0266	3.18	613
Doubly robust				
Least squares	0.0846***	0.0258	3.28	613
Probit	0.0911***	0.0288	3.17	598

Notes: Standard errors are adjusted for clustering at the municipality level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4.3. reports estimates of the long term effects on WTP for insurance through a PhilHealth program. None of the interventions has a statistically significant impact on WTP. The point estimate of *subsidy+info* is positive, which further supports that there is no evidence of recipients of the inducement anchoring their willingness to pay on the subsidized price.

Table 4.3 Long term effects of interventions on willingness to pay for health insurance

	Effect	Std error	*z*-Stat	*N*
subsidy+info				
Doubly robust				
Least squares	5.621	7.87	0.71	640
Probit	3.449	6.88	0.50	640
handholding				
Doubly robust				
Least squares	-12.759	10.04	-1.27	475
Probit	-11.368	9.95	-1.14	475
Combined				
Doubly robust				
Least squares	-1.974	8.62	-0.23	534
Probit	-5.787	7.27	-0.80	534

Notes: Standard errors are adjusted for clustering at the municipality level. *** p<0.01, ** p<0.05, * p<0.1

4.6 Conclusion

This chapter examined the long-term effects of health insurance demand inducements using a nationwide randomized experiment of two sets of interventions designed to encourage enrollment in the voluntary plan of the Philippines' National Health Insurance Program. The first *subsidy+info* intervention consisted of a one-off premium subsidy of up to 50%, plus information on the operation and benefits of the insurance program as well as SMS reminders. The *handholding* intervention reduced the indirect costs of enrollment by providing one-time assistance with completion and submission of the insurance application to a random sample of households that opted not to enroll even after being offered the premium subsidy. Only the *subsidy+info* intervention has a significant impact on enrollment four years after the inducements were offered and three years after they had been withdrawn. The long-term effect of this intervention is relatively large in two respects. First, it represents an increase in enrollment relative to the counterfactual of more than 80%. Second, it is around three quarters of the short-term effect. This large, sustained impact suggests that those who were induced to enroll by the offer of the subsidy were already on the margin of enrolling and the experience of holding insurance was positive. After the subsidy was withdrawn, a large proportion of these compliers were sufficiently pleased with the cover to continue paying for it even at the full price.

Although the *handholding* intervention had a strong impact in the short term, this was not maintained in the long run. The long-term effect of this intervention is only 11% of its short-term effect and is not statistically significant. Most likely the decision to enroll when offered a subsidy of up to 50% and the elimination of all indirect costs of application deviates so far from the decision to insure without these inducements that once they are withdrawn most households that had responded to them are not sufficiently interested in insurance to continue with enrollment when the direct and indirect costs rise substantially. Since a reduction in time costs of enrollment, combined with the premium subsidy, nudged these households into buying the insurance, it is not unlikely that they discount the future heavily or procrastinate paying continued payment of the premium.

While the nationwide nature of the experiment we have studied makes the findings more generalizable than much of the existing evidence on short- and long-term effects of health insurance inducements, obviously one must be careful about inferring effects in quite different contexts. Nevertheless, we demonstrate that temporary inducements, particularly a substantial price subsidy, for voluntary health insurance can have a sustained long-term impact on enrollment. Importantly, our study shows that short-term effects of interventions may not be predictive of their long-term impacts. One intervention may have a strong, short-term impact and yet its long-term effect can be smaller than that of another that initially is less effective. In order to determine the relative cost-effectiveness of temporary interventions, it is critical to know their long-lived impacts and these might not be consistent with their ranking in terms of short-run effects.

.

Appendices Chapter 4

Appendix 4.1

Table A4.1. Means of characteristics at baseline by whether household participated in 4-year follow-up survey

	Interviewed at 4-year follow-up		
	Yes (1)	No (2)	(1)=(2) p-value
Urban	0.468	0.648	0.000
Average per capita household expenditure	22101	29743	0.000
Head is working	0.876	0.852	0.229
Head has poor health	0.021	0.033	0.172
Head had at least college education	0.074	0.145	0.000
Has available health facility within 15 min	0.699	0.783	0.001
Has other insurance	0.023	0.036	0.176
Number of children under 21	1.868	1.574	0.004
Experienced adverse health outcome in the last year	0.268	0.264	0.885
National Capital Region	0.153	0.267	0.000
Rest of Luzon	0.465	0.433	0.274
Visayas	0.226	0.136	0.000
Mindanao	0.156	0.164	0.697
WTP for health insurance (Philhealth)	97.76	111.71	0.000
N	1000	420	

Notes: The baseline survey was conducted February-April 2011. The '4-year' follow-up was July-August 2015. There are 871 observations for WTP for PhilHealth amongst those interviewed at 4-year follow-up and 363 for those not followed up. This is due to missing observations for those not aware of PhilHealth.

Appendix 4.2

Table A4.2 Comparison of households in treatment and control groups on baseline characteristics and WTP for Philhealth

	(1) Control	(2) Treatment	p-value (1)-(2)
subsidy+info			
Urban	0.480	0.483	0.941
Average per capita household expenditure	19975	20530	0.657
Head is working	0.885	0.890	0.836
Head has poor health	0.022	0.019	0.739
Head had at least college education	0.071	0.073	0.917
Has available health facility within 15 min	0.685	0.701	0.676
Has other insurance	0.024	0.022	0.922
Number of children under 21	1.953	1.966	0.930
Experienced adverse health outcome in the last year	0.265	0.270	0.887
National Capital Region	0.127	0.136	0.757
Rest of Luzon	0.451	0.458	0.844
Visayas	0.245	0.235	0.780
Mindanao	0.177	0.171	0.820
WTP for health insurance (Philhealth)	95.31	97.07	0.577
N	271	469	
handholding			
Urban	0.531	0.519	0.802
Average per capita household expenditure	24067	25421	0.502
Head is working	0.881	0.865	0.632
Head has poor health	0.013	0.015	0.844
Head had at least college education	0.063	0.065	0.916
Has available health facility within 15 min	0.716	0.719	0.936
Has other insurance	0.018	0.015	0.835
Number of children under 21	1.746	1.738	0.961
Experienced adverse health outcome in the last year	0.270	0.277	0.862
National Capital Region	0.248	0.235	0.762
Rest of Luzon	0.406	0.423	0.705
Visayas	0.230	0.227	0.924
Mindanao	0.116	0.115	0.995
WTP for Philhealth	106.43	103.94	0.627
N	288	260	
Combined			
Urban	0.521	0.531	0.834
Average per capita household expenditure	28611	25683	0.510
Head is working	0.859	0.874	0.631
Head has poor health	0.015	0.016	0.877
Head had at least college education	0.072	0.072	0.994
Has available health facility within 15 min	0.723	0.722	0.975
Has other insurance	0.019	0.018	0.911
Number of children under 21	1.750	1.740	0.949
Experienced adverse health outcome in the last year	0.309	0.284	0.614
National Capital Region	0.232	0.232	1.000
Rest of Luzon	0.428	0.430	0.955
Visayas	0.217	0.216	0.997
Mindanao	0.124	0.122	0.927
WTP for Philhealth	103.60	104.79	0.784
N	271	342	

Chapter 5

Debiasing expectations

Joint work with Baillon, A. and O'Donnell, O.

5.1 Introduction

Since the early 1990s, economists have recognized the value of measuring subjective expectations alongside economic outcomes in surveys. Doing so allows the analyst to relax the assumption of rational expectations, separate expectations from preferences in the explanation of behavior and measure uncertainty at the individual level (Manski, 2004). Subjective probabilities have been elicited in many household surveys, such as the US Health and Retirement Study (HRS), and the responses obtained have proved useful in understanding the formation of expectations (Smith et al 2001) and in explaining a variety of economic behaviors (Hurd, 2009). For example, subjective probabilities of stock market returns suggest expectations are considerably below historical market averages and this has been proposed as an explanation for overly low rates of stock holding (Dominitz and Manski, 2007; Hurd, 2009; Hurd et al., 2011).

While measurement of beliefs undoubtedly holds much potential for understanding behavior, the reporting of probabilities is not a task that is familiar to most survey respondents. This can lead to biases (Tversky and Kahneman, 1974). Unpacking an event into subevents and then summing the reported probabilities assigned to these subevents tends to give a higher estimate of the probability of the event than that obtained by directly asking about the event likelihood (Fischhoff et al. 1978; Tversky and Kahneman 1983; Johnson et al. 1993; Tversky and Koehler 1994; Tversky and Fox 1995). This is the property of *subadditivity*. It implies that the probability of an unlikely event tends to be overestimated and that of a likely event to be underestimated.

Subadditivity of reported probabilities can be explained by the anchoring and adjustment heuristic (Tversky and Kahneman, 1974). When someone is asked to report the probability of an event, there is a tendency to start from an anchor, such as 50%, and then adjust the estimate using knowledge (Tversky and Kahneman, 1974). Yet, the adjustment is typically insufficient. The response is then 'contaminated' by the anchor and may reflect the ability of the respondent to report probabilities as much as his actual knowledge of the event likelihood. This contamination is generally found to be present in the subjective probability data used by economists to model behavior (Hurd, 2009).

Subadditivity of reported probabilities causes three main problems. First, it distorts the measured expectations. Second, because not everyone exhibits the same degree of subadditivity, correlations between expectations and behavior can also be biased. Third, subadditivity and noise can together create violations of monotonicity (i.e., reporting a lower probability for an event than for one of its subevents). Typically, 20-40 percent of respondents violate some consistency rules and are excluded by studies that use subjective probabilities to model beliefs and predict behavior (Delavande and Rohwedder, 2008; Hurd et al., 2011; van Santen et al., 2012). Dropping around a third of the sample is regrettable, to say the least. Not only does it substantially reduce power, but it also risks the introduction of biases due to endogenous selection. Less educated and less wealthy respondents are more likely to report probabilities that violate consistency (Delavande and Rohwedder, 2008) and respondents with lower education and cognitive functioning are more likely to give a focal response of 50% probability (Kleinjans and Van Soest, 2014; Bago d'Uva et al, 2015). Excluding these responses leaves a sample that is no longer representative of the population and underrepresents the most vulnerable groups that may be the intended beneficiaries of a policy (Delavande and Rohwedder, 2008).

This chapter introduces an approach to measuring subjective probability that takes account of inconsistencies and produces a measure of beliefs purged of subadditivity bias that is potentially better in explaining behavior. We achieve this by drawing on literature in psychology and decision analysis, which has studied biases in subjective probability elicitations for decades (Tversky and Kahneman, 1974). Our approach is based on a simple model of subadditive reported probabilities, which is in line with psychological models proposed by Fox and Rottenstreich (2003) and Clemen and Ulu (2008).[43] From this model, we obtain a method to debias reported probabilities and correct them for the attraction towards 50%. We apply our method to probabilities of stock market returns elicited from a sample of alumni of an Economics faculty in the Netherlands. We use typical questions on subjective probabilities of the sort suggested by Dominitz and Manski (1997) and Manski (2004) that are used in surveys such as the HRS. Reported chances of gains and losses above a series of thresholds provide points on the subjective cumulative distribution function. We add two questions (one in each domain of gains and of losses) to identify and quantify subadditivity.

The results confirm that most respondents give subadditive responses. Pooling over individuals, the correction for subadditivity gives a better Akaike information criterion. At the individual level, we model beliefs with and without correcting for subadditivity and in

[43] See Tversky and Koehler (1994) and Bearden et al. (2007) for alternative models.

each case obtain estimates of the mean and variance of the subjective probability distribution of forecast stock market returns. Correcting beliefs reduces both the mean and the variance of the individual-specific subjective probability distribution for most of the sample. The corrected estimates of the mean are more closely associated with the ownership of risky assets. Not only do we obtain measures of beliefs that are more informative of behavior, but we also keep a large fraction of the sample that would otherwise be excluded.

Section 5.2 introduces our model of reported probabilities. Section 5.3 first describes the methodology used to elicit subjective probabilities and the characteristics of our sample. It then explains how we model beliefs both with and without correction for subadditivity. Section 5.4 commences by assessing the extent to which respondents display subadditivity in their reported probabilities and violate other consistency requirements. It then investigates whether the model with correction for subadditivity improves the fit of the data, before comparing the distributions of estimated beliefs obtained from the two models. Finally, we show that correcting for subadditivity increases the extent to which estimated beliefs predict behavior. Section 5.5 concludes.

5.2 A simple model of reported probabilities

Let S be a *state space* and events are subsets of S. Respondents are asked to report probabilities of *events* and $r(E)$ represents the *reported probability* for event E. Researchers analyzing reported probabilities start by assuming a *belief model;* traditionally, a (additive) *probability measure* P. Often, a specific family of probability distributions is assumed; for instance, normal distributions (e.g. Dominitz and Manski, 2007; Hurd et al., 2011). Then, P is either equated with r or estimated from it. Estimation produces residuals that capture noise in the reporting process.

