Risk preferences and decision quality of the poor

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Abstract

Behavioral experiments and structural estimation afford us identification of two important components of individual choice: risk preferences and decision quality. Using a large, representative sample of households living in poverty and extreme poverty in Peru, we show that both components predict a variety of field behaviors and affect estimation results. The quality of decision-making improves after experiencing a bad shock, and households in which decision quality is high are more likely to be economically efficient. When decision quality is ignored, gender differences in risk aversion are overestimated, and the large negative impact of risk aversion on asset accumulation is underestimated.

JEL codes: C93, D81, D13, D91, C10

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1 Introduction

Behavioral experiments have been used to measure economic preferences and investigate the role they play in important life outcomes. Yet, these measures are based on individual decision-making that may be far from a precise reflection of true underlying preferences. Decisions may well reflect a mix of individual traits, behavioral biases, inconsistent choices and biases introduced by the elicitation method.[1] To wit, Harless and Camerer (1994) provide an early and influential model of behavior whereby subjects make mistakes at a constant rate suggesting a possible solution to this issue. In the model, one can infer from the overall behavior in the population whether an observed choice pattern is likely to be a reflection of preferences or decision error. von Gaudecker et al. (2011) generalized this model to allow heterogeneity in the propensity to make decision errors. Individual measures of risk aversion and the propensity to choose at random also can be imputed as suggested by Kimball et al. (2006, 2008). These approaches correct individual estimates of preference parameters according to how the entire population reacts to a set of measurement instruments. In this paper, we explore the extent to which estimated underlying risk preferences and the quality of decision-making can deepen our understanding of important economic outcomes of individuals and couples. We show that both structurally-estimated risk preferences that account for mistakes in decision-making and a measure of decision quality produce new empirical regularities between choice parameters and economic outcomes.

Our study is based on a representative sample of over 13,000 poor Peruvians who were asked to participate in a living standards survey and behavioral experiments. Our focus on this population stems not only from the fact that this group makes up a sizable portion of the world population (more than one in ten individuals in the world are poor and one in five in Peru), but also because the financial buffer for this group to recover from suboptimal decisions is very thin. Understanding decision quality and how to improve decision-making could have important economic returns. These are populations that are difficult to reach and for whom richer behavioral and survey data are needed. We find a clear typology of individuals – those who are highly consistent and those who mainly choose at random. Preferences play a larger role in explaining field behavior among those who are more consistent

[1] Recent work shows the prevalence and economic significance of decision-making quality (Abaluck and Gruber, 2011; Chetty et al., 2009; Choi et al., 2014; Finkelstein, 2009; Kleven and Waseem, 2013; Lacetera et al., 2012) and the need to modify welfare analysis to account for this (Bernheim and Rangel, 2009).

in their decision-making, and the quality of decision-making in the behavioral experiments correlates strongly with the quality of decision-making in the field. Our findings demonstrate that both preferences and decision quality are important determinants of a variety of life outcomes (e.g. timing of pregnancy, marriage, economic efficiency, asset accumulation).

The main components of our study are as follows. (1) Survey data and experimental data on risk preferences are collected from a sample of over 13,000 randomly selected individuals living in poverty or extreme poverty. Individuals may be members of a co-habitating or married couple. (2) Each individual is randomly assigned two risk elicitation instruments which are based on the pairwise comparison of several simple lotteries and allow for decision error. (3) Choices of individuals and couples are collected individually, privately and voluntarily. (4) Detailed information on field behavior, economic activity, welfare and assets are also collected for each individual and for the household. (5) To separately identify risk preferences from random choice we model decisions as von Gaudecker et al. (2011). The model allows for two sources of inconsistency, random utility and a propensity to choose at random (or a *trembling hand*), and is able to capture the basic patterns in our data.[2] (6) We systematically test the relevance of the estimated risk preferences and decision quality of an individual and a couple on a series of economic outcomes of interest.

There are several advantages of our approach. Collecting data from a representative sample allows us to extend our findings on risk preferences and decision-making qualify to the larger population of those living in poverty. The risk elicitation tasks should capture underlying preferences, and by randomly assigning different elicitation instruments and conditions to participants, we can separate risk preferences from biases introduced by the elicitation method itself. This is our main identification strategy and sidesteps the need to commit to one elicitation method ex-ante. While this approach can only uncover the existence and size of the bias across methods, it does also identify which methods are more prone to generate noisy behavior. By combining our estimates of risk preferences and decision-making quality with survey data, we can evaluate the role of these on important economic outcomes. Finally, by demonstrating the significance of preferences and decision quality on outcomes, we validate our approach and provide new information on the role of these traits on the

[2]The data generated from our experiments are not rich enough to explore other models. There is some disagreement on the empirical relevance of the constant error model (e.g. Loomes (2005)), however, it does provide a simple approach to inconsistency in behavior and can be applied to our data.

economic performance of those living in poverty.[3]

We have several key findings. First, and not surprisingly, measured risk preferences and the reliability of the measures are affected by the way preferences are elicited (see Andersen et al. (2006)). There is random behavior in all our elicitation tasks, and taking this noise into account can change conclusions about preferences. For example, gender differences in risk aversion disappear once we account for the fact that women are more likely to choose at random than men (Andersson et al., 2016). Methods that preclude decision error by preventing an individual from choosing at random would not provide information on this individual propensity.[4]

Second, structural estimation is used to separately identify preferences from decision error. We then calculate the posterior value of an individual's coefficient of absolute risk aversion given actual choices and the elicitation instrument. This approach diminishes measurement error caused by the elicitation process and extracts a measure of risk aversion that accounts for noise.[5] Using this cleaned measure of risk aversion, we relate this to field behavior. We find that an individual's willingness to take risks is significantly correlated with a large range of behaviors, including time of first pregnancy, participation in social organizations and credit markets, farm production decisions and the prevalence of unhealthy habits. Some of the effects are large. For instance, a one standard deviation increase in the coefficient of absolute risk aversion is equivalent to over a two-fifths standard deviation decrease in the participation in credit markets. This demonstrates the empirical relevance of individual risk preferences on field behavior.

Third, not only is our posterior estimate of risk preferences correlated with field behavior, so is decision quality (the propensity to choose at random). In general, those who are more likely to choose at random are more risk averse. Also, the propensity to choose at random

[3]The experimental economics literature suggests that the elicitation of preferences in low literacy and low numeracy populations is likely to be difficult (Andersen et al., 2006; Charness et al., 2013; Charness and Viceisza, 2016; Dave et al., 2010; Jacobson and Petrie, 2009). Our study suggests that simpler elicitation methods (e.g. choose one out of several lotteries) are not always better per se. Participants might still choose at random, and a researcher observing these choices will not be able to distinguish if participants' preferences are uniformly distributed or if they chose randomly. Our risk elicitation tasks do not obligate participants to choose consistently. We obtain robust evidence on the patterns of inconsistent behavior under different methods and the biases methods might introduce.

[4]We did not use equivalent protocols in which consistency was enforced. However, we have collected direct evidence that behavior across elicitation tasks, which do not allow for inconsistent choices, is no more likely to produce consistent behavior overall. Results are available from the authors upon request.

[5]This approach was also used in Castillo et al. (2018).

is higher among women, relatively less educated and older individuals. Importantly, we find that those who had recently experienced a bad shock (e.g. frost, drought, mudslides) are less likely to choose at random. This is consistent with recent evidence that scarcity (Mullainathan and Shafir, 2013; Shah et al., 2015) might improve the quality of decision making. In our study, however, we do not find evidence that recent shocks affect preferences directly (e.g. Callen et al. (2014); Cameron and Shah (2015); Eckel et al. (2009); Voors et al. (2012)).

Fourth, our study allows us the opportunity to compare independently collected measures of the risk preferences of husbands and wives and compare these with field behavior. The risk preferences of husbands and wives are significantly and positively correlated, with a correlation coefficient of 13% (p-value < 0.0001). A similar correlation holds for the propensity to choose randomly, at 17% (p-value < 0.0001). These correlations are significant even controlling for observable individual characteristics and are not a reflection of local conditions. We also find that the preferences of husbands and wives are both relevant in household decision-making.

Fifth, in our sample, farm production is an important source of income. Therefore, we evaluate if our estimates of risk aversion and decision-making quality correlate with measures of production efficiency using stochastic frontier analysis (Farrell, 1957; Simar and Wilson, 2007). For this, we take advantage of the detailed survey data we collected and auxiliary information on prices, weather, geography and soil characteristics. We find that individuals who are more likely to choose at random in the risk elicitation tasks are less efficient in farm production. A one standard deviation increase in the propensity to choose at random translates into 3.9% of a standard deviation lower efficiency levels. This illustrates that our estimates capture departures from economic rationality and that these errors in decision-making have costly economic consequences. Mistakes like these are particularly harmful for those living in poverty. We are not aware of previous research showing a relationship between economic efficiency and decision-making quality.

Finally, looking at household assets, we explore the interaction of risk aversion, decision-making quality and the preferences of husbands and wives. Household assets are lower when the head of household is less willing to take risks, conditional on current income and household characteristics. A one standard deviation increase in the coefficient of absolute risk aversion of the head of the household is correlated with a 10% decrease in the value of

household assets held. Further inquiry reveals that in households with a husband and a wife, it is the risk preferences of the husband that play a larger role in asset accumulation.