We propose a method to correct reported probabilities for subadditivity, which is a *bias*: a systematic error pattern that does not cancel out at the aggregate level, unlike noise. Our method is based on a simple, tractable model adapted from Fox and Rottenstreich (2003) and Clemen and Ulu (2008).[44] In line with these papers, it is assumed that reported

[44] Fox and Rottenstreich (2003) formulates a model in terms of odds and uses the belief model of Tversky and Koehler (1994). Clemen and Ulu's (2008) model is defined for settings in which an analyst interviews an expert using a partition of a state space while the expert has another partition in mind. Our model corresponds to the special case in which partitions are aligned and questions deal with one event at a time.

probabilities are biased towards 50%:

$$r(E) = a\frac{1}{2} + (1 - a)P(E), \tag{5.1}$$

for $0 < P(E) < 1$, where $0 \leq a \leq 1$ is the *subadditivity factor*. If $P(E) = 1$, then $r(E) = 1$ and if $P(E) = 0$, then $r(E) = 0$. No bias ($a = 0$) results in $r(E) = P(E)$ and extreme bias ($a = 1$) results in $r(E) = 0.5$ for all events E with $0 < P(E) < 1$. The subadditivity factor can be interpreted as the degree of attraction towards the 50-50 anchor.

The model preserves *binary complementarity,* i.e. additivity for complementary events: $r(E) + r(S - E)$=1. At the individual level, respondents may violate binary complementarity but no systematic pattern (i.e. no bias) has been found (Wright and Whalley, 1983; Tversky and Koehler, 1994 and Fox and Tversky, 1998). Hence, violations of complementarity can be attributed to noise.[45]

For a minority of respondents, there may be *violations of monotonicity* (or set inclusion) due to a subevent being judged more likely than the event it is part of. Such cases are often excluded from empirical analyses on the basis that they are due to misunderstanding of the survey task or imply implausibly large noise (e.g. Delavande and Rohwedder 2008; Hurd et al. 2011; van Santen et al. 2012). Yet, when the subadditivity factor a is large, relatively little noise suffices to generate violations of monotonicity. We use a model that allows for subadditivity plus noise in order to preserve as many observations as possible for data analysis.

To identify a, one can simply ask respondents to report the probability of an event E, a disjoint event F and that of their union $E \cup F$. Making use of the additivity of P:

$$r(E) + r(F) - r(E \cup F) = \frac{a}{2}. \tag{5.2}$$

After deriving a, the probabilities $P(E), P(F)$ and $P\ (E \cup F)$ can be recovered. The empirical approach we adopt involves eliciting $r(E), r(F)$, and $r(E \cup F)$ to ensure that a is identifiable but it also allows for an error term representing noise. The subadditivity factor a captures the non-additive part of the report due to systematic unidirectional errors.

The easy identification of a using Eq. 5.2 is a major practical advantage of our model because it means the additional data requirements are minimal. This is important in survey

[45] The model also preserves a form of additivity called *interior additivity* by Wu and Gonzalez (1999). If $P(E) > 0$, $P(F) > 0$, and $P(G) > 0$, then $r(E \cup F) - r(F) = r(E \cup G) - r(G)$. Evidence of Wu and Gonzalez (1999) and Clemen and Ulu (2008) supported interior additivity.

research, where adding questions can be very costly. If the survey budget constraint is not binding, then researchers may want to use a richer model that allows for nonlinearity or anchors that differ across respondents. But identification of the additional parameters would require asking more questions and raise survey costs. In this chapter, we demonstrate the added value of the most parsimonious approach we could think of.

We interpret subadditivity as a bias induced by the process of reporting a probabilistic judgment, and not as a part of a respondent's actual belief. If this is the case, then a measure of belief, P, that is purged of the bias should correlate with behavior more closely than the reported probability, r. We test this prediction in Section 5.4 and discuss the interpretation of subadditivity from which it derives in Section 5.5.

5.3 Method

5.3.1 Elicitation of probabilities

To test our approach, we elicited subjective probabilities of stock market returns from a sample of alumni of a Dutch university. Several papers investigate stock market expectations using survey data (Hurd, 2009; Dominitz and Manski, 2011; Hudomiet et al., 2011; Hurd et al., 2011). A major motivation is to understand why so few households own stocks given rates of return are high relative to those on other stores of wealth (Hurd, 2009). An implausibly high level of risk aversion would be required to explain the lack of stock holdings by agents with rational expectations. Low expectations offer an alternative explanation (Dominitz and Manski, 2007; Hurd et al., 2011). Hurd et al. (2011), for example, found stock market expectations to be lower than historical average returns in aggregate and correlated with stock ownership in a survey of several thousand households in the Netherlands. However, these findings were obtained after dropping about one third of respondents that violated certain consistency requirements from the initially representative sample.

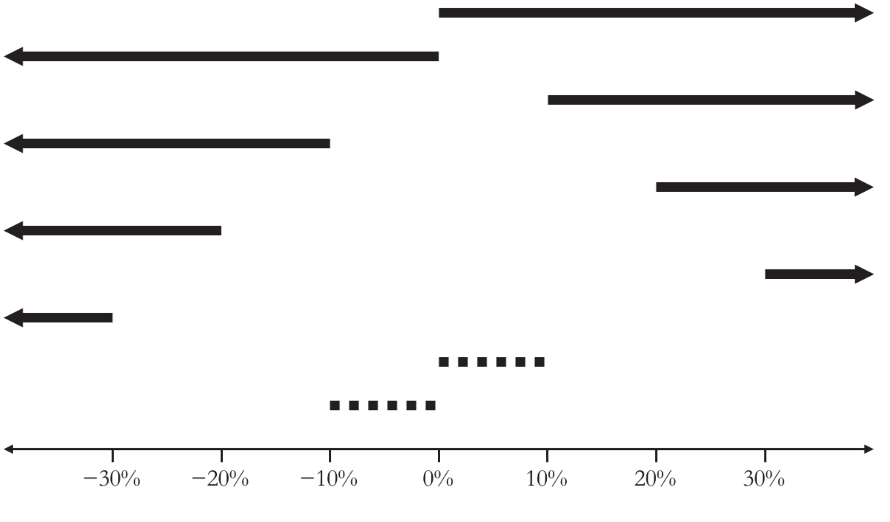
We used questions originating from the Health and Retirement Study (HRS) and included in the De Nederlandsche Bank Household Survey (DHS) used by Hurd et al. (2011). A short introduction asked the respondent to imagine that he had a rich relative who unexpectedly left him 10,000 Euro and that he was thinking of putting the money into a mutual fund invested in "blue chip" stocks (like those in the Amsterdam AEX stock market index, the Eurostocks index or the Dow Jones Industrial Average index).

The first question of the (gain) sequence was as follows:

Suppose you put the 10,000 Euro in the stock mutual fund and left it in for one year. What is the chance that you would make money where 0 means absolutely no chance and 100 means absolutely certain; that is, what is the chance that in a year your investment would be worth more than 10,000 Euro?

Similar questions asked for the chances that an investment in the mutual fund would generate gains of more than 10%, 20%, and 30% over a one-year horizon. These questions are represented by the arrows pointing to the right in Figure 5.1. Analogous questions asked about the chances of incurring losses of more than 0%, 10%, 20%, and 30% (arrows to left in Figure 5.1). The four questions within each sequence (gains and losses) were always presented in order of increasing absolute returns, but the order of the two sequences was randomized.

Figure 5.1 Ten events (range of returns) for which probabilities are reported



To identify the subadditivity factor *a,* we needed to elicit the subjective probability of two disjoint events and that of their union. We achieved this by asking respondents to report the chance that an investment in the mutual fund would generate a gain between 0% and 10%. Specifically:

What is the chance that the 10,000 Euro in your stock mutual fund would have gone up but by less than 10 percent; that is, it would be worth an amount between 10,000 and 11,000 Euro a year from now?

The range of returns for this question is indicated by the broken line to the right of 0 in Figure 5.1. We did the same for losses and thus elicited subjective probabilities of ten events in total.

In addition, we obtained information on ownership of risky assets, as well as gender, age, marital status, income (7 categories), employment (ever) in the financial sector and personal traits (trust, risk aversion and optimism) that may affect investment decisions.[46]

5.3.2 Sample

Data were collected between January 30 and February 26, 2015. A link to the anonymized questionnaire was distributed by the alumni office of Erasmus School of Economics through media such as LinkedIn® and a newsletter. Once on the website, respondents were given the choice to complete the questionnaire in Dutch or English. A total of 269 alumni completed the questionnaire in full. The item non-response on the questions eliciting subjective probabilities was low – no more than 2% per question, resulting in the exclusion of 13 respondents.

Table 5.1 reports the means of covariates. The vast majority of sample respondents are male (86%) and three-quarters live with a partner. About half of the sample is younger than 44 and a slight majority earns more than 60,000 euro a year. More than three fifths hold investments in stocks, bonds or mutual funds. A relatively large fraction (about 38%) of respondents work or have worked in the financial sector, which reflects sampling from the alumni of an economics faculty. One might expect this sophisticated sample to be less prone to report subadditive probabilities than would be the case for a random sample of the population.

[46] The precise wording of all questions was obtained from the DHS and a supplement added by Hurd et al (2011) to elicit information on stock market expectations and trading behavior not already included in the DHS.

Table 5.1 Definitions and means of covariates and outcomes

Variable label	Variable takes value of 1 (0 otherwise) if:	Mean	N
Female	Female	0.138	269
Has partner	Married or cohabiting	0.747	269
Female * Has partner	Female and either married or cohabiting	0.086	269
Age: young	Aged 44 or younger	0.509	269
Age: old	Aged 65 or older	0.115	269
Income >= €60,000	Total gross income not less than €60,000 in 2014	0.550	269
Financial sector	Works or worked in the Banking or Financial sector	0.383	269
Trust	Agrees with 'most people can be trusted'	0.584	269
Risk averse	Prefers current income to a 50:50 gamble of doubling it or losing a third of it	0.517	269
Optimistic	(Strongly) agrees with 'overall, I expect more good things to happen to me than bad things'	0.792	269
Owns risky assets	Holds stocks, bonds and/or mutual funds	0.632	269

5.3.3 Analysis

We assess the internal and external validity of the reported probabilities using an empirical model of beliefs from the literature and a corrected version that incorporates the subadditivity factor.

Belief model

We adopt the belief model derived by Hurd et al. (2011), which generalizes the approach of Dominitz and Manski (2007). The stock market index s_t is modelled as a random walk with drift (μ),

$$\ln\left(\frac{s_{t+1}}{s_t}\right) = \mu + v_t \tag{5.3}$$

where v_t are i.i.d. $N(0, \sigma^2)$.[47] Hence, the expectation of the return in the next period is μ with volatility σ^2. The probability that the stock market return is within the range $[\tau, \tau']$ over the next year is

$$\begin{aligned} P\left(1+\tau < \frac{s_{t+1}}{s_t} < 1+\tau'\right) &= P\left(\ln(1+\tau) < \ln\frac{s_{t+1}}{s_t} < \ln(1+\tau')\right) \\ &= \Phi\left(\frac{\ln(1+\tau')-\mu}{\sigma}\right) - \Phi\left(\frac{\ln(1+\tau)-\mu}{\sigma}\right) \end{aligned} \tag{5.4}$$

[47] Hurd et al. (2011) show that normally distributed returns is not an overly unreasonable approximation to the behavior of the Amsterdam AEX index over the period 1983-2006.

where Φ is the standard normal cumulative distribution function. Following the literature (Dominitz and Manski, 2007; Hurd et al., 2011), we assume that respondents' beliefs can be modelled as in Eq. 5.4, with respondent-specific expected returns and volatility.

From beliefs to reported probabilities

We obtain reported probabilities for 10 intervals that we generically denote $[\tau_j, \tau_j']$ for $j \in \{1, \dots, 10\}$. If reported probabilities correspond to beliefs plus noise, then from Eq. 5.4 we can retrieve the respondent's subjective expected return μ_i and volatility σ_i^2 using:

$$r_{ij} = \Phi\left(\frac{\ln(1+\tau_j') - \mu_i}{\sigma_i}\right) - \Phi\left(\frac{\ln(1+\tau_j) - \mu_i}{\sigma_i}\right) + \varepsilon_{ij}, \tag{5.5}$$

with r_{ij} the reported probability of respondent i for interval j and with ε_{ij} an error term. We call Eq.5.5 the *uncorrected model*. It assumes that only noise can explain why probabilities are not additive or may be inconsistent. Inconsistencies cannot systematically lie in one direction. The corresponding estimates of μ_i and σ_i are also called *uncorrected*. To allow for the systematic biases discussed in section 5.2, we combine the belief model (Eq. 5.4) with the model of reported probabilities (Eq. 5.1) plus an error term (ε_{ij}) to obtain:

$$r_{ij} = a_i \frac{1}{2} + (1 - a_i)\left[\Phi\left(\frac{\ln(1+\tau_j') - \mu_i}{\sigma_i}\right) - \Phi\left(\frac{\ln(1+\tau_j) - \mu_i}{\sigma_i}\right)\right] + \varepsilon_{ij}. \tag{5.6}$$

Eq. 5.6 will be referred to as the *corrected model*, and the estimates derived from it will be called *corrected*.

Fitting data

To assess internal validity of the corrected model, we compare its performance to that of the uncorrected model in fitting the data. We pool data across all individuals and estimate the population averages of the parameters by nonlinear least squares. We allow the parameters to vary with covariates to capture observed heterogeneity between respondents. Standard errors are clustered at the individual level to allow for violation of independence due to heterogeneity that remains unobserved. We use the Akaike information criterion (AIC) to choose between the models on the basis of parsimony and best approximation to the information in the data.