In sum, our findings show that risk preferences and decision quality are strongly correlated with a host of field behaviors and life outcomes. Also, household decisions are affected by the preferences and decision-making quality of both husbands and wives.

The robustness of our main results are tested using alternative methods to deal with decision error. For instance, simply counting the number of risk-averse decisions as a measure of risk preferences reproduces our main results, but they are not always significant.[6] We obtain similar weaker results if we correct this naive estimate using instrumental variables (Gillen et al., 2015) or account for potential bias in random-utility models (Apesteguia and Ballester, 2018). Results become stronger if we treat decisions as a noisy measure of preferences, however, they are not as precise as the structural estimation method we use and cannot neatly separate preferences from decision quality. All of our robustness checks point to the strength of using our estimated measures of risk preferences and decision quality to understand field behavior.

The main contributions of our paper are the following. We show that simple behavioral measures of risk preferences paired with structural estimation can be used to uncover individual risk preferences and decision quality. These estimated measures relate to a variety of field behaviors, and we find that both risk preferences and the quality of decision-making are important determinants of economic outcomes and decision-making within poor households. Ex-ante, it is unclear how decision-making biases might affect the estimation of individual preferences or its relation to field behavior since previous studies do not allow a direct comparison between elicitation methods. Our approach provides a method and evidence to answer this. Our findings suggest that data collection protocols might benefit from explicitly measuring behavioral biases in the elicitation of preferences since these are likely relevant in understanding decision making (e.g. Lacetera et al. (2012)). Recent research shows that individuals might want to randomize across identical decisions (Agranov and Ortoleva, 2017) and that standard experimental elicitation of preferences might underestimate the presence of noisy behavior (Brown and Healy, forthcoming).[7]

[6] Similar patterns of weaker results with naive measures of risk preferences are found in Castillo et al. (2018) and Jacobson and Petrie (2009)

[7] The type of randomization in Agranov and Ortoleva (2017) occurs for different reasons than the ones suggested in this study. In our paper, randomization is an expression of lack of responsiveness to incentives.

While our study provides a proof of concept of a potentially fruitful approach to the measurement of preferences, we do not claim to have found the best way to collect preference data. There are many alternative proposed measurement approaches that we have not explored and on which we cannot opine. Instead, the findings from our approach encourage further exploration. A larger suite of behavioral experiments would allow to both identify additional important preference parameters, such as loss aversion and discount rates, as in Tanaka et al. (2010) and von Gaudecker et al. (2011), and to test alternative ways to account for decision errors (Halevy et al., forthcoming; Loomes, 2005). Richer designs would allow for construction of both non-parametric rankings of preferences (as in Heufer (2014)) and decision quality (as in Choi et al. (2007) or Echenique et al. (2011)). More importantly, our approach suggests a way to integrate models of behavior in experiments with models of behavior in the field.

The paper is organized as follows. Section 2 describes the data collection process, including the experimental design and the construction of our sample. Section 3 presents the estimation approach. Section 4 presents the results on selection into experiments and estimates of the models. Section 5 presents results on the relationship between individual measures of risk aversion, decision quality and field behavior. Section 6 concludes.

2 Data collection

2.1 Experimental Design

To measure risk preferences, we use a multiple price list (MPL) instrument. This instrument asks participants to choose between two risky lotteries or express indifference. This basic decision is repeated several times over a series of different pairwise comparisons. The choices reveal the participant's risk preferences.

We use four MPL instruments that reflect a 2×2 design. The first dimension of our design is whether lottery probabilities are fixed or variable. One set of MPL keeps the lottery prizes

Our study contributes to the growing literature showing the empirical relevance of risk preferences and decision quality on field behavior (Bonin et al., 2007; Burks et al., 2009; Castillo et al., 2018; Choi et al., 2014; Dohmen et al., 2011; Jacobson and Petrie, 2009; Jaeger et al., 2010; Kimball et al., 2008; Liu, 2013). Our paper adds to this literature by estimating these parameters and showing they are separately relevant over a large set of outcomes for a representative sample of a hard to reach population. Previous studies have used non-representative samples (e.g. Harrison et al. (2010); Liu (2013); Tanaka et al. (2010)).

constant and varies the probabilities (as in Holt and Laury (2002)) and another set of MPL varies the lottery prizes but keeps probabilities constant (as in Binswanger (1980)).[8] The second dimension of the design is whether or not the lottery prizes include losses. Either all lotteries on the MPL have non-negative prizes, or they have mixed (non-negative and negative) prizes. This gives us four instruments to test. Each participant makes decisions for two instruments, and Table 1 shows the assignment of instruments to participants. For practical reasons, out of the 24 total possible combinations of instruments and presentation orders ($4(instruments) \times 3 \times 2(orders)$), we use six combinations. These combinations include both paid and non-paid decisions.[9] The two MPL that a participant completes were randomized by whether or not the lottery was paid, the gender of the interviewer, and the combination of instruments used.

Data collection proceeded as follows. First, a pair of one male and one female enumerator is assigned to a set of households to be visited. Two enumerators per household are used to facilitate data collection from husbands and wives who responded to two different household surveys. Prior to visiting a household, one of the six measurement conditions is randomly chosen to use for both the husband and the wife, thus maximizing comparability within a household. Upon arrival at a household, the enumerators flip a coin to determine who would implement the experimental instrument with the husband and the wife. The gender of the interviewer is duly recorded.[10] Once the gender of the interviewer is determined for each member of the couple, the husband and the wife are separated and then invited to participate in the experiment. A brief introduction of the experiment is given, during which the average and minimum payment for the instrument randomly chosen is revealed, and the husband and wife can choose to participate or not.[11] This procedure allows for independent

[8] Our design builds on the experimental approach of Dave et al. (2010).

[9] Due to budgetary limitations, not all participants were paid for their decisions. This design element is controlled for in our analysis.

[10] Enumerators were trained so that randomization was performed correctly.

[11] In the case of paid decisions, individuals were also given a fixed payment for participation. Participants were told, "We would like to ask you a few questions about how you make decisions about money and risk. One out of 20 individuals responding to these questions will be compensated. The payment you receive will depend on your answers but, on average, is around S/. 40 with a minimum payment of S/. 0. To decide whether you will be paid, we will take a number from this bag that has tickets numbered from 1 to 20 [show the bag and tickets]." In the case of hypothetical choices, participants were told "We would like to ask you a few questions about how you make decisions about money and risk. Please respond to these questions in a way that reflects as closely as possible what you would do if such a situation were real. However, keep in mind that no payment will take place at this time."

participation decisions of the husband and wife. We note that the minimum payment is a random variable since it depended on the instrument assigned to the couple. This random assignment is used later in our analysis to model selection into the experiment.

The decision sheets presented to participants are shown in Figures A.1-A.4 in the Appendix. Figures A.1 & A.2 are MPL versions of the design in Binswanger (1980), and Figures A.3 & A.4 are equivalent to Holt and Laury (2002). Our design puts the four MPL on a more equal footing since each instrument asks participants to make a series of decisions that are pairwise comparisons of lotteries. The design also permits a test for decision quality as it allows for the possibility of noisy behavior to emerge.

In all the MPL, for each decision over a pairwise comparison, a participant was asked to reveal whether option A or B was preferred or to reveal whether she was indifferent between the options (in which case a coin would be tossed to determine option A or B).[12] For the MPL with fixed probabilities, variable prizes and non-negative payoffs (Figure A.1), in the first decision, a participant chooses between a sure payment option (S/.28) and a lottery that pays S/.24 with 50% probability and S/.36 with 50% probability. In each subsequent decision, the mean and variance of the lotteries increase by subtracting S/.4 from the smallest prize and adding S/.8 to the highest prize.[13] If the lotteries were collapsed into a multiple-choice condition, a participant would have to choose one out of 8 options (similar to the design of Binswanger (1980)). Our instrument would be a MPL representation of a multiple-choice instrument except for the fact that decision 4 is modified to allow for the existence of a first-order, stochastically dominated lottery. In decision 4, option A provides a higher expected payoff in all states of the world.[14] Figure A.2 shows lottery options with mixed payoffs. In this instrument, the safest lottery (Decision 1) pays nothing and successive lotteries are constructed by decreasing the lowest prize by S/.3 and increasing the highest payoffs by S/.9. Figures A.3-A.4 show the lotteries with fixed prizes and variable probabilities. Note that in both of these instruments, the last decision presents an obviously dominated option (B).

Participants in the paid conditions were informed that one of their decisions would be chosen at random to calculate payments. Depending on the instruments the participant

[12] In practice, indifference was expressed in 3.3% of all choices (2.9% in variable probabilities, non-negative prizes; 3.4% in variable probabilities, mixed prizes; 2.8% in fixed probabilities, non-negative prizes and 4.1% in fixed probabilities, mixed prizes).

[13] Lottery prizes are presented in Peruvian soles. At the time of the study, 3.0 soles = US$1.

[14] Most theories of decision-making under risk exclude this possibility. Note, however, that this is a weak test of dominance since payoffs are relatively close.

completed, this could be chosen from 14, 17 or 20 separate lottery decisions. Prior to making any choices, participants were shown the randomizing device to be used in the selection of the decision to be used for payment, to resolve the lotteries, and to resolve indifference if the participant expressed it.