Predicting behavior

To assess whether correcting for subadditivity affects the extent to which the estimated beliefs predict behavior, we follow the procedure of Hurd et al. (2011), first using non-linear least squares to estimate μ_i and σ_i from the uncorrected model for each individual independently, and then running a probit regression of ownership of risky assets on these estimates and covariates. We then follow the same procedure but using the corrected model in the first stage. Bootstrap standard errors are used to allow for the generated regressors problem (Pagan, 1984) arising from the inclusion of estimates in the probit regressions.

5.4 Results

5.4.1 Raw data

On average, respondents report a 59.6% chance of a stock market gain and a 37.8% chance of a stock market loss (Table 5.2). The mean reported probability of a gain (loss) falls monotonically as the magnitude of the gain (loss) increases.

Table 5.2 Summary of answers to stock market expectation questions

			Percentiles				
	N	Mean	5	25	50	75	95
Gain > 0%	269	59.64	24	50	60	75	88
Gain > 10%	269	31.70	5	15	25	50	75
Gain > 20%	269	16.30	0	4	11	24	51
Gain > 30%	269	9.43	0	1	5	10	40
Gain 0-10%	269	50.79	7	33	50	75	90
Loss > 0%	269	37.75	10	25	40	50	75
Loss > 10%	269	24.32	2	10	20	30	65
Loss > 20%	269	14.74	0	5	10	19	51
Loss > 30%	269	9.77	0	2	5	10	45
Loss 0-10%	269	35.04	5	19	30	50	77

Notes: Cell entries give reported probabilities in %

Figure 5.2 depicts the mean reported probability to gain money alongside the mean of the sum of the reported probabilities to gain up to 10% and to gain more than 10%. The right-hand columns show the equivalent means in the domain of losses. In both cases there is clear evidence of subadditive beliefs, i.e., the sum of the probability of two disjoint events exceeds the probability of their union.

Figure 5.2 Mean and 95% confidence interval for the reported probability to gain (lose) money and for the sum of the reported probabilities to gain (lose) up to 10% and to gain (lose) more than 10%.

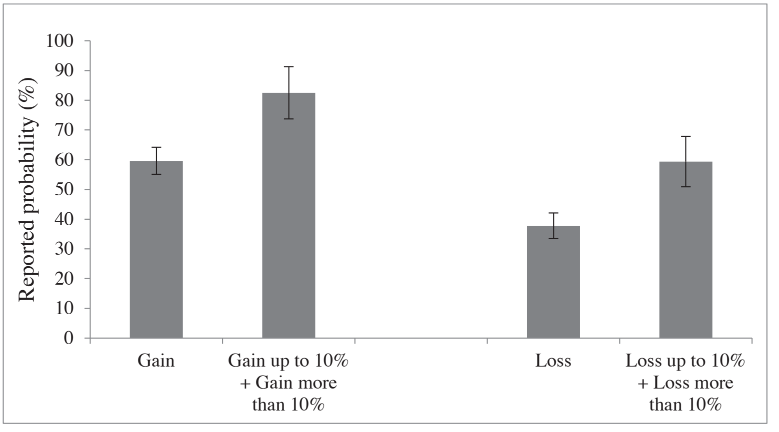


Figure 5.3a depicts the distribution of the difference between a) the sum of the reported probabilities to gain (lose) up to 10% and to gain (lose) more than 10%, and b) the reported probability of any gain (loss). A systematic error pattern (bias) is apparent, with the sum of the two disjoint events being greater than the probability of their union for most respondents.[48] We then separate respondents who violate monotonicity from those who do not. Violation of monotonicity is identified by reported probabilities that are not weakly decreasing as the threshold is increased from 0% to 10% to 20% to 30% in either the domain of gains or losses.[49]

As expected, respondents who violate monotonicity (figure 5.3b) are more prone to subadditivity than respondents who do not (figure 5.3c). This is evident in both domains. In gains, the mode of the distribution lies far above zero for respondents who violate monotonicity, and is slightly below zero for those who do not.

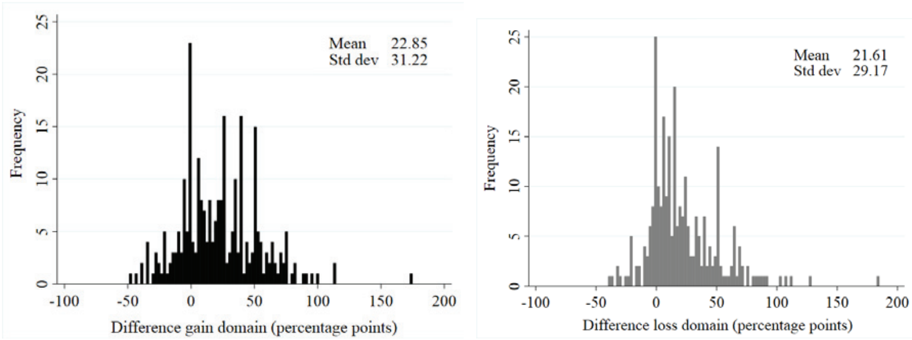
---

[48] The means of all distributions differ from 0 (p =0.000).

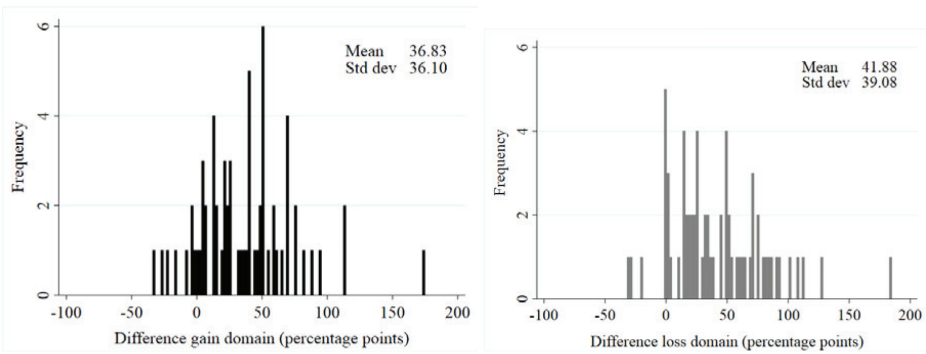
[49] If, in addition, we require that the reported probability of a gain (loss) is not smaller than the reported probability of a gain (loss) between 0-10%, the number of respondents with any violation of monotonicity rises from 66 to 150. Each additional question concerns an event with likelihood close to that of the event of which it is a subset. Hence, little noise is enough to lead to violations of monotonicity. This explains the rise of the number of respondents identified as violating monotonicity. The pattern of the distributions in Figure 5.3 is similar if we identify non-monotonicity in this way.

Figure 5.3 Subadditivity: distribution of the difference between a) the sum of reported probabilities to gain (lose) up to 10% and to gain (lose) more than 10%, and b) the reported probability of any gain (loss)

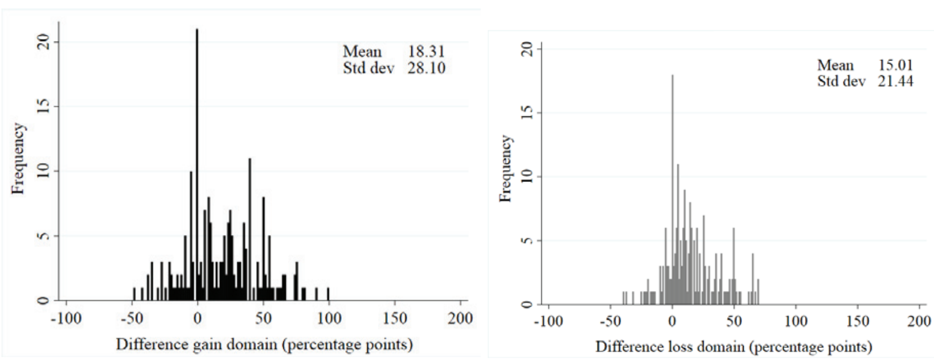
5.3a All respondents (N=269)



5.3b Respondents who violate monotonicity (N=66)



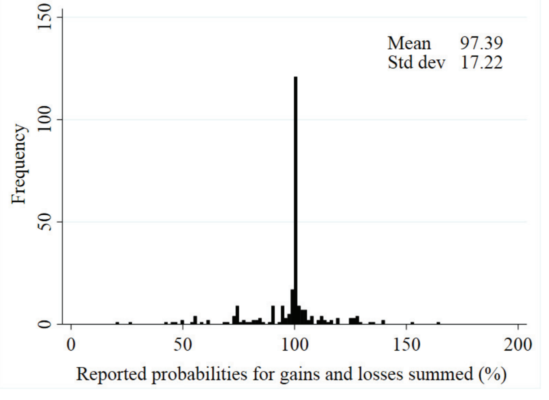
5.3c Respondents who do not violate monotonicity (N=203)



A Kolmogorov-Smirnov test indicates a difference between the distributions for the two groups of respondents in both the gain (p=0.004) and loss (p=0.000) domains.

While there is clear evidence of subadditivity, there is little systematic error pattern that indicates violation of binary complementarity (Figure 5.4). Almost half of respondents report probabilities of a gain and a loss that add up to 100 percent.[50] The mean of this sum is 97.4% (H_0: mean=100%, p=0.014). The slight shortfall, on average, may result from the fact that respondents were not asked for the probability of a zero annual return. The violations of binary complementarity are roughly symmetrically distributed, suggesting that they are best explained by noise.

Figure 5.4 Binary additivity: the sum of the reported probabilities of a gain and a loss



[50] In the literature (e.g. Hurd et al 2011), respondents for whom the reported probabilities of a gain and loss add up to more than 100 are often also excluded on the grounds that this violates consistency. In our sample, 27% violate this condition. Excluding these respondents would result in the loss of another 19% of the sample in addition to those who dropped because of violation of monotonicity resulting in the removal of 44% in total.

5.4.2 Fitting data

Table 5.3 presents the pooled data estimates of the uncorrected model and of the corrected model for the reported probabilities of experiencing gains/losses. Comparison of the Akaike Information Criteria (AIC) provides decisive evidence in favor of the model with the subadditivity correction.[51] Consistent with what is evident in the raw data, the estimate of the subadditivity factor is positive. The point estimate of 0.100 suggests that the average reference individual (single male aged 45-64 earning €0-€60,000 with no financial sector work experience) reports probabilities that are biased towards the 50-50 anchor by 10% (see Eq. 5.1). Rather surprisingly, respondents with financial sector experience appear to display greater subadditivity, although the coefficient is significant only at the 10% level and the corresponding coefficient in a median regression of individual-specific estimates of the subadditivity factor is not at all significant (see next sub-section and Appendix Table A5.1).

Allowing for subaddivity makes a difference to the estimates of the population averaged subjective distribution of returns. The corrected model gives an estimate of 1.3% for the reference respondent's expected return, which is about two fifths of that obtained from the uncorrected model and is no longer significant. Failing to correct for subadditivity results in overestimation of expected returns, which may lead to false rejection of the hypothesis that low expectations explain low stockholding. The corrected model gives a point estimate of the reference respondent's perceived standard deviation of returns that is less than three quarters of the uncorrected estimate. This suggests that without allowing for subadditivity there is a risk of overly attributing low stockholding to the perceived volatility of returns. There is also less evidence of heterogeneity (by marital/cohabitation status and financial sector experience) in the perceived risk of investing in a stock mutual fund once the bias correction is introduced.

[51] This model has an Akaike weight (Burnham and Anderson, 2002) extremely close to 1, indicating that there is little or no doubt that it provides the better approximation to the information in the data while respecting the principle of parsimony.

Table 5.3 Pooled data estimates of reported probability models

		Uncorrected model	Corrected model
Expected return (μ)	[Reference]	0.031*** (0.010)	0.013 (0.009)
Shift in expected return:			
Female		0.024 (0.020)	0.005 (0.015)
Has partner		-0.002 (0.009)	0.005 (0.008)
Female * Has partner		-0.039* (0.021)	-0.014 (0.016)
Age: young		0.003 (0.006)	0.002 (0.006)
Age: old		0.027** (0.011)	0.023** (0.011)
Income>=60000		-0.003 (0.006)	-0.001 (0.005)
Financial sector		-0.006 (0.006)	-0.010* (0.006)
Standard deviation of return (σ)	[Reference]	0.124*** (0.012)	0.089*** (0.010)
Shift in standard deviation:			
Female		0.030 (0.025)	-0.019 (0.013)
Has partner		-0.019* (0.010)	-0.003 (0.008)
Female * Has partner		-0.071*** (0.027)	-0.011 (0.016)
Age: young		0.011 (0.008)	0.003 (0.007)
Age: old		0.012 (0.011)	0.014 (0.011)
Income>=60000		-0.007 (0.007)	-0.005 (0.007)
Financial sector		0.020*** (0.007)	0.006 (0.006)
Subadditivity factor (*a*)	[Reference]		0.100*** (0.026)
Shift in subadditivity factor:			
Female			0.072 (0.048)
Has partner			-0.028 (0.023)
Female * Has partner			-0.091* (0.052)
Age: young			0.009 (0.015)
Age: old			-0.009 (0.024)
Income>=60000			0.002 (0.015)
Financial sector			0.028* (0.015)
N		2690	2690
AIC		-717.2	-1015.3

Notes: Nonlinear least squares estimates. Standard errors clustered at individual level in parentheses. There are 10 observations per individual. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

5.4.3 Individual-specific estimates of subadditvity and beliefs

Figure 5.5 shows the sample distribution of the estimates of the subadditivity factor (*a*) obtained from nonlinear least squares estimation of the corrected model for each individual. Consistent with Figure 5.3a, it confirms that the vast majority of respondents report subadditive probabilities.[52] The reference respondent identified above, who is estimated to

[52] The same conclusion arises from nonparametric estimates of the subadditivity factor obtained directly from Eq. 5.2 without allowing for noise. The nonlinear least squares estimates, which rest on the assumption of log-normal returns, are highly correlated with the nonparametric estimates. The correlation coefficient is 0.721 using the mean of the nonparametric estimates obtained from reported probabilities in the domain of gains and losses. The distributions of the estimates do differ, however. The median of the nonparametric estimates obtained from the reported probabilities in the domain of gains (losses) is 0.3 (0.26).

have a subadditivity factor of 0.100, is located around the third quartile of the distribution. The median (0.044) corresponds to a lesser degree of attraction towards the 50-50 anchor. At the 95th percentile, the degree of attraction towards the anchor is 25%. One fifth of respondents report probabilities consistent with a negative subadditivity factor. Such respondents may use anchors of 0% (for unlikely events) and 100% (for very likely events) instead of 50% for all events. Median regressions of the estimated subadditivity factor on covariates reveal that the only strongly significant heterogeneities in the degree of subadditivity are with respect to gender and marital/cohabitation status, with single females displaying most bias (see Appendix Table A5.1).

Figure 5.5 Distribution of subadditivity factor (a) (N=229) [53]

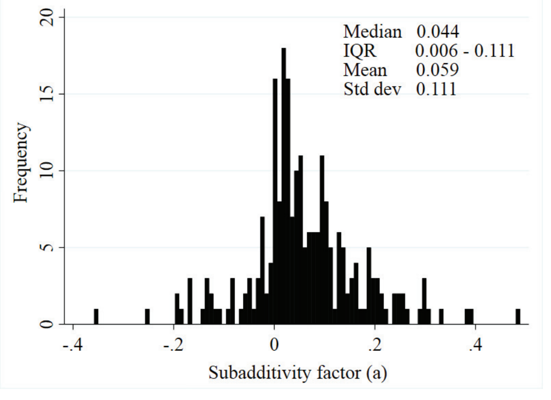


Figure 5.6a shows cumulative distributions of individual-specific nonlinear least squares estimates of the mean (μ_i) of the subjective probability distribution of returns. The dashed curve is drawn using the estimates from the uncorrected model. The solid curve is from the corrected model.[54] The mean and the median uncorrected estimates are both higher than the respective corrected estimates. This suggests that, at least on average, failing to purge the bias may result in overestimation of the expected return. However, the distributions of estimates are close where there is greatest density and the distribution without the

---

We concentrate on the parametric estimates since they are obtained along with the estimates of the subjective probability distribution moments, and they allow for noise.

[53] For 40 respondents, nonlinear least squares (computed using Stata®) failed to produce an estimate, most likely due to peculiar configurations of the 10 probabilities reported by those individuals.

[54] To maximise comparability, the estimates of the uncorrected model are obtained using all 10 probability responses that are used to identify the subadditivity factor in the corrected model. Figure A5.2 in the Appendix reveals that the distribution of estimates from the uncorrected model differs somewhat if 8 (as in Hurd et al, 2011) rather than 10 responses are used. However, the difference is much less marked than that due to changing the model and keeping the number of observations constant (Figure 5.6a).

correction does not first order stochastically dominate the distribution with the correction.[55] So, the correction does not reduce the estimate of the expected return at all points in the distribution, and there is no theoretical reason that it should.

Figure 5.6 Cumulative distributions of individual-specific nonlinear least squares estimates of moments of subjective probability distribution of returns

5.6a Mean (μ_i) 5.6b Standard deviation (σ_i)

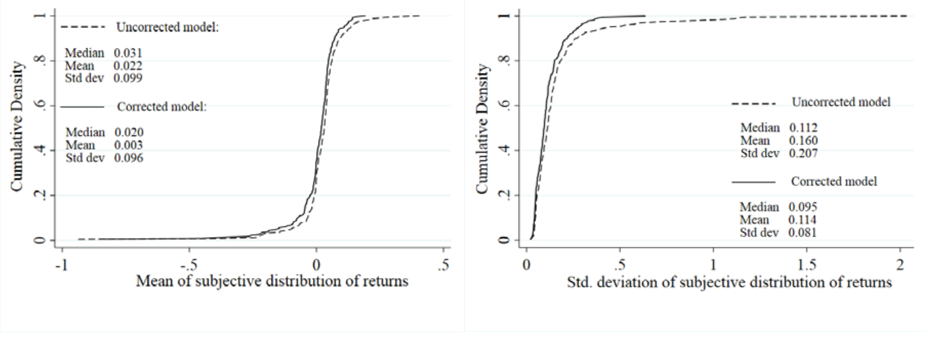


Figure 5.6b presents the respective empirical cumulative distributions of estimates of the standard deviation (σ_i) of returns from the two models. In this case, the distribution of estimates obtained without the bias correction stochastically dominates. Correcting subadditivity unambiguously results in lower estimates of the volatility of the subjective distribution of returns. Presumably, this is because subadditivity leads to higher reported probabilities of extreme events. Not correcting for it gives estimates of volatility that are biased upwards.

Median regressions of the estimates of the subjective expectation and standard deviation of returns on covariates reveals little evidence of heterogeneity in beliefs irrespective of whether any adjustment is made for subadditivity (see Appendix Tables A5.3 and A5.4). Older individuals have higher expected returns.

---

[55] Dominance is tested using a two-stage procedure (Bennett, 2013) that first tests the null of equality against the alternative of inequality using a two-sided Kolmogorov-Smirnov (KS) test. If the null is rejected, then the minimum of the one-sided KS test statistics is used to distinguish between dominance in each direction and crossing of the distributions. We adopt a conservative approach (with respect to concluding dominance) of using a 1% level of significance at the first stage and a 10% level at the second stage. We adopt the critical values derived by Bennett (2013) for his asymptotic test.

5.4.4 Predicting behavior

We have demonstrated that correcting for subadditivity affects estimates of beliefs. The regressions of ownership of risky assets presented in Table 5.4 show that the correction also affects the extent to which the estimated beliefs predict behavior. The probability of owning risky assets is more strongly associated with the mean and variance of the subjective distribution of returns that are estimated from the corrected model than it is with the mean and variance obtained from the uncorrected model. Without correcting estimated beliefs for subadditivity, an increase of 0.1 in the expected annual return (i.e. an additional 10% gain) is associated (insignificantly) with an increase of 0.052 in the probability of holding risky assets.[56, 57] This is very close to one of the two estimates produced by Hurd et al (2011) from a larger, representative sample of the Dutch population.[58] With correction, the marginal effect of the expected return doubles in magnitude and obtains significance.

Correcting for subadditivity also has an impact on the association between owning risky assets and the estimated standard deviation of the subjective distribution of returns. Without the correction, there is no significant relationship. Correcting the bias produces an increase in magnitude and significance, such that higher perceived variance of returns is estimated to be associated with greater propensity to own risky assets (albeit only at a 10% significance level).[59] This is counter intuitive and may be attributable to reverse causality: holding risky assets may make investors more aware of the volatility of the stock market.

---

[56] A 0.1 increase in the mean return corresponds to a shift from the median to the 95th (99th) percentile of the distribution of estimated expected returns obtained using the uncorrected model (Eq. 5.5) (Corrected model (Eq. 5.6)). The sample probability of holding risky assets is 0.63 (Table 5.1).

[57] There is no significant relationship between stock ownership and the estimates of μ obtained from the uncorrected model (Eq. 5.5) using 8 (as opposed to 10) subjective probability responses (marginal effect = -0.004, SE = 0.283). The association with estimates of σ also declines when only 8 responses are used (marginal effect = 0.009, SE = 0.125). One reason for these decreases in magnitudes and significance is that there is less information in fewer responses and so there is greater measurement error in the estimates of beliefs. Another likely explanation is that a consequence of restricting analysis to 8 responses and not using the probabilities of a gain and a loss of 0-10% is that more weight is placed on the reported probabilities of more extreme events that are more vulnerable to subadditivity bias. Consistent with this, if we drop respondents who violate (weak) monotonicity (associated with subadditivity) and/or report probabilities of a gain and of a loss that sum to more than 100 percent and use 8 responses, then the marginal effect of a 0.1 rise in μ increases to 0.0705 (SE=0.932). This is quite close to one of the estimates of Hurd et al (2011) who impose these exclusions and use 8 responses (see next footnote).

[58] Using data from a 2006 survey, they get an estimate of 0.049 (SE=0.0193). With data from 2004, they get an estimate of 0.0291 (0.0123).

[59] The regressions presented in Table 5.4 are estimated using the respondents for whom we obtain estimates of μ and σ from both the uncorrected model (Eq. 5.5) and the corrected model (Eq. 5.6). The results are robust to allowing the number of observations to differ by using respondents for whom we obtain estimates

Consistent with Hurd et al (2001), we find that ownership of risky assets is lower among the young and higher among the better-off. There is also evidence that those who work, or have worked, in finance are more likely to own risky assets. Conditional on beliefs about the distribution of returns, stock ownership is not associated with personal traits (trust, risk aversion and optimism). This is also consistent with Hurd et al (2011).[60]

Table 5.4 Probit estimates of marginal effects on probability of owning risky assets

	Uncorrected model	Corrected model
Mean (μ) of the fitted subjective probability distribution	0.520	1.051**
	(0.473)	(0.495)
Standard deviation (σ) of the fitted subjective probability distribution	0.136	0.852*
	(0.266)	(0.444)
Female	-0.178	-0.175
	(0.267)	(0.321)
Has partner	-0.006	-0.007
	(0.079)	(0.074)
Female * Has partner	0.037	0.044
	(0.290)	(0.344)
Age: young	-0.368***	-0.352***
	(0.057)	(0.057)
Age: old	-0.119	-0.150
	(0.106)	(0.109)
Income >= 60,000	0.147**	0.158***
	(0.059)	(0.056)
Financial sector	0.102*	0.129**
	(0.062)	(0.057)
Trust	-0.014	-0.019
	(0.058)	(0.057)
Risk averse	-0.055	-0.048
	(0.060)	(0.058)
Optimistic	0.006	0.013
	(0.074)	(0.073)
Observations	224	224

Notes: Mean (μ) and standard deviation (σ) of subjective probability distribution obtained from individual-specific nonlinear least squares estimates of the uncorrected model (Eq. 5.5) (left column) and the corrected model (Eq. 5.6) (right column). Sample restricted to respondents for whom estimates of μ and σ are obtained from both models. Estimates are marginal effects averaged over the sample. Bootstrapped standard errors with 500 replications in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.10$

Following the usual practice of dropping respondents who violate weak monotonicity and/or report probabilities of a gain and of a loss that sum to more than 100 percent would

of μ and σ from the uncorrected model (Eq. 5.5) in the left-hand regression and those for whom estimates are obtained from the corrected model (Eq. 5.6) in the right-hand regression (see Appendix Table A5.4).

[60] In data from one of the two years used, Hurd et al (2011) find a rather surprising negative association of stock ownership with optimism.

reduce the sample by 40%.[61] If we impose these exclusions, then the effect sizes of the associations of stock ownership with the mean and standard deviation of the subjective distribution of returns estimated from the corrected model change little from those given in the right column of Table 5.4 (see Appendix Table A5.5). Significance is lost, which is understandable given the reduced power of a sample that now consists of only 135 observations. The uncorrected estimates are less robust. Excluding respondents that do not satisfy the two consistency requirements doubles the marginal effect of the expected return, such that it becomes very close to the estimate obtained from the corrected model (see Appendix Table A5.5, middle column). This is consistent with the earlier observation that respondents who violate monotonicity have stronger subadditivity bias. Dropping respondents who report inconsistent subjective probabilities and correcting subadditivity bias appear, at least in this application, to have similar effects in terms of producing more informative estimates of beliefs that are correlated with behavior. The bias correction has the important advantage of preserving the power and representativeness of the sample.

5.5 Conclusion

We have introduced a simple method of correcting estimates of subjective probability distributions for subadditivity bias that does not require exclusion of (a large fraction of) sample respondents who violate consistency requirements. In an application to forecast stock market returns, we demonstrated that a model correcting for subadditivity provides a better approximation to the information in the data than a model than does not take account of this bias. Estimates of beliefs obtained from the corrected model differ from those derived from the alternative model. On average across the sample, both the estimated means and variances of the subjective probability distributions are reduced by correcting for the bias. In fact, the variance falls across the whole distribution of estimates, which is consistent with subaddivity increasing the reported probability of extreme events. The corrected estimates are more closely associated with behavior.

Alternative approaches have been explored. Rather than adopt a different model as we do, one might try to deal with inconsistent reporting behavior by changing the method of eliciting subjective probabilities. For example, Delavande and Rohwedder (2008) introduce a visual format that forces additivity by asking respondents to simultaneously report

[61] Hurd et al (2011) lose about the same proportion by imposing these exclusions.

probabilities of all elements of a partition. While this avoids one bias, it creates other anchors and the reported probabilities become partition dependent (Fox and Clemen, 2005). Forcing additivity prevents certain violations of consistency, such as non-monotonicity, but the reported probabilities are still distorted by anchors. Hudomiet and Willis (2013) propose a method to correct for the tendency to report focal responses, such as 50%. Yet, as shown by the anchoring and adjustment heuristic of Tversky and Kahneman (1974), even people who do not report precisely 50% can be biased. Our method handles such cases.