Key features of our design are that we obtain multiple measures of risk preferences for each individual and each instrument is different. These elements allow us to separate noisy behavior from preferences and identify different ranges of utility parameters. For instance, if θ is the coefficient of absolute risk aversion of a participant, then the instrument with fixed prizes, variable probabilities and non-negative payoffs can identify $\theta \in [-0.047, 0.060]$, the instrument with fixed prizes, variable probabilities and mixed payoffs can identify $\theta \in [-0.045, 0.061]$, the instrument with fixed probabilities, variable prizes and non-negative payoffs can identify $\theta \in [0.000, 0.121]$ and the instrument with fixed probabilities, variable prizes and mixed payoffs can identify $\theta \in [0.000, 0.203]$.

2.2 Sample Selection

The experiment was implemented as part of a representative sample household survey of poor, rural Peruvians. The number of individuals contacted is 13,153, and of those, 12,576 (95.6%) were at home when contacted. Table 2 provides descriptive statistics of the sample. Fifty-five percent of the sample are non-Spanish speakers and 18.3 percent are non-Catholic. The average number of years of schooling is 4.6, which is less than the number of years needed to complete primary school. The percent of income devoted to consumption is, on average, 69 percent. Eighty-eight percent of the households have adobe walls and 90 percent have dirt floors. A quarter of the population has a source of water within the household and 78 percent cook using wood fire. Participants are unlikely to take credit either formally (7.2 percent) or informally (9.6 percent). These data confirm that the target population is indeed poor.

Regarding the experiments, 9,682 individuals participated. This includes 3,390 couples and 2,902 households with a missing spouse. The decision to participate in the experiment was individual since husbands and wives were invited separately by the assigned enumerator. When we examine whether the target participant was present at the time the enumerators approached the household and whether the participant agreed to take part in the experiment,

we find these are not independent of the participant's characteristics or the instrument.[15]

Males are almost 5 percentage points more likely to participate in the experiments. Non-Spanish speakers, non-Catholics, those with no schooling, and poorer individuals are all less likely to participate. We find no evidence that the gender of the interviewer, which was randomly assigned, affected the willingness to participate in the experiment. There is some differential participation by instrument. This is likely due to the fact that in the Northern Sierra departments only two of the six possible instruments were used due to budgetary restrictions. If we exclude those departments, the parameters associated with these instruments are half the size. To account for these results, we control for the type of instrument used and other covariates in our main results.

3 Theoretical Framework and Empirical Model

Our empirical analysis is based on the theoretical framework and empirical model outlined in this section.

3.1 Utility Specification

We use an expected utility theory (EUT) framework to model individual decisions when choosing among risky alternatives. Following von Gaudecker et al. (2011), we consider an exponential utility function:[16]

$$U(x;\theta) = -\frac{1}{\theta}e^{-\theta x} \tag{1}$$

Where $x \in \mathbb{R}^+$ is the lottery prize and $\theta \in \mathbb{R}$ is the coefficient of absolute risk aversion (CARA).[17]

[15] Full results are reported in Table A.1 in the Appendix.

[16] In the Appendix in Tables **??** -**??**, we show that a power utility specification does not fit the data as well as exponential utility.

[17] In the experiments, individuals were given a fixed payment for participation so that negative payoffs were not possible, and we assume that individuals did this integration. While this is immaterial in the case of an exponential utility function, it is a normalization in the case of a power utility function.

3.2 Stochastic Decision Making

We assume that individuals compare expected utilities when choosing between a pair of lotteries. Individual $i \in \{1....N\}$ faces $j \in \{1, ..., J_i\}$ separate choices between two binary lotteries $L_j^A = (A_j^{low}, A_j^{high}, p_j^{high})$ and $L_j^B = (B_j^{low}, B_j^{high}, p_j^{high})$

The difference in expected utility of the two lotteries in the decision task j is defined as:

$$\Delta EU_{ij} = EU(L_j^A, \theta_i) - EU(L_j^B, \theta_i) \tag{2}$$

Where θ_i represents parameters of an individual i's utility function. In the absence of optimization errors, individual i chooses lottery L_j^A if and only if $\Delta EU_{ij} > 0$. Let $Y_{ij} = 1$ if individual i chooses L_j^A over L_j^B. Then, we have:

$$Y_{ij} = \mathbb{I}\{\Delta EU_{ij} > 0\} \tag{3}$$

To model stochastic decision-making, we allow for the possibility that individuals make two kinds of optimization errors and incorporate these in the specification we estimate. The first type of error is modeled using the so-called "Fechner's error" specification (Loomes, 2005; Wilcox, 2008). In this specification, an individual's computation of expected utilities are subject to random errors. We model these random errors as a standard Type I extreme value distribution. Formally, in this framework an individual chooses lottery L_j^A if and only if:

$$Y_{ij} = \mathbb{I}\{\Delta EU_{ij} + \varepsilon_{ij} > 0\} \tag{4}$$

Where ε_{ij}'s are independent of each other and the random coefficients in the utility specification.

The second type of error captures the tendency to choose randomly between alternatives. This error accounts for the failure to understand the decision problem or for attention lapses during decision making and reflects decision quality. We model this using a "trembling hand" parameter ω (Harless and Camerer, 1994; Moffatt and Peters, 2001; Wilcox, 2008).[18]

[18] Figure A.5 in the Appendix illustrates the stochastic decision making process of individuals that we model in our analysis.

3.3 Econometric Estimation

Following von Gaudecker et al. (2011), we estimate a structural econometric model allowing individual heterogeneity in the risk aversion parameter (θ) and in the tendency to choose at random (ω). Our model accounts for both observed and unobserved heterogeneity in both parameters. Given this specification, the likelihood of observing choice Y_{ij}, if it is not an indifference, of individual i in decision task j is:

$$l_{ij}(L_j^A, L_j^B, Y_{ij}, \theta_i, \omega_i) = (1-\omega_i)\Lambda((2Y_{ij}-1)\Delta EU(L_j^A, L_j^B, \theta_i)) + \frac{\omega_i}{2} \tag{5}$$

Where $\Lambda = (1+e^{-t})^{-1}$ is the cumulative standard logistic distribution function.

Following Andersen et al. (2008) and Wilcox (2011), we treat an indifference response Y_{ij} as two different responses, one indicating choosing $L_j^A(Y_{ij}=1)$ and one indicating choosing $L_j^B(Y_{ij}=0)$, given the difference in expected utilities of the two lotteries $\Delta EU(L_j^A, L_j^B, \theta_i)$. The likelihood of indifference is then taken as the geometric mean of these two responses since it is based on one observation. Thus the likelihood of observed choice Y_{ij} if it is an indifference is given by:

$$l_{ij}(L_j^A, L_j^B, Y_{ij}, \theta_i, \omega_i) = (l_{ij}(A))^{0.5}(l_{ij}(B))^{0.5} \tag{6}$$

Where

$$l_{ij}(A) = (1-\omega_i)\Lambda(\Delta EU(L_j^A, L_j^B, \theta_i)) + \frac{\omega_i}{2}$$

$$l_{ij}(B) = (1-\omega_i)\Lambda(-\Delta EU(L_j^A, L_j^B, \theta_i)) + \frac{\omega_i}{2}$$

To incorporate observed and unobserved heterogeneity, we estimate the distribution of individual specific parameters θ_i and ω_i in the population using a random coefficients model (Conte et al., 2011; von Gaudecker et al., 2011).

We use the specifications:

$$\theta_i = X_i^\theta \beta^\theta + \xi_i^\theta \tag{7}$$

$$\omega_i = \Lambda(X_i^\omega \beta^\omega + \xi_i^\omega) \tag{8}$$

To restrict ω to the interval $[0,1]$, we use a cumulative logistic distribution function transformation. X_i^θ and X_i^ω are matrices of covariates with corresponding coefficients β^θ

and β^{ω}. We assume that $\xi_i = (\xi_i^{\theta}, \xi_i^{\omega})'$ follows a mean zero bivariate normal distribution independent of the covariates and that the covariance matrix Σ of ξ_i is diagonal. In our model, ξ_i captures the unobserved heterogeneity in the population. The contribution of individual i to the likelihood function can be written as:

$$l_i = \int_{\mathbb{R}^2} \left[\prod_{j \in J_i} l_{ij}(L_j^A, L_j^B, Y_{ij}, \theta_i, \omega_i) \right] \phi(\xi) d\xi \tag{9}$$

Since the integral in equation 9 does not have an analytical solution, we approximate it with simulations that employ Halton sequences of length R = 1,000 per individual (Train, 2009). The likelihood function for the entire sample is maximized using a two-step hybrid approach a multiple number of times as discussed in Liu and Mahmassani (2000) to avoid local maxima. In the first step we employ a genetic algorithm to find parameters that maximize a simulated log-likelihood of the sample.[19] In the second step, we used the solution of the genetic algorithm as a starting point for the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm with numerical derivatives to maximize the log-likelihood function. The variance-covariance matrix of the parameter estimates is computed using the inverse of the Hessian and evaluated on the simulated maximum likelihood estimates. Standard errors for transformed parameters are calculated using the delta method.

3.4 Posteriors

The results from the structural estimation allow us to calculate posterior estimates of the coefficient of risk aversion and decision quality. These are then correlated with field behavior. The procedure used to calculate posteriors is as follows.