We have interpreted subadditivity as a bias affecting reports that should be corrected. Our finding that corrected reported probabilities explain behavior better than the uncorrected ones is in line with this interpretation. An alternative interpretation could be that beliefs themselves are subadditive. There is evidence that subadditivity in judgments is linked to subadditivity in decision weights (Fox and Tversky 1998). If this is the case, then neglecting subadditivity, as is done in most empirical studies that make use of expectations data, is even more worrisome. Beliefs should then be approximated not by a probability measure but by a non-additive measure (Jaffray, 1989).

Measures of expectations have been used to predict behavior and to understand heterogeneity in behavior in a wide variety of contexts (e.g. Smith et al 2001; Dominitz and Manski 2007; Hudomiet et al 2011; Kaufmann 2014; Wiswall and Zafar 2015; Armantier et al 2015). Caplan (2016) has made a cogent argument that the measurement of beliefs could and should assume a central role in the testing and development of economic theory. Consistent with this, we demonstrate that a simple extension of the standard survey instrument used to elicit expectations can greatly improve the information content of the data. The proposed method can be applied widely and is relevant for different domains. The sample we used is rather homogeneous. It consists of highly educated respondents with a degree in Economics who have some knowledge of probabilities. Since there is evidence that people become more sensitive to probabilities when they gain experience working with them (van der Kuilen 2009; Wakker 2010), it is expected that less educated respondents will have a greater tendency to report expectations that are subadditive. Given that application of the method will typically require adding only one sub-question to the expectations module of a survey, it offers a high benefit-cost ratio to survey researchers.

Appendices Chapter 5

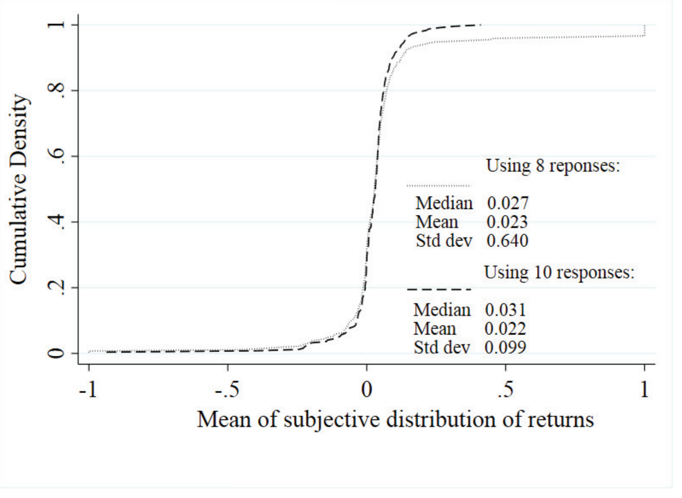
Table A5.1. Median regression of estimated subadditivity factor (a) on covariates

Female	0.062***
	(0.013)
Has partner	0.015
	(0.015)
Female * Has partner	-0.098***
	(0.016)
Age: young	-0.002
	(0.011)
Age: old	-0.034
	(0.022)
Income >= 60,000	0.014
	(0.010)
Financial sector	0.015
	(0.017)
Constant	0.029*
	(0.015)
Observations	229

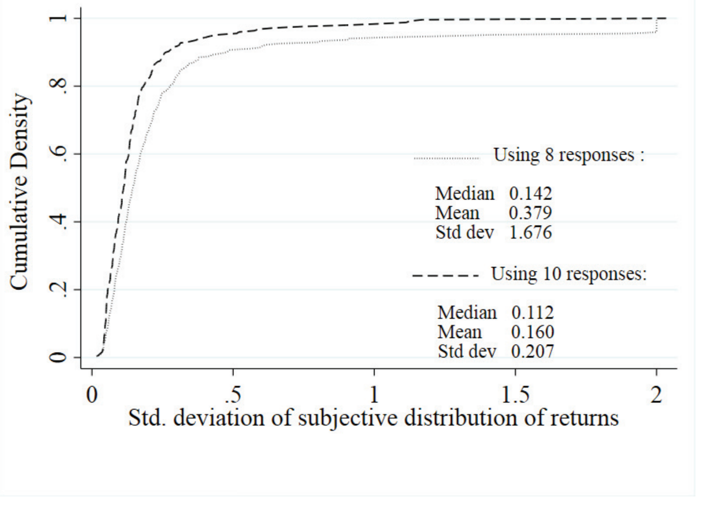
Notes: Estimates of subadditivity factor obtained from individual-specific nonlinear least squares (NLS) estimates of the corrected model (Eq. 5.6). 40 (/269) respondents not used because NLS returned an error. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Figure A5.2 Cumulative distributions of individual-specific nonlinear least squares estimates of the uncorrected model using 8 and 10 responses

A1 a. Mean (μ_i)[62]



A1 b. Standard deviation[63] (σ_i)



[62] The distribution using 8 responses is truncated at -1 (2 observations) and 1 (2 observations). The median, mean and standard deviation are computed before truncation

[63] The distribution using 8 responses is truncated at 2 (4 observations). The median, mean and standard deviation are computed before truncation

Table A5.3 Median regression of estimated mean (μ) of the subjective probability distribution of the stock market returns

	Uncorrected model	Corrected model
Female	0.001	0.014
	(0.026)	(0.022)
Has partner	-0.003	0.012
	(0.011)	(0.011)
Female * Has partner	-0.023	-0.046*
	(0.029)	(0.023)
Age: young	0.005	-0.004
	(0.009)	(0.007)
Age: old	0.034**	0.025**
	(0.013)	(0.012)
Income >= 60,000	0.004	-0.009
	(0.009)	(0.007)
Financial sector	-0.009	-0.010
	(0.008)	(0.006)
Constant	0.027**	0.021*
	(0.013)	(0.012)
Observations	224	224

Notes: Values of dependent variable are individual-specific nonlinear least squares estimates of mean of subjective distribution obtained from uncorrected model (Eq. 5.5) and corrected model (Eq. 5.6). Sample restricted to respondents for whom estimates of μ and σ are obtained from both models. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table A5.4 Median regression of estimated standard deviation (σ) of subjective probability distribution of the stock market returns

	Uncorrected model	Uncorrected model
Female	0.034	-0.013
	(0.031)	(0.015)
Has partner	-0.013	-0.011
	(0.015)	(0.013)
Female * Has partner	-0.064*	-0.013
	(0.036)	(0.023)
Age: young	0.008	-0.005
	(0.012)	(0.009)
Age: old	0.012	0.004
	(0.021)	(0.018)
Income >= 60,000	-0.000	-0.007
	(0.013)	(0.009)
Financial sector	-0.003	-0.002
	(0.012)	(0.008)
Constant	0.122***	0.113***
	(0.017)	(0.015)
Observations	224	224

Notes: Values of dependent variable are individual-specific nonlinear least squares estimates of standard deviation of subjective distribution obtained from uncorrected model (Eq. 5.5) and corrected model (Eq. 5.6). Sample restricted to respondents for whom estimates of μ and σ are obtained from both models. Robust standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A5.5 Probit estimates of marginal effects on probability of owning risky assets, robustness to sample selection

	Uncorrected model	Corrected model
Mean (μ) of the fitted subjective probability distribution	0.607	1.070**
	(0.421)	(0.453)
Standard deviation (σ) of the fitted subjective probability distribution	0.163	0.822*
	(0.213)	(0.463)
Female	-0.195	-0.182
	(0.238)	(0.308)
Has partner	-0.004	-0.010
	(0.068)	(0.074)
Female * Has partner	0.123	0.044
	(0.260)	(0.319)
Age: young	-0.362***	-0.350***
	(0.048)	(0.055)
Age: old	-0.124	-0.157
	(0.099)	(0.096)
Income >= 60,000	0.136**	0.158**
	(0.053)	(0.062)
Financial sector	0.090	0.129**
	(0.056)	(0.059)
Trust	-0.009	-0.022
	(0.054)	(0.058)
Risk averse	-0.058	-0.054
	(0.054)	(0.054)
Optimistic	-0.030	0.022
	(0.071)	(0.071)
Observations	248	229

Notes: Compare with estimates in Table 5.4. In Table 5.4, the same respondents are used in the two regressions – those for which estimates of μ and σ are obtained from both models. Bootstrapped standard errors with 500 replications in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A5.6 Probit estimates of marginal effects on probability of owning risky assets, sample restricted to respondents giving consistent responses

	Uncorrected model	Corrected model
Mean (μ) of the fitted subjective probability distribution	1.131	1.237
	(1.169)	(1.052)
Standard deviation (σ) of the fitted subjective probability distribution	0.378	0.898
	(0.517)	(0.670)
Female	-0.070	-0.055
	(0.367)	(0.366)
Has partner	-0.003	0.009
	(0.101)	(0.105)
Female * Has partner	-0.021	-0.037
	(0.401)	(0.392)
Age: young	-0.399***	-0.372***
	(0.075)	(0.135)
Age: old	-0.071	-0.084
	(0.113)	(0.163)
Income >= 60,000	0.159**	0.176**
	(0.080)	(0.089)
Financial sector	0.038	0.081
	(0.085)	(0.080)
Trust	-0.023	-0.036
	(0.084)	(0.081)
Risk averse	-0.025	-0.013
	(0.073)	(0.076)
Optimistic	-0.042	-0.026
	(0.112)	(0.115)
Observations	135	135

Notes: Compare with estimates in Table 5.4. In this table, regressions only use respondents who report subjective probabilities that satisfy weak monotonicity and the sum of probabilities of a gain and of a loss is less than or equal to 100%. The sample consists of those respondents for whom estimates of μ and σ are obtained from both model (5) and model (6). Bootstrapped standard errors with 500 replications in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Chapter 6 Conclusion

This thesis contributes to an accumulation of research that uses behavioral economics to provide insights into social issues of substantial policy interest. The main body of the thesis uses data on non-standard risk and time preferences, as well as subjective beliefs of medical expenditure that I collected as part of a nationwide household survey in the Philippines. I used these data to explain the discrepancy between estimates of large potential gains from health insurance in low- and middle-income countries (LMIC) that are derived from standard economic models and low observed take up of voluntary health insurance. Chapter 2 examined the association of elicited risk preferences defined by prospect theory and time preferences defined by quasi-hyperbolic discounting with health insurance enrollment. Chapter 3 introduced and applied a new decomposition of the willingness to pay (WTP) for insurance into its fair price and four behavioral deviations from that price that arise from subjective beliefs about the distribution of medical expenses, two dimensions of risk attitudes consistent with prospect theory and a residual term representing determinants not captured by the behavioral model. Chapter 4 added to the meagre literature that tests whether temporary incentives can permanently change behavior and so continue to have effects, in this case on health insurance enrollment, after they are withdrawn.

The main, most consistent finding of chapter 2 is that individuals who discount the future more are less likely to insure. This suggests that one reason many Filipinos do not take out health insurance is because they value the premium they must pay when enrolling above the highly discounted benefit they will only enjoy, if at all, at some time over the course of the following year. This finding is in line with evidence from the randomized experiment in the Philippines presented in chapter 4 demonstrating that reducing the indirect costs of insurance (application) at enrollment can be highly effective in increasing take-up, at least in the short run (Capuno et al 2016). Amongst individuals with some knowledge of how health insurance operates low take-up of insurance is also association with present bias. This suggests that a financial device that facilitates commitment to enrollment at a later date might raise take-up once people are aware of how insurance operates.

The findings from chapter 2 also demonstrate that, consistent with prospect theory, the majority of respondents have a strong convex curvature of the utility function in the domain of losses. Chapter 3 quantifies the extent to which this decreases the perceived value of health insurance. Such risk seeking in the domain of losses would suggest that framing insurance in terms of gains as opposed to losses, focusing more on the reimbursements received if insured, as opposed to the expenditures one may incur if uninsured, would be an effective strategy to raise demand. However, chapter 2 reveals that respondents who exhibit more risk seeking in the domain of losses are actually more likely to insure. This appears counterintuitive, although it is consistent with evidence on risk preferences and demand for other forms of insurance. Since these results are not robust to controlling for socioeconomic factors, an alternative explanation could be a spurious relationship between insurance and risk preferences arising from correlation of each with socioeconomic factors. Most studies on correlates of risk preferences are cross-sectional and it is therefore hard to determine whether socioeconomic characteristics antecede risk preferences or vice versa.

The decomposition of WTP in chapter 3 reveals that, in addition to risk seeking in the domain of losses, the transformation of probabilities into decision weights reduces the perceived value of insurance. Chapter 2 demonstrates that respondents who overweight moderate and large probability losses are more likely to purchase health insurance, which is consistent with the relatively high average probability of medical expenditure that is demonstrated in chapter 3. About 80% of people report out of pocket medical expenditures in the past year.