For a given individual, $F(\theta_i | X_i, \hat{\beta}^{\theta}, \hat{\Sigma})$ represents the population-level distribution of the coefficient of risk aversion, θ, for individuals with characteristics equal to X_i. Given an individual's choices in the experiment, we can use this distribution as a "prior" and calculate the "posterior" distribution of θ. The posterior distribution $F(\theta_i | Y_i, X_i, \hat{\beta}^{\theta}, \hat{\Sigma})$ that is obtained by updating the population-level prior using individual-level choices reflects all

[19] Genetic algorithms are very effective in searching many peaks of the likelihood function based on a rich "population" of solutions and thus reduces the probability of being trapped at a local maximum. They do not require the computation of gradients and are thus computationally very efficient for a global search of the parameters.

available information about a given individual's risk aversion parameter.

The expectation of the posterior distribution is computed via simulation as follows (Revelt and Train, 2000):

$$E(\theta_i|Y_i, X_i, \hat{\beta}^{\theta}, \hat{\Sigma}) = \frac{\sum_r \theta^r P(Y_i|X_i, \hat{\beta}^{\theta}, \hat{\Sigma})}{\sum_r P(Y_i|X_i, \hat{\beta}^{\theta}, \hat{\Sigma})} \tag{10}$$

Similarly, the expected posterior of the random choice propensity, or decision quality, parameter ω_i of an individual can be computed using:

$$E(\omega_i|Y_i, X_i, \hat{\beta}^{\omega}, \hat{\Sigma}) = \frac{\sum_r \omega^r P(Y_i|X_i, \hat{\beta}^{\omega}, \hat{\Sigma})}{\sum_r P(Y_i|X_i, \hat{\beta}^{\omega}, \hat{\Sigma})} \tag{11}$$

In computing expectations of posterior distributions, we used 10,000 Halton draws from the prior distributions for each individual.

4 Results

We first discuss the main patterns in the data and then turn to the parametric estimates and robustness checks of our econometric specification.

4.1 Data patterns

To assess the consistency of behavior across instruments, we measure the proportion of choice patterns (e.g. choosing option A or B) across the seven or ten decisions on a MPL that follow a threshold strategy given all possible choice patterns. A threshold strategy requires for the participant to switch between option A and B at most once. To make this implementable, we introduce the concept of a run. A run is a maximal subsequence of all left or all right choices. For example, say a participant chose AAABABBAAB when presented with ten different decisions. In this sequence, there are 6 runs: AAA,B,A,BB,AA,B. To put this in perspective, for all of our instruments, behavior consistent with expected utility theory would require a minimum of one run and a maximum of two runs. More than two runs indicates the presence of optimization errors. In general, the larger the number of runs the larger the

magnitude of decision errors.[20] To make optimization errors measured in number of runs comparable across different measurement instruments, we construct a normalized measure which is the observed number of runs divided by the maximum possible number of runs in a given instrument (which is equal to the length of the MPL). Our data show some evidence of optimization errors. The average normalized measure is 0.38, and it is larger for paid lotteries, Spanish speakers and in fixed probabilities and variable prizes lotteries.[21]

Another way of looking at choice patterns is examining consistency with expected utility. Figure 1 shows the distribution of the distance to expected utility by instrument. A sizable proportion of participants are close to or consistent with expected utility maximization. They need either no or one change in their choices to exhibit a consistent choice pattern, however, this changes by instrument. For instance, in the lotteries with fixed prizes, variable probabilities and non-negative payoffs, over 50 percent of participants make decisions that need to change at most one choice to be consistent with expected utility. This proportion increases to almost 60 percent when the payoffs are mixed (upper right-hand panel in Figure 1). For lotteries with variable prizes and fixed probabilities, about 60 percent of participants need at most one choice changed to be consistent. This suggests that over half of the population is close to being a rational expected utility decision-maker, but just under half of the population is close to random behavior.

We also examine the choice trend over the decisions presented to participants in each MPL. Each MPL is constructed so that option B becomes less favorable or riskier as the decisions progress. As expected, the proportion of participants who choose option B declines as the decisions progress. Recall that in the MPL with variable probabilities, decision 1 presents a risky option A and ends with a dominant option A in decision 10. We then expect that participants should choose option B less frequently in lotteries further down the MPL. The same reasoning holds with the MPL with fixed probabilities. Decision 1 is between a sure payment and a lottery with larger mean and variance. As decisions progress, lotteries with larger means and variances are presented. A risk neutral participant would choose option B always, while a risk averse participant could choose B first and then switch

[20] We note, however, that one or two runs does not necessarily indicate behavior consistent with expected utility and, thus, absent of optimization errors. For instance, in a fixed-probability, variable prizes instrument, a participant should not follow a threshold strategy that switches from risk-averse to risk-taking behavior.

[21] Full results are shown in Table A.2 in the Appendix.

(permanently) to option A. This means that we should expect the proportion of option B chosen to decrease as decisions progress. These are the patterns we observe in the aggregate data in all instruments and confirm are statistically significant.[22]

These patterns of behavior are even sharper in the population of participants that had at most one inconsistent choice.[23] Importantly, these participants recognized more frequently that option B in decision 4 in the fixed probability, non-negative payoffs instrument was dominated. This evidence supports our modelling assumption that participants either make decisions based on their preferences or choose at random.

4.2 Parametric estimates

Table 3 presents the parametric estimates of the model with constant absolute risk aversion. The estimates of the coefficient of risk aversion are presented under the heading θ and the estimates of the propensity to choose randomly are presented under the heading ω. Table 3 presents two versions of the model, *Minimal* estimates a mixed logit model without covariates and *Instrument* allows parameters θ and ω to depend on the risk elicitation instrument.

The Minimal model identifies that the average individual is risk averse ($\theta = 0.018$) and the propensity to choose randomly is 49 percent ($\omega = 0.49$). The model also shows that preference parameters are heterogeneous in the population ($\sigma = 0.086$). These estimates align with the overall choice patterns observed in the data. A sizable portion of participants do not seem to call upon their preferences when deciding which lotteries to choose.

Random assignment of elicitation instruments to participants allows us to identify biases in the measurement of preferences. The Instrument model presents these results. We note that the estimated distribution of preferences is economically and statistically significantly affected by the risk elicitation instrument used. In Table 3, Fixed probability equals 1 if the

[22]The general patterns across instruments are illustrated in Figure A.6 in the Appendix. We run a linear probability model with fixed effects at the participant level on each separate measurement instrument, on a constant, and on the number of the decision (1-7 in the fixed probability instrument and 1-10 in the fixed prizes instrument). The trend is significant in each of the instruments: (-0.024 (p-value<0.0001) for the variable probabilities, non-negative payoffs instrument; -0.025 (p-value<0.0001) for the variable probabilities, mixed payoffs instrument; -0.010 (p-value<0.0001) for the fixed probabilities, non-negative payoffs instrument; and -0.013 (p-value<0.0001) for the fixed probabilities, mixed payoffs instrument).

[23]The trend is significant in each of the instruments: (-0.052 (p-value<0.0001) for the variable probabilities, non-negative payoffs instrument; -0.049 (p-value<0.0001) for the variable probabilities, mixed payoffs instrument; -0.019 (p-value<0.0001) for the fixed probabilities, non-negative payoffs instrument; and -0.027 (p-value<0.0001) for the fixed probabilities, mixed payoffs instrument).

lottery used keeps probabilities constant, Mixed prizes equals 1 if the lotteries have mixed prizes (non-negative and negative) and Fixed probability $\times$ Mixed prizes equals 1 if the lottery keeps the probabilities constant and uses mixed prizes. This means that the omitted category is the lottery that varies probabilities and uses non-negative prizes.

Table 3 shows that, depending on the instrument, an individual can be estimated to be risk averse or risk taking. The difference in the coefficient of risk aversion of an individual in a fixed probability instrument is measured to be 0.095 larger than if measured with a variable probability instrument. Consistent with loss aversion, we also find that an individual will appear more risk averse in a mixed prize lottery than in a non-negative prize lottery (coefficient = 0.0068). This effect, however, does not seem to be uniform across measurement instruments. An individual facing mixed prizes instead of non-negative prizes in a fixed probability instrument will behave *less* risk averse (coefficient = -0.051). These effects are large.

The Instrument model also shows that the measurement error varies systematically across instruments. We observe that choices in fixed probability lotteries are noisier (a 10 percent increase in the probability of choosing at random).[24] Finally, we see that mixed prize lotteries dramatically reduce noise in choices. While this is a positive finding, we remark that allowing for losses might require the estimation of additional preference parameters. This issue is discussed in more detail in the robustness section.

We should emphasize that an important feature of our experimental design was to assign each participant two alternative ways to measure their preferences. The effects we are identifying therefore occur at the individual level. Note that while repeated measures of the same elicitation instrument allows for identification of the level of measurement error associated with a particular instrument, it is the collection of repeated measures of alternative instruments that allows for identification of biases in the measurement of preference parameters.

We find that individual characteristics are related to the coefficient of risk aversion and to the probability of choosing randomly. Older, wealthier and non-Catholic participants are relatively less risk averse. Non-Spanish speakers and those in the paid lotteries are relatively

[24]This result suggests that the multiple-choice version of this elicitation instrument might produce less reliable estimates of preferences. The simplicity of multiple-choice instruments have a downside in that they do not provide the necessary information to correct for measurement error.

more risk averse. This last result is consistent with the findings of Holt and Laury (2002).[25]

Regarding decision quality, male participants are less likely to choose at random, as are older and non-Spanish speakers. The paid condition produced noisier behavior. Importantly, we find that participants who are relatively better educated are less likely to choose at random. This result is consistent with studies on rationality (Choi et al., 2014) but highlights the methodological difficulty of measuring preferences in this population. Our result suggests that having one simple instrument might not be enough to elicit reliable estimates of preferences. The reason for this is that with one single measure we cannot assess the importance of measurement error or lack of responsiveness to incentives.