Inconsistent with claims that optimism bias is highly prevalent, low WTP for health insurance in the Philippines is not explained by downwardly biased expectations of medical expenditures. Most people seem to be aware of the risk they face of incurring medical expenses. Hence, efforts to communicate this risk would not be effective in raising insurance take-up. The decomposition shows that WTP is reduced by factors not included in the behavioral model based on prospect theory. The findings of chapter 2 suggest that time preferences are an important driver of the demand for insurance that is not captured by the standard single-period expected utility model of insurance, or even a prospect theory counterpart.

Elicitation of preferences and beliefs in large household surveys in LMIC is still very rare. This thesis introduced methods that are applicable in a time constrained survey administered to low educated respondents. Compared with relying on the assumptions of standard economic theory, I believe this approach has advantages and that these are evident from partial success in explaining low WTP for and take up of health insurance in the Philippines. However, this approach also requires the imposition of various assumptions, such as those implicit in the functional forms chosen for the preferences. Although it is becoming much more common to collect data on beliefs and preferences in the context of a survey conducted in the field in LMIC, most tests of the suitability of these functional forms have been conducted in western countries, and usually with student samples. As such, there is a need to test the extent to which the implicit assumptions match with the behavior of representative samples on low income populations.

The explosion of research activity in development economics and other fields that uses randomized field experiments to test the effectiveness of policy interventions has provoked two serious criticisms. First, demonstration that policy X works in setting Y is of little use if we do not learn why it works and so are not in a position to consider whether it will be as effective in setting Z. Second, the financing of many interventions cannot be maintained in perpetuity. In which cases, a temporary intervention is only interesting if it can permanently change behavior. This thesis makes a small contribution to addressing both criticisms.

Examination of the role of risk and time preferences to explaining why people make certain economic decisions, such as insuring, can complement and inform targeted policy interventions and their randomized evaluation (Cardenas and Carpenter 2008; Deaton 2010). Investigating preferences alongside experiments can potentially provide insights into why they do or do not have the intended effect, potentially increasing generalizability (Deaton 2010). While the associations estimated in this thesis between elicited preferences and beliefs regarding medical expenditures do not support causal inference, they do suggest the broad mechanisms through which innovations in policy design might try to operate in order to be effective in raising take up. First, many will likely remain unpersuaded of the advantages of health insurance unless the balance between upfront costs and future, uncertain benefits becomes more appealing. Second, insurance that promises to deliver reimbursement benefits may be more appealing than the same insurance marketed as covering losses.

Examination of long-term effects of policy interventions is important not only because one wants to know whether short-term positive effects are sustained, but also because there may be a risk of unintended, negative effects in the long run. For example, a one-off subsidy, such as that offered for health insurance in the Philippines evaluated in chapter 4, could potentially result in recipients anchoring their WTP on the discounted price (Dupas 2014). I did not find any evidence to support this hypothesis in the context of the experiment in the Philippines. But I did find that the short-term relative effectiveness of two interventions was a very poor guide to their relative effects in the long-term. A substantial temporary price subsidy had a sustained long-term impact on insurance enrollment. Reducing the indirect costs of enrollment by providing one-time assistance with completion and submission of the insurance application had a much stronger short-term impact, and yet its long-term effect was smaller than that of the subsidy. This is an important finding. It alerts us to the possibility that an intervention has a strong immediate effect because of the offer of high-powered incentives during an experiment without having any permanent impact on behavior. Another intervention may be less impressive in the short-term but have a lasting effect through changing preferences or overcoming fixed costs that need not be incurred again in the future.

While the nationwide nature of the data analyzed in this thesis makes the findings more generalizable than much of the existing evidence, obviously one must be careful about drawing inferences about behavior in quite different contexts. Preferences and beliefs will vary across settings, as will short- and long-term effects of health insurance inducements. The degree of financial protection a health insurance scheme offers, and the (quality of) health services accessible, might differ substantially and could, in turn, influence beliefs and the demand for health insurance coverage.

Chapter 5 stands apart from the others because it is the only one not to examine the demand for health insurance and use the data collected in the Philippines. However, it is connected to the other chapters through the focus on belief elicitation. The simple method of correcting the common subadditivity bias in estimates of subjective probability distributions introduced in this chapter can potentially be widely applied in survey research, such as the expectations modules now included in surveys such as the US Health and Retirement Study and related ageing studies. The finding that correcting reported probabilities for subadditivity improves their ability to explain (stock holding) behavior demonstrates the potential return on the method. Although the sample used in chapter 5 is rather homogeneous and it would be interesting to see how the results replicate in different domains, the proposed method can be applied widely. Given that application of the method will typically require adding only one sub-question to the expectations module of a survey, it offers a high benefit-cost ratio to survey researchers.

I started this thesis with the observation that in recent years economists have begun to widen their horizons from the collection and analysis of objective data on constraints and outcomes to the elicitation and analysis of data on the more subjective concepts of beliefs and preferences. I hope this thesis can make a small contribution to encouraging others to join this exciting trend in economic research.

References

Acharya, A., Vellakkal, S., Taylor, F., Masset, E., Satija, A., & Burke, M. (2013). The Impact of Health Insurance Schemes for the Informal Sector in Low- and Middle-Income Countries: A Systematic Review. *World Bank Research Observer,* 28(2), 236-266.

Andersen, S., Harrison, G. W., Lau, M. I., & Rutström, E. E. (2008). Eliciting risk and time preferences. *Econometrica*, 76(3), 583-618.

Anderson, L. R., & Mellor, J. M. (2008). Predicting health behaviors with an experimental measure of risk preference. *Journal of Health Economics*, 27(5), 1260-1274.

Andreoni, J., Kuhn, M. A., & Sprenger, C. (2015). Measuring time preferences: A comparison of experimental methods. *Journal of Economic Behavior & Organization*, 116, 451-464.

Armantier, O., Bruine de Bruin, W., Topa, G., van der Klaauw, W. & Zafar, B. (2015). Inflation expectations and behavior: Do survey respondents act on their beliefs? *International Economic Review,* 56(2): 505-536.

Ashraf, N., Karlan, D., & Yin, W. (2006). Tying Odysseus to the mast: Evidence from a commitment savings product in the Philippines. *The Quarterly Journal of Economics*, 121(2), 635-672.

Asuming, P.O., Kim, H.B. & Sim, A. (2017). Long-Run Consequences of Health Insurance Promotion: Evidence from a Field Experiment in Ghana. IZA DP 11117 http://ftp.iza.org/dp11117.pdf

Attanasio, O. P. (2009). Expectations and perceptions in developing countries: their measurement and their use. *The American Economic Review*, 99(2), 87-92.

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.

Bago d'Uva, T., Erdogan-Ciftci, E., O'Donnell, O., & Van Doorslaer, E. (2015). Who can predict their own Demise? Accuracy of Longevity Expectations by Education and Cognition. (No. 15-052/V). Tinbergen Institute.

Baicker, K., Congdon, W. J., & Mullainathan, S. (2012). Health Insurance Coverage and Take-Up: Lessons from Behavioral Economics. *Milbank Quarterly,* 90(1), 107-134.

Barberis, N. C. (2013). Thirty years of prospect theory in economics: A review and assessment. *The Journal of Economic Perspectives*, 27(1), 173-195.

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.

Barsky, R.B., Miles, K., Thomas Juster, F. & Shapiro, M. (1997). Preference parameters and behavioral heterogeneity: an experimental approach in the health and retirement study. *Quarterly Journal of Economics,* 112 (2), 537–579.

Bearden, J. N., Wallsten, T. S., & Fox, C. R. (2007). Contrasting stochastic and support theory accounts of subadditivity. *Journal of Mathematical Psychology*, 51(4), 229-241.

Bennett C. (2013). Inference for dominance relations. *International Economic Review* 54(4), 1309-1328.

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.

Bredenkamp, C., Capuno, J., Kraft, A., Poco, L., Quimbo, S., & Tan Jr, C. A. (2017). *Expansion of Health Insurance in the Philippines: Evidence from Panel Data*. Health. Nutrition and Population Discussion Paper; World Bank, Washington, DC.

Bredenkamp, C., Evans, T., Lagrada, L., Langenbrunner, J., Nachuk, S., & Palu, T. (2015). Emerging challenges in implementing universal health coverage in Asia. *Social Science & Medicine*, 145, 243-248.

Browne, M. J., Knoller, C., & Richter, A. (2015). Behavioral bias and the demand for bicycle and flood insurance. *Journal of Risk and Uncertainty*, 50(2), 141-160.

Brune, L., Giné, X., Goldberg, J. & Yang, D. (2016). Facilitating Savings for Agriculture: Field Experimental Evidence from Malawi. *Economic Development and Cultural Change*, 64(2), 187-220.

Bundorf, M. K., & Pauly, M. V. (2006). Is health insurance affordable for the uninsured? *Journal of Health Economics, 25*(4), 650-673.

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.

Burnham, K. P., & Anderson, D. R. (2002). Model selection and multimodel inference: A practical information-theoretic approach. New York: Springer-Verlag

Caplin, A. (2016). Economic Data Engineering. Mimeo, New York: New York University.

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 enrolllment 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.

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

Chernew, M., Frick, K., & McLaughlin, C.G.1997. The Demand for Health Insurance Coverage by Low-Income Workers: Can Re-duced Premiums Achieve Full Coverage? *Health Services Research,* 32(4), 453–70.

Chuang, Y., & Schechter, L. (2015). Stability of experimental and survey measures of risk, time, and social preferences: A review and some new results. *Journal of Development Economics*, 117, 151-170.

Clemen, R. T., & Ulu, C. (2008). Interior additivity and subjective probability assessment of continuous variables. *Management Science,* 54(4), 835-851.

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.

Currie, J., & J. Gruber. 1996. Health Insurance Eligibility, Utilization of Medical Care, and Child Health. *Quarterly Journal of Economics,* 111(2), 431–66.

Cutler, D., & Glaeser, E. (2005). What explains differences in smoking, drinking, and other health-related behaviors. *American Economic Review*, 95(2), 238-242.

Das, J., & Leino, J. (2011). Evaluating the RSBY: Lessons from an experimental information campaign. *Economic & Political Weekly*, 46(32), 85-93.

Deaton, A. (2010). Instruments, randomization, and learning about development. *Journal of Economic Literature,* 48(2), 424-455.

Delaney, L., & Lades, L. K. (2015). Present Bias and Everyday Self-Control Failures. Stirling Economics Discussion Paper.

Delavande, A. (2014). Probabilistic expectations in developing countries. *Annual Review of Economics,* 6(1), 1-20.

Delavande, A., & Rohwedder, S. (2008). Eliciting subjective probabilities in Internet surveys. *Public Opinion Quarterly*, 72(5), 866-891.

Delavande, A., Giné, X., & McKenzie, D. (2011a). Measuring subjective expectations in developing countries: A critical review and new evidence. *Journal of Development Economics*, 94(2), 151-163.

Delavande, A., Giné, X., & McKenzie, D. (2011b). Eliciting probabilistic expectations with visual aids in developing countries: how sensitive are answers to variations in elicitation design? *Journal of Applied Econometrics,* 26(3), 479-497.

DellaVigna, S. (2009). Psychology and economics: Evidence from the field. *Journal of Economic literature,* 47(2), 315-72.

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

Dominitz, J. & Manski, C. (2007). Expected equity returns and portfolio choice: evidence from the Health and Retirement Study. *Journal of the European Economic Association*, 5(2-3), 369-379

Dominitz, J., & Manski, C. F. (1997). Using expectations data to study subjective income expectations. *Journal of the American Statistical Association,* 92(439), 855-867.

Dominitz, J., & Manski, C. F. (2011). Measuring and interpreting expectations of equity returns. *Journal of Applied Econometrics*, 26(3), 352-370.

Duflo, E., Kremer, M., & Robinson, J. (2011). Nudging farmers to use fertilizer: Theory and experimental evidence from Kenya. *The American Economic Review*, 101(6), 2350-2390.

Dupas, P. (2011). Health behavior in developing countries. *Annual Review of Economics*, 3(1), 425-449.

Dupas, P. (2014). Short-run subsidies and long-run adoption of new health products: Evidence from a field experiment. *Econometrica*, 82(1), 197-228.

Fischhoff, B., Slovic, P., & Lichtenstein, S. (1978). Fault trees: Sensitivity of estimated failure probabilities to problem representation. *Journal of Experimental Psychology: Human Perception and Performance*, 4(2), 330

Fox, C. R., & Clemen, R. T. (2005). Subjective probability assessment in decision analysis: Partition dependence and bias toward the ignorance prior. *Management Science*, 51(9), 1417-1432.

Fox, C. R., & Rottenstreich, Y. (2003). Partition priming in judgment under uncertainty. *Psychological Science,* 14(3), 195-200.

Fox, C. R., & Tversky, A. (1998). A belief-based account of decision under uncertainty. *Management Science*, 44(7), 879-895.

Frederick, S., Loewenstein, G., & O'Donoghue, T. (2002). Time discounting and time preference: A critical review. *Journal of Economic Literature*, 40(2), 351-401.

Fuchs, V.R. (1982). Time preference and health: an exploratory study. In: Fuchs, V.R. (Ed.), Economic Aspects of Health. University of Chicago Press for the NBER, pp. 93–120.

Genoni, M.E. (2012). Health Shocks and Consumption Smoothing: Evidence from Indonesia*, Economic Development and Cultural Change,* 60(3), 475-506.

Gertler, P. & J. Gruber (2002). Insuring Consumption Against Illness*, American Economic Review* 92(1), 51-70.