Recent research in behavioral economics suggests that the quality of decision-making might be affected by the level of scarcity experienced by an individual (Mullainathan and Shafir, 2013; Shah et al., 2015). Our study can examine this question directly. The experiments were embedded in a large study evaluating barriers to escape from poverty and collected a rich data set on individuals and their circumstances. We make two observations that are consistent with the notion that scarcity and decision-making quality are correlated. First, non-Spanish speakers, who are by far the most disadvantaged population in Peru, are significantly less likely to make decisions at random.[26] Second, those experiencing recent, bad economic shocks are also significantly less likely to make choices at random. This result is robust to our definition of a bad shock and holds even when we restrict the estimation to those shocks that are out of the control of the individual.[27]

4.3 Robustness Checks

As an alternative to CARA preferences, we estimate the model under the assumption that preferences over lotteries can be represented by a constant relative risk aversion (CRRA) utility function. The fit of the CRRA model is worse than the model with CARA prefer-

[25]Table A.3 in the Appendix presents regression results of the posterior estimates of the coefficient of absolute risk aversion and the propensity to make mistakes on individual characteristics. Table A.4 replicates the results using inverse probability weighting to account for selection into the experiments.

[26]Non-Spanish speakers in our sample have significantly fewer years of schooling (t-test p-value < 0.0001), hold fewer assets (p-value < 0.0001) and experience more negative shocks (p-value < 0.0001).

[27]The results maintain if we restrict the estimation to frost and drought and eliminate mudslides, exposure to which might be endogenous. The results are available from the authors upon request.

ences.[28] We confirm that a CRRA utility fits the data less well than a CARA by comparing the estimated propensities to choose randomly by both models. A model with CRRA preferences estimates that the probability to choose randomly is 10 percentage points larger than under CARA.

While the estimates using a CRRA utility function are not as good of a fit of the data, most of our main findings are reproduced. Participants appear more risk averse in the fixed probability and mixed prize instrument, and they are less likely to choose at random in lotteries with mixed prizes. The model using CRRA, however, shows that noisier behavior is more likely in the fixed probability and mixed prize instrument.

Apesteguia and Ballester (2018) show that standard random utility models might fail monotonicity in the sense that the probability of making risk averse decisions does not necessarily increases with the parameter of risk aversion.[29] This poses an estimation challenge when using standard random utility models. To address this, we run a Monte Carlo simulation with our random parameter model and show that our results are unlikely due to bias in our estimation approach (see Appendix B and Table **??**). We also estimate a version of the model proposed by Apesteguia and Ballester (2018) and confirm that all our results are qualitatively similar.[30]

To benchmark the magnitude of our parameter estimates, we compare them to the estimates of a similar model using data from a random sample of the urban population of the Netherlands (von Gaudecker et al., 2011). This comparison is shown in Table A.5 and Figure A.7 in the Appendix. Our sample from Peru and the Dutch sample are comparable regarding the estimated parameter of absolute risk aversion, however, the Peruvian sample is less risk averse and the variance in behavior is larger. Regarding the propensity to choose randomly, the estimates for both populations are quite different. The Peruvian sample shows a much

[28]The results are shown in Table **??** in the Appendix. The difference in log likelihoods is 3690 for the *Minimal* and 4123 for the *Instrument* model. This represents about a 4 percent change in the likelihood functions. These differences are significant (Voung test, p-value < 0.01).

[29]This occurs because as agents become more risk averse the difference in utility decreases and the probability of predicting choices at random increases.

[30]To do the estimation, we assume that utility functions are drawn from a known distribution and individuals possess a particular utility function and choose without error with probability $1-\omega$ and at random with probability ω. The estimated model is identical to the model in Table 3 except that individuals do not follow a random utility model. The estimates confirm that all our main results are qualitatively similar, including the correlation of preferences across members of a couple, determinants of preferences and the relationship between preferences parameters and field data. Results are available upon request.

larger propensity to choose at random. Note that von Gaudecker et al. (2011) find that the propensity to choose at random for low-educated individuals with low income and wealth is 40 percent. Our sample is primarily composed of poor and low educated participants.

5 Applications of structural estimates

We turn to evaluation of the validity of the structural estimates along various dimensions. We explore their ability to detect within person correlation of behavior across instruments, gender differences in risk attitudes, correlation with field behavior, correlation of preferences within couples and household decision-making.

5.1 Within person correlation across instruments

We begin by evaluating the usefulness of using structural estimation methods to estimate individual preferences. In particular, we investigate if naive measures of risk attitudes might underestimate the within person correlation across measurement instruments. To do this, we recalculate the posterior estimates of the CARA coefficient and propensity to choose at random using only one measurement instrument at a time. In addition, we calculate a naive measure of risk preferences that counts the number of (consistent) safe decisions.[31] The individual-level correlations for the estimates and the naive measure are shown in Table 4. The first four columns show correlations using the structural estimates, and the last four columns repeat the analysis using the naive measure.

The first observation is that all the correlations in Table 4 are positive and significant (p-value < 0.001). This means that the instruments are measuring risk preferences in the same direction, however, the correlations vary greatly across instruments. Looking at the top left-hand panel, we see that changing prizes from non-negative to mixed decreases the correlation by over 60 percentage points in both fixed and variable probability instruments (e.g. reading from row 1 to 2 and row 3 to 4). Second, fixed probability and variable probability instruments produces risk measures that have a low correlation. This suggests that using fixed or variable probabilities have a larger impact on the measurement of preferences than the use of non-negative or mixed prizes.

[31] We calculate the number of safe decisions in the consistent pattern closest to an individuals actual choices.

Table 4 again highlights the importance of having repeated measures of individual preferences. One way to read the correlations in this table is that we should be suspicious of results that are based on a single measurement of preferences or even repeated measures of the same family of instruments. Different instruments might be correlated with different underlying abilities that in turn affect the expression of preferences and not preferences themselves. For instance, Andersson et al. (2016) show that the relationship between cognitive ability and risk aversion might be specific to the use of multiple price listings to elicit risk preferences.

The bottom right-hand panel of Table 4 shows the correlations between measures of risk preferences based on the naive measure of risk preferences. We find that the correlations across instruments are much lower using this approach. While these correlations are still significant in our sample, due to its size, we see that some of these correlations would likely be insignificant in smaller sample sizes. This highlights the benefits of accessing large samples of a population in the presence of measurement error and instrument biases.

Finally, the bottom left-hand panel of Table 4 shows the correlation between the structural estimates and the naive measure. If the number of safe decisions provides an unbiased estimate of individual preferences, we would expect that these correlations be close to one. We observe that is not always the case and that in some cases correlations are far from one. Overall, these results show that the number of safe decisions, while correlated with underlying structural estimates of preferences, does not completely eliminate measurement error.[32]

5.2 Differences by gender

Table 5 shows decisions of male and female participants. The first row reports the percent of decisions that are consistent with risk neutrality. Fifty-four percent of decisions by women are consistent with risk neutrality while 55 percent of men's decisions are consistent with risk neutrality. This difference is significant. The second row presents the same calculation, but rather than using the raw individual decisions it uses the closest pattern of behavior to a participant's decision that is consistent with expected utility theory. Using this alternative measure, that takes into account inconsistent decision-making, we find that 52.7% of choices

[32] We do not know if the number of safe decisions improves its performance as more measures are taken from the same individual. We warn, however, against a potential false sense of security; our results suggest that this might produce a less noisy measure of a still biased preference parameter.

made by female participants are consistent with risk neutrality while 53.8% of choices made by male participants are consistent with risk neutrality. This difference is again significant.

The two previous measures show that female participants are more risk averse than male participants. The third row in Table 5 shows the difference in the estimated coefficient of absolute risk aversion (parameter θ from the structural model in Table 3). We observe no significant gender difference in this coefficient. Importantly, the fourth row shows that there is a significant difference in the propensity of male and female participants to choose at random. Female participants are much more likely to choose at random.

To test whether the propensity to choose at random is associated with the observed gender difference in risk aversion, we test for gender differences in the propensity to choose as a risk-neutral decision-maker in the sample of participants with at most one decision not consistent with expected utility and the sample of participants with at least two decisions not consistent with expected utility. While we find no gender difference in risk preferences in the sample of participants with at most one decision not consistent with expected utility, we do find female participants to be more risk averse in the sample with at least two decisions not consistent with expected utility. The last two rows in Table 5 show gender differences in the coefficient of absolute risk aversion for participants below the median propensity to make decisions at random and participants above the median propensity. Female participants with a relatively higher level of decision quality are less risk averse than male participants while the opposite is true for participants with a relatively lower level of decision quality.

This simple exercise shows that decision quality (the propensity to choose at random) can be confounded with the detection of gender differences in individual preferences. In our particular case, if the propensity to make decision errors is correlated with individual characteristics and with the measurement of individual preferences, differences in the propensity to make decision errors might be erroneously attributed to differences in individual preferences. Our estimation approach separately estimates preferences and decision errors. We see that, once this is taken into account, a clearer view of gender differences in risk attitudes can be obtained. For those who make higher quality decisions, there is a significant gender difference in risk aversion, but for those who make more mistakes, there is no gender gap.[33]

[33]Gender differences in preferences may vary across cultures has been shown by Gneezy et al. (2009)

5.3 Field behavior

We discuss the relationship between individual measures of preferences and field behavior. For this, we take advantage of the fact that the experiments were part of a larger household survey which collected survey and preference data independently from husbands and wives. We will first look at behavior at the individual level and then at the behavior of couples. As in the previous section, the analysis uses as a regressor the estimated posterior expected value of the parameter θ (see section 3.4 for the method used).

Linear regressions of several field behaviors, such as age of marriage, age at first pregnancy, number of social organization memberships, use of credit, bad habits and production decisions, on the estimated coefficient of absolute risk aversion of the person making the decision are shown in Table 6.[34] Most decisions are individual, but for those involving credit and production in the household, the regressions are restricted to the person listed as the head of the household. To reduce the possibility of selecting only outcomes for which there is a significant relationship between the estimated risk parameter and field behavior, we include a wide array of field behaviors. In all regressions, in addition to the estimated parameter θ, we include a series of covariates. The parameter estimates are based on the model with instruments in Table 3. To eliminate the potential bias created by the correlation between the prediction error of the preference model and the included covariates, we follow the approach of Kimball et al. (2008) and use the GMM estimation method. Table 6 reports these consistent regression estimates and provides corrected R-squares.[35]

We find that the estimate of the individual coefficient of absolute risk aversion, θ, is correlated with several field behaviors and individual characteristics. More risk averse women tend to have pregnancies at an earlier age. More risk averse individuals marry later, are less likely to participate in social groups, engage in unhealthy habits, suffer from diseases, ask for credit and are more likely to use purchased seeds and fertilizer.[36]

All the variables in Table 6 are standardized and the last row in the table provides the

[34] Table A.6 in the Appendix has descriptive statistics of the field behaviors we consider.

[35] Estimates are similar using standard linear regression. As expected, however, the uncorrected R-squares are smaller.

[36] Liu (2013) shows that farmers who are more risk averse or more loss averse are more likely to adopt genetically modified seeds later. This is consistent with farmers viewing these seeds as being riskier. This results does not hold for all modified seeds (e.g. Duvick (2001); Fitzgerald (1993)). We do not have detailed information on the risk profiles of commercial seeds available to this population.

mean and standard deviation of the variable. The table also provides the (corrected) R-squared of the regressions with and without the measure of individual risk attitudes. While the estimates of θ explain a small portion of the observed variance, the actual effect can be quite large. For instance, one standard deviation of θ can explain almost half of the probability of asking for formal credit.

A natural question is whether alternative measures of risk preferences constructed from experimental data might correlated with field behavior in the same manner as the posteriors obtained from structural estimates. This is important to answer since parametric estimates make identifying assumptions that might not be appropriate. To test this, we construct an alternative measure of risk preferences which is the total number of safe choices made by an individual. To account for the possibility of errors in decision making, we use the maximum number of safe choices that are consistent with expected utility and minimize the distance between this pattern of behavior and the actual choices of participants. The results using this measure of risk aversion coincide with those already presented, however, this alternative measure of risk aversion is less likely to be statistically significant.[37] This suggests that ad-hoc measures of risk aversion might not always account for measurement error and is consistent with Castillo et al. (2018) who show that structural estimates of children's risk preferences outperform naive measures of risk aversion in predicting field behavior.

A recent alternative approach to address measurement error in experimental data has been proposed by Gillen et al. (2015). They suggest using repeated measures of preferences as instrumental variables to eliminate the bias produced by measurement error. Their approach is an improvement from traditional estimation methods dealing with measurement error in that they propose an estimator that make full use of all the measures of preferences available. It is also an improvement over a naive measure of risk aversion in that it deals directly with the measurement problem.

We estimate the effects of risk preferences on field behavior using the proposed method of Gillen et al. (2015). For the estimations, we count the number of risk neutral decisions chosen in each instrument separately. Since each participant chose among risky lotteries in two instruments, we have two independent measures of risk preferences for each participant. The estimates reproduce the patterns of behavior already observed in Table 6, however, these

[37] Table A.7 in the Appendix show these results. Similar results hold if we also control for the number of inconsistent decisions.

estimates are less precise.[38]

Importantly, both of the alternative approaches we have discussed do not directly address the fact that the correlation between measures might be due to decision error rather than underlying preferences. For instance, two instruments might over or underestimate the risk aversion of an individual choosing randomly. Correlation between measures might be due to the tendency to make mistakes rather than risk aversion. Depending on the context, this tendency to make mistakes might or might not be consistent with risk aversion. The structural estimation approach we use, by construction, attempts to separate random decisions from preferences. To illustrate the independent effect of decision quality from preferences, Table 7 shows the effects of risk preferences and the propensity to choose at random on field behavior. For the most part, the propensity to choose at random has the same sign as the CARA coefficient. Note that we would expect these to have opposite signs if the estimate of the propensity to choose at random only captures the reliability of the CARA coefficient estimate. These results parallel those of Choi et al. (2014).

5.4 Preferences of couples

We analyze the relation between the preferences of husbands and wives. The analysis is based on the estimated posterior expected value of the parameters θ and ω (see section 3.4). The estimated posteriors are the best predictors of what the true preference parameters are of an individual given their choices in the experiment and the structural estimates of the model in the population.

Table 8 presents linear regressions of wives' estimated coefficient of absolute risk aversion (Wife's θ) and the probability of choosing randomly (Wife's ω) on their husbands' corresponding estimated parameters (Husband's θ and Husband's ω). The first set of estimates includes no additional covariates (columns "No covariates") and the second set of estimates includes the individual characteristics of each member of the couple and household level characteristics (columns "With covariates").

The preference parameters of husbands and wives are positively and significantly correlated. Risk averse women are married to, or co-habitating with, relatively more risk averse men, and women who make higher quality decisions are married to men who make higher quality decisions. One possible explanation for these correlations is assortative matching

[38]Results are reported in Table A.8 in the Appendix.

based on economic characteristics. Research shows that people match in terms of income and abilities. This correlation might therefore be due to the fact that those marrying are likely to have similar backgrounds and face similar conditions. Table 8 shows that the positive correlation between the preference parameters of husbands and wives persists even after including individual and household characteristics.[39] Both sets of parameter estimates are almost identical. These results are also robust to functional form assumptions as we find the same results assuming constant relative risk aversion preferences.

Husbands and wives may have correlated θ's and ω's simply because they share similar backgrounds. We test this by estimating the correlation of preferences of a man and a woman paired at random. This permutation test shows that none of the 500 trials produces a correlation coefficient that exceeded the actual correlation between the preferences of husbands and wives. This result also holds when we restrict random matches to live in the same district. Thus, we find no evidence to support the correlation between the preferences of husband and wives to be due to similar backgrounds.

We also examine the relationship between the preferences of husbands and wives on field behavior. As mentioned before, husbands and wives participated in the experiment independently and in isolation.[40] This allows us to see to what extent the field behavior of individuals and couples is affected by each others preferences. We analyze the field behavior for those households for which we have information on the husband's and wife's preferences. The estimates use Kimball et al. (2006)'s method to deal with potential biases due to the inclusion of covariates.[41] We note that due to the high correlation between the preferences of husbands and wives, we might have difficulty identifying some of the relationships between preferences and field behavior.

The results show that the timing of the first pregnancy is significantly related to the preferences of the wife rather than the husband. More risk averse women have earlier pregnancies. The preferences of both husbands and wives are important in production decisions. All the estimates control for decision quality. In general, decision quality and risk aversion move in the same direction. This is consistent with the hypothesis that decision quality is itself informative. Evidence of this has been provided in another developing country context

[39] The correlation is calculated using the residuals of a linear regression of the parameters on a set of covariates.

[40] In many cases, husbands were in the field while wives were at home.

[41] Table A.9 in the Appendix show these results.

by Jacobson and Petrie (2009).

5.5 Economic efficiency

Economic efficiency might be affected by risk preferences and decision quality. To explore this, we estimate a stochastic multi-output production frontier (Ali and Flinn, 1989; Farrell, 1957) and calculate an index of efficiency for each household. The methodology to construct the efficiency index is presented in Appendix C. The index is equal to one if the household has profits as large as the potential for the region and zero if the profits equal the lower bound for the region. The average efficiency index for our sample is 0.33 (s.d. 0.236). We note that production analysis, due to the fact that production decisions and profits are measurable, affords us a measure of economic efficiency without needing repeated observations for the same household. This is not possible for consumption decisions since underlying preferences are not observable. While the production efficiency estimation requires making strong identification assumption, e.g. farmers in the same locale face the same production technology and market opportunities, it allows us to investigate how risk preferences and decision quality affects economic efficiency.

Table 9 present linear regressions of the efficiency index on household characteristics and the estimates of the coefficient of absolute risk aversion and the propensity to choose at random. The first column shows estimates of characteristics of both the husband and the wife on economic efficiency. Errors are clustered at the household level to avoid double counting observations. The second column restricts the analysis to the head of the household. The last column controls for the husband's and wife's preference parameters and the characteristics of the head of the household.

All the specifications show that decision quality is positively correlated with economic efficiency. That is, in households where members are more likely to choose at random, economic efficiency is lower. The size of the coefficient indicates that a one standard deviation change in the propensity to choose at random decreases economic efficiency by 3.9% of a SD ($-0.03 \times 0.31/0.24$). Importantly, these results show that our estimate of decision quality captures deviations from optimal economic decision-making.