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., Goldberg, J., Silverman, D., & Yang, D. (2018). Revising commitments: Field evidence on the adjustment of prior choices. *The Economic Journal,* 128(608), 159-188

Giné, X., Karlan, D. & Zinman,J. (2010). Put Your Money Where Your Butt Is: A Commitment Savings Account for Smoking Cessation. *American Economic Journal: Applied Economics,* 2(4), 1-26.

Giné, X., Townsend, R., & Vickery, J. (2008). Patterns of rainfall insurance participation in rural India. *The World Bank Economic Review*, 22(3), 539-566.

Gollier, C., (2003). To insure or not to insure? An insurance puzzle. *The Geneva Papers on Risk and Insurance Theory,* 28, 5–24.

Halevy, Y. (2015). Time consistency: Stationarity and time invariance. *Econometrica*, 83(1), 335-352.

Harrison, G. W. & Rutström, E. E. (2008). Experimental evidence on the existence of hypothetical bias in value elicitation methods. *Handbook of Experimental Economics Results*, 1, 752–767.

Holt, C. A., & Laury, S. K. (2002). Risk aversion and incentive effects. *American economic review*, 92(5), 1644-1655.

Hudomiet, P., & Willis, R. J. (2013). Estimating second order probability beliefs from subjective survival data. *Decision Analysis*, 10(2), 152-170.

Hudomiet, P., Kézdi, G., & Willis, R. J. (2011). Stock market crash and expectations of American households. *Journal of Applied Econometrics,* 26(3), 393-415.

Hurd, M. (2009). Subjective probabilities in household surveys. *Annual Review of Economics*, 1, 543–564

Hurd, M., van Rooij, M. & Winter, J. (2011) Stock market expectations of Dutch households. *Journal of Applied Econometrics*, 26(3), 416-436.

Imbens, G.W. (2004). Nonparametric Estimation of Average Treatment Effects Under Exogeneity: A Review. *Review of Economics and statistics,* 86(1), 4-29.

Islam, A. & P. Maitra (2012). Health Shocks and Consumption Smoothing in Rural Households: Does Microcredit have a Role to Play? *Journal of Development Economics,* 97(2), 232-243.

Jaffray, J.-Y. (1989). Linear Utility Theory for Belief Functions. *Operations Research Letters,* 8(2), 107–112.

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.

Johnson, E. J., Hershey, J., Meszaros, J., & Kunreuther, H. (1993). Framing, probability distortions, and insurance decisions. *Journal of Risk and Uncertainty*, 7(1), 35-51.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47, 263-291.

Kaufmann, K. M. (2014). Understanding the income gradient in college attendance in Mexico: The role of heterogeneity in expected returns. *Quantitative Economics*, 5(3), 583-630.

Khwaja, A., Sloan, F., & Chung, S. (2007). The relationship between individual expectations and behaviors: mortality expectations and smoking decisions. *Journal of Risk and Uncertainty*, 35(2), 179-201.

Kleinjans, K. J., & Soest, A. V. (2014). Rounding, focal point answers and nonresponse to subjective probability questions. *Journal of Applied Econometrics*, 29(4), 567-585.

Komlos, J., Smith, P. K., & Bogin, B. (2004). Obesity and the rate of time preference: is there a connection? *Journal of Biosocial Science*, 36(02), 209-219.

Kőszegi, B., & Rabin, M. (2006). A model of reference-dependent preferences. *The Quarterly Journal of Economics,* 121(4), 1133-1165.

Laibson, D. (1997). Golden eggs and hyperbolic discounting. *The Quarterly Journal of Economics*, 112(2), 443-477.

Levy, H. & DeLeire, T. (2008/2009) What Do People Buy When They Don't Buy Health Insurance and What Does that Say about Why They Are Uninsured? *Inquiry Winter,* 45(4), 365–379.

Limwattananon, S., Neelsen, S., O'Donnell, O., Prakongsai, P., Tangcharoensathien, V., Van Doorslaer, E., & Vongmongkol, V. (2015). Universal coverage with supply-side reform: The impact on medical expenditure risk and utilization in Thailand. *Journal of Public Economics,* 121, 79-94.

Liu, K. (2016). Insuring Against Health Shocks: Health Insurance and Household Choices. *Journal of Health Economics,* 46, 16-32.

Loewenstein, G. (1987). Anticipation and the valuation of delayed consumption. *The 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.

Manski, C. F. (2004). Measuring expectations. *Econometrica,* 72(5), 1329-1376.

Mohanan, M. (2013). Causal Effects of Health Shocks on Consumption and Debt: Quasi-Experimental Evidence from Bus Accident Injuries, *Review of Economics and Statistics* 95(2): 673-681.

Mullainathan, S., & Shafir, E.(2014). Scarcity: The New Science of Having Less and How It Defines Our Lives (4th ed) . London: Macmillan/Picador.

Murphy, J. J., Allen, P. G., Stevens, T. H., & Weatherhead, D. (2005). A meta-analysis of hypothetical bias in stated preference valuation. *Environmental and Resource Economics*, 30(3), 313-325.

Pagan, A. (1984). Econometric issues in the analysis of regressions with generated regressors. *International Economic Review*, 25(1), 221-247.

Pauly, M. V., Blavin, F. E., & Meghan, S. (2009). How private, voluntary health insurance can work in developing countries. *Health Affairs*, 28(6), 1778-1787.

Pettigrew, L. M., & Mathauer, I. (2016). Voluntary Health Insurance expenditure in low- and middle-income countries: Exploring trends during 1995–2012 and policy implications for progress towards universal health coverage. *International Journal for Equity in Health,* 15(1), 67.

PHIC (2014). Implementing guidelines for the mandatory PhilHealth coverage of senior citizens pursuant to Republic Act No. 10645. Philhealth Circular No. 0033/2014. http://www.philhealth.gov.ph/circulars/2014/circ33_2014.pdf, accessed 17 July 2016

Prelec, D. (1998). The probability weighting function. *Econometrica*, 66, 497-527.

PSA (2015). Philippines in figures 2015. https://www.psa.gov.ph/sites/default/files/2015%20PIF%20Final_%20as%20of%20022916.pdf, accessed 24 August 2016

Republic of the Philippines (2013). Amendment to the National Health Insurance Act of 1995 (RA 10606).

Robins, J.M. & Rotnitzky A. (1995). Semiparametric Efficiency in Multivariate Regression Models with Missing Data, *Journal of the American Statistical Association,* 90(429), 122-129.

Rosenbaum, P.R. (1987). Model-Based Direct Adjustment, *Journal of the American Statistical Association,* 82(398), 387-394.

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.

Schmidt, U. (2016). Insurance demand under prospect theory: A graphical analysis. *Journal of Risk and Insurance,* 83(1), 77-89.

Scholten, M., & Read, D. (2006). Discounting by intervals: A generalized model of intertemporal choice. *Management Science*, 52(9), 1424–1436

Sharot, T. (2011). The Optimism Bias. New York: Pantheon Books.

Simonsohn, U., & Loewenstein, G. (2006). Mistake# 37: The effect of previously encountered prices on current housing demand. *The Economic Journal,* 116(508), 175-199.

Simonson, I., & Tversky, A. (1992). Choice in context: Tradeoff contrast and extremeness aversion. *Journal of marketing research,* 29(3), 281.

Smith V.K., Taylor, D.H. Jr., Sloan, F.A., Johnson, F.R., & Desvousges, W.H. (2001). Do Smokers Respond to Health Shocks? *Review of Economics and Statistics*, 83(4), 675-687

Stott, H. P. (2006). Cumulative prospect theory's functional menagerie. *Journal of Risk and uncertainty*, 32(2), 101-130.

Sutter, M., Kocher, M. G., Glätzle-Rützler, D., & Trautmann, S. T. (2013). Impatience and uncertainty: Experimental decisions predict adolescents' field behavior. *American Economic Review*, 103(1), 510–531.

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.

Tangcharoensathien, V., Patcharanarumol, W., Ir, P., Aljunid, S. M., Mukti, A. G., Akkhavong, K., Banzon, E., Huong, D.B., Thabrany, H. & Mills, A. (2011). Health-financing reforms in Southeast Asia: challenges in achieving universal coverage. *The Lancet,* 377(9768), 863-873.

Thaler, R. H. (1981). Some empirical evidence on dynamic inconsistency. *Economic Letter*, 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.

Townsend, R.M. (1994). Risk and Insurance in Village India, *Econometrica,* 62(3): 539-591.

Tversky, A., & Fox, C. R. (1995). Weighing risk and uncertainty. *Psychological Review,* 102(2), 269.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science,* 185(4157), 1124-1131.

Tversky, A., & Kahneman, D. (1983). Extensional versus intuitive reasoning: the conjunction fallacy in probability judgment. *Psychological Review*, 90(4), 293.

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, 5(4), 297-323.

Tversky, A., & Koehler, D. J. (1994). Support theory: a nonextensional representation of subjective probability. *Psychological Review,* 101(4), 547.

Van de Kuilen, G. (2009). Subjective probability weighting and the discovered preference hypothesis. *Theory and Decision,* 67(1), 1-22.

Van Doorslaer, E., O'Donnell, O., Rannan-E liya, R. P., Somanathan, A., Adhikari, S. R., Garg, C. C., Harbianto, D., Herrin, A.N., Huq, M.N., Ibragimova, S. & Karan, A (2007). Catastrophic payments for health care in Asia. *Health Economics,* 16(11), 1159-1184.

Van Santen, P., Alessie, R., & Kalwij, A. (2012). Probabilistic survey questions and incorrect answers: Retirement income replacement rates. *Journal of Economic Behavior & Organization,* 82(1), 267-280.

Vieider, F. M., Lefebvre, M., Bouchouicha, R., Chmura, T., Hakimov, R., Krawczyk, M., & Martinsson, P. (2015a). 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., Truong, N., Martinsson, P., & Khanh, N. P. (2015b). Risk preferences and development revisited. Working paper. http://www.ferdinandvieider.com/Vietnam_risk.pdf (accessed 31-08-2016)

Wagstaff, A., Flores, G., Hsu, J., Smitz, M.F., Chepynoga, K., Buisman, L.R., van Wilgenburg, K. & Eozenou, P. (2017). Progress on catastrophic health spending in

133 countries: a retrospective observational study. *The Lancet Global Health*. (Forthcoming)

Wagstaff, A., Nguyen, H. T. H., Dao, H., & Bales, S. (2016). Encouraging health insurance for the informal sector: a cluster randomized experiment in Vietnam. *Health Economics*, 25(6), 663-674.

Wakker, P. P. (2010). Prospect theory: For risk and ambiguity. Cambridge University Press: Cambridge.

Wakker, P., Thaler, R., & Tversky, A. (1997). Probabilistic insurance. *Journal of Risk and Uncertainty*, 15(1), 7-28.

Wang, M., Rieger, M. O., & Hens, T. (2016). How time preferences differ: Evidence from 53 countries. *Journal of Economic Psychology*, 52, 115-135.

Weinstein, N. D. (1980). Unrealistic optimism about future life events. *Journal of Personality and Social Psychology*, 39(5), 806.

Weinstein, N. D., & Klein, W. M. (1996). Unrealistic optimism: Present and future. *Journal of Social and Clinical Psychology*, 15(1), 1-8.

Wiswall, M. & Zafar, B. (2015). Determinants of college major choice: Identification using an information experiment. *Review of Economic Studies,* 82(2): 791-824.

World Health Organization. (2010). *World Health Report, 2010: health systems financing the path to universal coverage*. World Health Organization.

Wright, G., & Whalley, P. (1983). The supra-additivity of subjective probability. In B.P. Stigum & F. Wenstøp (Eds.) *Foundations of utility and risk theory with applications* (pp. 233-244). Dordrecht, Springer Netherlands.

Wu, G., & Gonzalez, R. (1999). Nonlinear decision weights in choice under uncertainty. *Management Science,* 45(1), 74-85.

Yates, F. J., & Watts, R. A. (1975). Preferences for deferred losses. *Organizational Behavior and Human Performance*, 13(2), 294–306.

Yilma, Z., O'Donnell, O., Mebratie, A., Alemu, G., & Bedi, A. S. (2015). Subjective Expectations of Medical Expenditures and Insurance in Rural Ethiopia. Tinbergen Institute Discussion Paper. TI 2015-120/V.

Summary

This thesis contributes to an accumulation of research that uses behavioral economics to provide insights into social issues of substantial policy interest. The main body of the thesis uses data on non-standard risk and time preferences, as well as subjective beliefs of medical expenditure collected as part of a nationwide household survey in the Philippines. This data is used to explain the discrepancy between estimates of large potential gains from health insurance in low- and middle-income countries (LMIC) that are derived from standard economic models and low observed take up of voluntary health insurance.

Chapter 2 examines the association of elicited risk preferences defined by prospect theory and time preferences defined by quasi-hyperbolic discounting and examines their associations with health insurance enrollment. It finds consistent evidence that individuals who discount future returns more aggressively are less likely to enroll. In the full sample, insurance take-up is not related to present bias. But it is among individuals with some knowledge of how health insurance operates. Respondents who exhibit more risk seeking in the domain of losses, characterized by more convex utility, are more likely to insure. This appears counterintuitive, although it is consistent with evidence on risk preferences and demand for other forms of insurance. Respondents who overweight moderate and large probability losses are more likely to purchase health insurance, which is consistent with the relatively high average probability of medical expenditure in our sample. Both findings concerning the association of insurance with risk preferences are not robust to controlling for socio-economic factors.