5.6 Asset accumulation

Risk aversion and decision quality can also affect household asset accumulation conditional on income. To examine this, we use the (log) value of household assets and correlate this with the preference parameters of the household head and household characteristics.[42] Table 10 presents the main results. Columns (2)-(4) use the structural estimates of risk preferences and decision quality of the household head and columns (5)-(7) use naive measures (number of safe decisions for the closest pattern of consistent choices and number of inconsistent choices). We find a robust negative relationship between risk aversion and the value of household assets accumulated. This holds whether we use the structural estimate of the coefficient of absolute risk aversion or the number of safe decisions. The implied effect is large – a standard deviation increase in the coefficient of absolute risk aversion is equivalent to a 10.9 percentage point decrease in the value of household assets (-1.7×0.06).

A negative relationship between risk aversion and asset accumulation is expected since risk aversion is akin to a higher discount rate. The findings in Table 6 also suggest a direct mechanism: risk aversion is associated with lower participation in social organizations and credit markets. We find a positive relationship between the propensity to choose at random and asset accumulation, however, this weakens once we account for the fact that the relationship is estimated on a selected sample.[43] A likely explanation of the positive relationship between the propensity to choose at random and asset accumulation is the fact that the estimated relationship between preferences and asset accumulation is affected by measurement error. This suggests that the propensity to choose at random captures factors other than the quality of economic decisions as in Choi et al. (2014).

We also examine the role of the preferences of couples on the value of household assets. The analysis is restricted to the sample of households for which both members of the couple were present at the time of the interview. Covariates included correspond to the head of the household.[44] Results show that it is the risk preferences of the husband that correlate strongly with asset accumulation. Given that women have a higher propensity to choose at random, these result might be an expression of attenuation bias. The risk preferences of the

[42] The assets we consider include, among others, TV sets, radio, computers, refrigerators, sewing machines, looms, copy machines, soldering equipment, meat grinders, drills, bicycles, motorcycles, cars, trucks, etc.

[43] Using inverse probability weighting, the coefficient on the probability of choosing at random (Column 4) becomes 0.169 (p-value=0.075) and on the number of switches (Column 7) becomes 0.332 (p-value=0.007).

[44] Table A.10 in the Appendix present these results.

wife are correlated with asset accumulation once we account for the interaction between risk preferences and decision quality.[45] Nonetheless, our estimates still show that the preferences of the husband have a larger effect on asset accumulation than those of the wife. For instance, if both the husband and the wife have a propensity to choose at random of 0.25, the estimates of the effect of the CARA coefficient are -1.99 (s.e. 0.624) and -0.93 (s.e. 0.641) respectively. Our estimates are consistent with unequal bargaining power within the household.

6 Conclusion

We assess the ability of experimental methods to accurately capture the risk preferences and decision quality of poor populations and relate these with actual field behavior. We take advantage of a unique data set that combines exogenously-assigned experimental risk elicitation methods and household survey data from a representative, random sample of poor households. The experimental risk instruments were designed to detect several potential sources of biases in the elicitation of preferences in the field and allowed participants to express any desire to choose at random.

We find that while preference elicitation instruments may be prone to measurement error and introduce biases, structural estimation methods can be successfully used to identify and correct for them. Ignoring decision error and biases has a price. Naive measures of risk preferences do not explain field behavior, and one might erroneously conclude that preferences and decision quality are not important in explaining important economic outcomes. We show that, once error and biases are accounted for, both individual estimates of risk preference parameters and decision quality (the propensity to choose at random) significantly explain field behavior, within household correlation of preferences, household decision-making, economic efficiency and asset accumulation.

The main findings from our study are the following. The risk preferences and decision quality of husbands and wives are significantly and positively correlated. That is, wives who are more risk averse are more likely to have husbands who are risk averse, and those who make higher quality decisions tend to be with men who do the same. In terms of field behavior, risk aversion is negatively correlated with asset accumulation, and those who make lower quality decisions are also less likely to make optimal production decisions. Alternative

[45] Results are similar if we restrict the sample to those couple with lower propensities to choose at random.

analytical approaches that do not explicitly model the possibility of decision error tend to underestimate the correlation between repeated measures and the importance of risk preferences and decision quality in field behavior.

Our study shows that instruments that prevent individuals from expressing their quality of decision-making might lose a potentially rich alternative source of information on individual decision-making – decision error. There is a large variation in decision quality in our data, and our results show that this is predictive of behavior. Improving the quality and consistency of decision-making could have large impacts on outcomes and welfare.

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Figure 1: Distribution of inconsistent choices by instrument

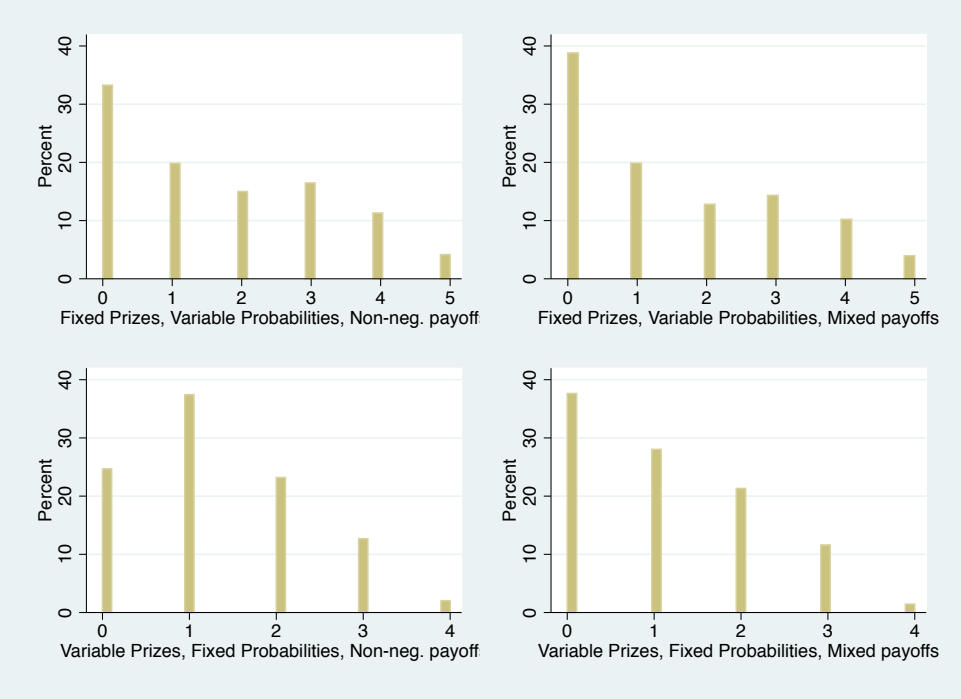


Table 1: Risk Preference Measurement Instrument assignment

Measurement instrument	Participants	Paid (%)	Male interviewer (%)
Fixed Prob. (*Non-neg. prizes*) & Fixed Prob. (*Mixed prizes*)	5,274	11.07	50.46
Fixed Prob. (*Non-neg. prizes*) & Variable Prob. (*Non-neg. prizes*)	3,980	15.27	51.66
Variable Prob. (*Non-neg. prizes*) & Variable Prob. (*Mixed prizes*)	2,170	25.12	51.47

Note: There are three possible combinations of instruments, plus two orderings, yielding six instruments.

Table 2: Sample descriptive statistics

	Mean	S.D.
Male (percent)	50.2	50.0
Age in years	43.74	14.77
Years of schooling	4.624	3.383
Non-Spanish speaker (percent)	54.6	49.8
Non-Catholic (percent)	18.3	38.7
Consumption (Monthly)	354.30	256.20
Age of marriage	23.09	6.67
Age of first pregnancy	24.51	7.10
Number rooms in house	3.50	1.41
Adobe walls (percent)	88.4	32.0
Dirt floors (percent)	90.7	29.0
Running water in house (percent)	25.2	43.4
Cooks with wood (percent)	78.4	41.2
Solicited informal credit (percent)	9.6	29.5
Solicited formal credit (percent)	7.2	25.8
At home at the time of interview (percent)	95.6	20.5
Agreed to participate in the experiment (percent)	77.0	42.1
Number of obs (at home when contacted)		12,576

Table 3: Estimation of θ and ω

	Coefficient of absolute risk aversion θ		Propensity to choose at random ω	
	Minimal	Instrument	Minimal	Instrument
Constant	0.018*** (0.0011)	-0.020*** (0.0009)	0.49*** (0.011)	0.55*** (0.10)
Fixed probability		0.095*** (0.0021)		0.10*** (0.029)
Mixed prizes		0.0068*** (0.0008)		-0.34*** (-0.021)
Fixed probability × Mixed prizes		-0.051*** (0.0024)		-0.24*** (0.034)
σ	0.086*** (0.0020)	0.099*** (0.017)	2.25*** (0.061)	3.01*** (0.10)
N	9676	9676	9676	9676
Log-Likelihood	97964	96376	97964	96376

$*p < 0.1, **p < 0.05, ***p < 0.01$

Table 4: Within person correlation of measures of risk preferences

Instruments

	Variable Payments Fixed Probabilities		Fixed Payments Variable Probabilities		Variable Payments Fixed Probabilities		Fixed Payments Variable Probabilities	
	Non-negative	*Mixed prizes*	*Non-negative prizes*	*Mixed prizes*	*Non-negative prizes*	*Mixed prizes*	*Non-negative*	*Mixed prizes*
	Coefficient of absolute risk aversion[&]				Number of Safe Decisions[+]			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	**1.000**	-	-	-	-	-	-	-
(2)	0.356	**1.000**	-	-	-	-	-	-
(3)	0.115	-	**1.000**	-	-	-	-	-
(4)	-	-	0.335	**1.000**	-	-	-	-
(5)	**0.259**	0.131	0.108	-	**1.000**	-	-	-
(6)	0.273	**0.844**	-	-	0.084	**1.000**	-	-
(7)	0.098	-	**0.850**	0.291	0.111	-	**1.000**	-
(8)	-	-	0.289	**0.881**	-	-	0.276	**1.000**

[&] Individual estimates are calculated using *only one* experimental instrument at a time.
[+] Number of safe decisions corresponding to the consistent pattern of decisions closest to actual choices.