Chapter 3 introduces and applies a new decomposition of the willingness to pay (WTP) for insurance into its fair price and four behavioral deviations from that price that arise from subjective beliefs about the distribution of medical expenses, two dimensions of risk attitudes consistent with prospect theory and a residual term representing determinants not captured by our behavioral model. Low WTP is not explained by downwardly biased expectations of medical expenditures. Both convex utility in the domain of losses and the transformation of probabilities into decision weights push the WTP below the fair price, reducing the demand for insurance. WTP is further reduced by other factors not included in our model. Time preferences and self-insurance options could be amongst these.

Understanding of preferences and beliefs regarding medical expenditure risk can be used to (better) design policy interventions that aim to raise health insurance take up.

Increasingly, randomized field experiments are being conducted to test the effectiveness of inducements to enroll. There is some evidence of a positive immediate effect. But this may be insufficient to establish cost-effectiveness if the effects last only as long as the interventions are offered. In Chapter 4, a randomized experiment is used to establish whether a one-off premium subsidy of up to 50% and another intervention that reduced the indirect costs of enrollment by providing one-time assistance with the insurance application had sustained effects on enrollment up to four years after the inducements were withdrawn. Although the second intervention had the stronger impact in the short term, only the effect of the premium subsidy was maintained in the long run. This shows that the short-term effects of interventions may not be indicative of their long-term impacts.

Chapter 5 stands apart from the others because it is the only one not to examine the demand for health insurance and use the data collected in the Philippines. However, it is connected to the other chapters through the focus on belief elicitation. Elicitation of preferences and beliefs often involves respondents undertaking tasks that requires them to make decisions. If they do so using heuristics, then the design of the task could affect the results. A common bias in the reporting of probabilities is subadditivity: the reported probability of the union of two disjoint events is smaller than the sum of the reported probabilities of those events. This subadditivity bias can result in overestimation of the probability of an unlikely event and violation of monotonicity. Chapter 5 introduces a simple correction that preserves sample power and representativeness by avoiding the common practice of dropping a substantial fraction of respondents who report inconsistent probabilities. Application to forecasting of stock market returns demonstrates that our correction improves data fit and gives estimates of beliefs that are more closely associated with stock ownership.

Acknowledgements

My greatest thanks without a doubt go to Owen and Aurélien. I enjoyed the process of writing this thesis and this is for a very large part thanks to your support. Working with you has always kept me motivated. Owen, your critical eye for detail has taught me so much, while at the same time you always made me feel confident in my work. Besides that, I always felt you were there for me, despite the geographical distance. Aurélien, your positive attitude and ideas, seeing endless chances and possibilities, have been very inspiring. Thanks too for your patience and time in explaining all the ins and outs of behavioral theory.

I would not have been able to write this thesis without our colleagues from the University of the Philippines and the World Bank. Ellen, thanks a lot for introducing me to them. Caryn, Stella, Dockoy, Aleli, Carlos, Rhea, Sylvia and Issa, thanks for giving me the opportunity to work with you in the development of the Daisy III questionnaire. Thanks too for always creating a welcoming atmosphere. Rhea, Sylvia and Chila, I still have my pizza socks that remind me of the good times hanging out with you.

My time at ESE was definitely as good as it was because of my colleagues from the Health Economics team. Eddy, thanks for heading such an amazing group of researchers and most of all people. Teresa, Pilar, Hans, Tom, Jan, Raf, Carlos, Titus, Hale, Hao, Bastian, Max, Sylvia, Jenny, Rita, Sara and Joaquim, thanks for all the inspiration, fun, feedback, sharing and caring. I'm happy I still get to see you often and feel part of the group by joining for lunch and dinners. I would also like to thank the rest of the colleagues at Applied Economics for the interesting conversations, amusing outings and support. Also many thanks Tinbergen colleagues for your support. And thanks to all fellow PhD students for the reflections, fun and enjoyable lunches. Thanks a lot too ESHPM colleagues, especially Arthur, Leander, Pieter, Pieter, Job, Ellen, Sven and Anne-Fleur, I really enjoyed your company at conferences and parties.

Caroline, I couldn't have wished for anybody better to share the office with than you. It definitely gave me a reason to come "all the way" to Rotterdam. It has been great to be able to share this journey together from beginning to end and to share many moments in our lives along with that. Thank you for standing by my side as paraymph. Jan, thanks for sharing your office with me during the last months of my PhD. Our productive garden walk has left a leaving impression.

Sven, one of the many good things that came out of doing my PhD is definitely our friendship. I have so many good memories of lakeside lunches, coot watching, cooking, beach fun, parties and of course the laughs. And yes even the hard talk. Thank you for your feedback and inspiration in all forms. Max, it has been so nice having you as my office neighbor, Rotterdam housie and most importantly friend. I enjoy our reflections on work and life, and am very grateful you were there for me when life caught up on me once or twice. Matthijs, thanks for the dinners, coffees and ice creams that made long working days something to look forward to.

Tessa, Gabriela and Kateryna, I really enjoyed my time in Geneva because of your company and hope to get to work with you once again in the future.

Attie and Meindert, thank you for hosting me in Rotterdam and for everything you've done to make me feel at home.

Although I am pretty sure I mentioned many of the essential ingredients of my perfect PhD journey there have been numerous of you that spiced up the PhD years.

Anouk, there are no words to explain how much our friendship means to me. That is exactly what I am so grateful for: we don't need words, yet we like to use them endlessly. There is always a new perspective, something exciting, a good laugh or something to learn. Thanks for inspiring me to live life to the fullest and see the beauty in what is.

Pino, thanks for sharing many of the experiences along the way of this life journey. The fun, the tears, the laughs, the caring and trust all mean a lot to me. I'm very grateful we keep on finding such a deep understanding time after time. Mar, Anna, Fem, I always enjoy our quality time together. It is special to look back and see how we have grown.

Anne, Wietske and Ans, I wouldn't know where to start, thinking of all the experiences we shared together. Thanks for always being there for me, for better and for worse. Nienke, Jonne, Karen, Kristel and Inge, I get a big smile on my face thinking of all the fun we had together. I always enjoy it when we find our way back to each other once in a while.

Han, Roger, Jaap, Barbe, Jantje, Stijn, Rene, Huib, Bonny, Douwe, Debs and Tim. So many good memories: the priceless Sinterklaas song, festivals, skiing holidays, rum, and so much more fun. Thank you too for the care in times things got a little rough. Njord, thanks for all the support, fun and inspiration, the time we shared has meant a lot to me and I think back to it with a lot of gratitude.

Steef, thanks for showing me there was more than my PhD cave. I enjoyed all the fun moments together. Mirre, I liked sharing my house with you a lot. You have been so appreciative and sweet. Rosa, Joanne, Tomas, Simon and Martijn, I'm very glad I got to know you better over the years through Nouk, such beautiful people you are.

Paulien and Nina, I'm happy working in Rotterdam has brought me closer to you again. I'm very thankful for our friendship and having known each other so long makes it extra dear to me. I hope we will keep on spending time until we are grey and old.

Alex, the crunch that tops it off. I'm so grateful and happy with you in my life. Thanks for being every bit of you.

Grandma, Jeanette, Roger, James, Mike and Mel, I always love seeing you as it makes me feel at home and brings up many good memories. I'm so thankful that you are my family. Pap, thanks for giving me all the freedom in the world to explore while always being there for me with infinite support. Mum, I know you would have been very proud. Bonnie, I'm grateful to see how our relationship transformed is such a loving one. I enjoy our mutual understanding and laughs and am very happy I get to see more of you now you moved back to the Netherlands.

About the author

Kim van Wilgenburg (1984) obtained a bachelor's degree in Psychology in 2007 at the University of Amsterdam followed by a master's degree in International Health (Queen Margaret University Edinburgh) and Health Economics (Erasmus University Rotterdam). After working at the healthcare department of a large consultancy company for three years she joined the Health Economics group at the Erasmus School of Economics as a PhD candidate in 2013 supervised by Prof. dr. Owen O'Donnell and Prof. dr. Aurélien Baillon. During her PhD she also worked as a consultant for the World Health Organization. She was involved in the monitoring of financial protection in health at the global level and provided technical oversight in a methodological study with the aim to develop better and new instruments to measure health expenditure in household surveys. Since February 2018 she joined the Erasmus School of Health Policy & Management as an assistant professor in Health Economics. Her research applies insights from behavioral economics to health policy challenges.

The Tinbergen Institute is the Institute for Economic Research, which was founded in 1987 by the Faculties of Economics and Econometrics of the Erasmus University Rotterdam, University of Amsterdam and VU University Amsterdam. The Institute is named after the late Professor Jan Tinbergen, Dutch Nobel Prize laureate in economics in 1969. The Tinbergen Institute is located in Amsterdam and Rotterdam. The following books recently appeared in the Tinbergen Institute Research Series:

664 I. BARRA, Bayesian Analysis of Latent Variable Models in Finance

665 S. OZTURK, Price Discovery and Liquidity in the High Frequency World

666 J. JI, Three Essays in Empirical Finance

667 H. SCHMITTDIEL, Paid to Quit, Cheat, and Confess

668 A. DIMITROPOULOS, Low Emission Vehicles: Consumer Demand and Fiscal Policy

669 G.H. VAN HEUVELEN, Export Prices, Trade Dynamics and Economic Development

670 A. RUSECKAITE, New Flexible Models and Design Construction Algorithms for Mixtures and Binary Dependent Variables

671 Y. LIU, Time-varying Correlation and Common Structures in Volatility

672 S. HE, Cooperation, Coordination and Competition: Theory and Experiment

673 C.G.F. VAN DER KWAAK, The Macroeconomics of Banking

674 D.H.J. CHEN, Essays on Collective Funded Pension Schemes

675 F.J.T. SNIEKERS, On the Functioning of Markets with Frictions

676 F. GOMEZ MARTINEZ, Essays in Experimental Industrial Organization: How Information and Communication affect Market Outcomes

677 J.A. ATTEY, Causes and Macroeconomic Consequences of Time Variations in Wage Indexation

678 T. BOOT, Macroeconomic Forecasting under Regime Switching, Structural Breaks and High-dimensional Data

679 I. TIKOUDIS, Urban Second-best Road Pricing: Spatial General Equilibrium Perspectives

680 F.A. FELSŐ, Empirical Studies of Consumer and Government Purchase Decisions

681 Y. GAO, Stability and Adaptivity: Preferences over Time and under Risk

682 M.J. ZAMOJSKI, Panta Rhei, Measurement and Discovery of Change in Financial Markets

683 P.R. DENDERSKI, Essays on Information and Heterogeneity in Macroeconomics

684 U. TURMUNKH, Ambiguity in Social Dilemmas

685 U. KESKIN, Essays on Decision Making: Intertemporal Choice and Uncertainty

686 M. LAMMERS, Financial Incentives and Job Choice

687 Z. ZHANG, Topics in Forecasting Macroeconomic Time Series

688 X. XIAO, Options and Higher Order Risk Premiums

689 D.C. SMERDON, 'Everybody's doing it': Essays on Trust, Norms and Integration

690 S. SINGH, Three Essays on the Insurance of Income Risk and Monetary Policy

691 E. SILDE, The Econometrics of Financial Comovement

692 G. DE OLIVEIRA, Coercion and Integration

693 S. CHAN, Wake Me up before you CoCo: Implications of Contingent Convertible Capital for Financial Regulation

694 P. GAL, Essays on the role of frictions for firms, sectors and the macroeconomy

695 Z. FAN, Essays on International Portfolio Choice and Asset Pricing under Financial Contagion

696 H. ZHANG, Dealing with Health and Health Care System Challenges in China: Assessing Health Determinants and Health Care Reforms

697 M. VAN LENT, Essays on Intrinsic Motivation of Students and Workers

698 R.W. POLDERMANS, Accuracy of Method of Moments Based Inference

699 J.E. LUSTENHOUWER, Monetary and Fiscal Policy under Bounded Rationality and Heterogeneous Expectations

700 W. HUANG, Trading and Clearing in Modern Times

701 N. DE GROOT, Evaluating Labor Market Policy in the Netherlands

702 R.E.F. VAN MAURIK, The Economics of Pension Reforms

703 I. AYDOGAN, Decisions from Experience and from Description: Beliefs and Probability Weighting

704 T.B. CHILD, Political Economy of Development, Conflict, and Business Networks

705 O. HERLEM, Three Stories on Influence

706 J.D. ZHENG, Social Identity and Social Preferences: An Empirical Exploration

707 B.A. LOERAKKER, On the Role of Bonding, Emotional Leadership, and Partner Choice in Games of Cooperation and Conflict

708 L. ZIEGLER, Social Networks, Marital Sorting and Job Matching. Three Essays in Labor Economics

709 M.O. HOYER, Social Preferences and Emotions in Repeated Interactions

710 N. GHEBRIHIWET, Multinational Firms, Technology Transfer, and FDI Policy

711 H.FANG, Multivariate Density Forecast Evaluation and Nonparametric Granger Causality Testing

712 Y. KANTOR, Urban Form and the Labor Market

713 R.M. TEULINGS, Untangling Gravity