Table 5: Differences in risk preferences by gender

		Female ($N = 4722$) Mean (s.e.)	Male ($N = 4952$) Mean (s.e.)	t-test (p-value)
(1)	Percent of risk neutral decisions	54.40 (0.31)	55.31 (0.31)	-2.08 (0.0368)
(2)	Percent of risk neutral decisions in closest consistent pattern	52.73 (0.41)	53.76 (0.34)	-1.80 (0.0717)
(3)	Coefficient of Absolute risk aversion (θ)	-0.020 (0.0009)	-0.020 (0.0010)	-0.05 (0.9598)
(4)	Minimum number of switches necessary for consistency	1.92 (0.018)	1.82 (0.017)	3.96 (0.0001)
(5)	Propensity to choose at random (ω)	58.63 (0.45)	52.01 (0.45)	10.42 (0.0000)
(6)	Percent of risk neutral decisions in closest consistent pattern if *at most 1 switch* necessary for consistent ($N = 4179$)	61.62 (0.63)	60.95 (0.59)	0.78 (0.4323)
(7)	Percent of risk neutral decisions in closest consistent pattern if *at least 2 switches* necessary for consistent ($N = 5495$)	46.42 (0.50)	47.93 (0.51)	-2.10 (0.0357)
(8)	Coefficient of Absolute risk aversion (θ) if propensity to make mistakes is below the median ($N = 4822$)	-0.028 (0.0017)	-0.023 (0.0016)	-2.04 (0.0410)
(8)	Coefficient of Absolute risk aversion (θ) if propensity to make mistakes is above the median ($N = 4852$)	-0.014 (0.0009)	-0.017 (0.0010)	2.24 (0.0252)

Table 6: Relation between preferences and field behavior

Variable	Age of first pregnancy	Age of marriage	No. soc. organizations	No. unhealthy habits	No. diseases	Asked for informal credit	Asked for formal credit	Used purchased seeds	Used purchased fertilizer
θ (CARA coeff.)	-0.024***	0.017*	-0.024**	-0.066***	-0.014	-0.021	-0.023*	0.036***	0.053***
	[0.009]	[0.009]	[0.010]	[0.010]	[0.010]	[0.014]	[0.014]	[0.013]	[0.013]
	(0.005)	(0.080)	(0.016)	(0.000)	(0.171)	(0.135)	(0.093)	(0.004)	(0.000)
Male		0.159***	0.171***	0.366***	0.016	0.006	-0.024*	-0.094***	-0.092***
		[0.010]	[0.010]	[0.011]	[0.011]	[0.015]	[0.014]	[0.015]	[0.015]
		(0.000)	(0.000)	(0.000)	(0.150)	(0.693)	(0.084)	(0.000)	(0.000)
Age (log)	0.505***	0.363***	0.021**	-0.025**	0.114***	-0.044***	0.056***	0.111***	0.131***
	[0.008]	[0.011]	[0.010]	[0.011]	[0.011]	[0.014]	[0.014]	[0.013]	[0.013]
	(0.000)	(0.000)	(0.036)	(0.021)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)
Non-Catholic	0.001	-0.002	0.263***	-0.133***	0.027**	0.010	0.037**	-0.011	0.002
	[0.008]	[0.010]	[0.011]	[0.009]	[0.010]	[0.014]	[0.015]	[0.013]	[0.013]
	(0.867)	(0.868)	(0.000)	(0.000)	(0.010)	(0.487)	(0.011)	(0.381)	(0.845)
Non-Spanish speaker	0.002	-0.018*	-0.072***	-0.216***	-0.046***	-0.024*	-0.074***	0.278***	0.294***
	[0.009]	[0.010]	[0.010]	[0.011]	[0.011]	[0.014]	[0.014]	[0.014]	[0.014]
	(0.782)	(0.092)	(0.000)	(0.000)	(0.000)	(0.076)	(0.000)	(0.000)	(0.000)
Years of schooling (log)	0.101***	0.115***	0.071***	-0.178***	-0.036***	0.017	0.082***	0.205***	0.201***
	[0.009]	[0.012]	[0.010]	[0.011]	[0.012]	[0.017]	[0.017]	[0.016]	[0.016]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.307)	(0.000)	(0.000)	(0.000)
Consumption (log)	-0.097***	-0.048***	-0.017*	0.149***	0.028***	-0.011	0.113***	-0.128***	-0.083***
	[0.010]	[0.011]	[0.010]	[0.010]	[0.011]	[0.014]	[0.014]	[0.013]	[0.013]
	(0.000)	(0.000)	(0.082)	(0.000)	(0.009)	(0.432)	(0.000)	(0.000)	(0.000)
N	3219	8731	9674	7966	9652	5409	5412	5412	5412
R^2 including θ	0.513	0.168	0.113	0.236	0.022	0.004	0.036	0.135	0.135
R^2 excluding θ	0.510	0.167	0.112	0.226	0.021	0.003	0.035	0.132	0.129
Mean	22.612	22.945	0.401	0.969	0.121	0.105	0.074	0.789	0.829
S.D	4.868	6.308	0.611	1.139	0.350	0.307	0.261	0.408	0.377

p-values in parentheses. *** p<0.01, ** p<0.05, * p<0.10

Unhealthy habits: smoking, drinking and chewing coca leaves. **Diseases**: Tuberculosis, yellow fever, pneumonia, influenza, cholera, malaria, hepatitis, typhoid.

Estimations. All the estimates are based on linear regressions of the outcome on the estimated individual coefficient of absolute risk aversion of the decision maker and the covariates included in Table A.3.

Table 7: Relation between preferences and field behavior (controlling for decision quality)

Variable	Age of first pregnancy	Age of marriage	No. soc. organizations	No. unhealthy habits	No. diseases	Asked for informal credit	Asked for formal credit	Used purchased seeds	Used purchased fertilizer
θ (CARA coeff.)	-0.024***	0.013	-0.014	-0.064***	-0.017	-0.025*	-0.019	0.039***	0.056***
	[0.009]	[0.010]	[0.010]	[0.010]	[0.010]	[0.014]	[0.013]	[0.012]	[0.013]
	(0.007)	(0.175)	(0.153)	(0.000)	(0.105)	(0.069)	(0.152)	(0.001)	(0.000)
ω (prob. random choice)	-0.003	0.020*	-0.056***	-0.019**	0.015	0.028**	-0.022	-0.018*	-0.016
	[0.009]	[0.010]	[0.010]	[0.009]	[0.010]	[0.013]	[0.013]	[0.011]	[0.011]
	(0.758)	(0.051)	(0.000)	(0.034)	(0.115)	(0.035)	(0.105)	(0.097)	(0.126)
Male		0.160***	0.168***	0.366***	0.017	0.007	-0.025*	-0.095***	-0.092***
		[0.010]	[0.010]	[0.011]	[0.011]	[0.015]	[0.014]	[0.015]	[0.015]
		(0.000)	(0.000)	(0.000)	(0.137)	(0.630)	(0.071)	(0.000)	(0.000)
Age (log)	0.505***	0.364***	0.021**	-0.025**	0.114***	-0.045***	0.056***	0.111***	0.132***
	[0.008]	[0.011]	[0.010]	[0.011]	[0.011]	[0.014]	[0.014]	[0.013]	[0.013]
	(0.000)	(0.000)	(0.036)	(0.021)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Non-Catholic	0.001	-0.002	0.263***	-0.133***	0.027**	0.010	0.037**	-0.011	0.003
	[0.008]	[0.010]	[0.011]	[0.009]	[0.010]	[0.014]	[0.015]	[0.013]	[0.013]
	(0.870)	(0.845)	(0.000)	(0.000)	(0.011)	(0.490)	(0.011)	(0.383)	(0.841)
Non-Spanish speaker	0.002	-0.016	-0.078***	-0.219***	-0.045***	-0.021	-0.077***	0.276***	0.292***
	[0.009]	[0.010]	[0.010]	[0.011]	[0.011]	[0.014]	[0.014]	[0.014]	[0.014]
	(0.803)	(0.134)	(0.000)	(0.000)	(0.000)	(0.131)	(0.000)	(0.000)	(0.000)
Years of schooling (log)	0.101***	0.115***	0.069***	-0.179***	-0.035***	0.018	0.082***	0.205***	0.201***
	[0.009]	[0.012]	[0.010]	[0.011]	[0.012]	[0.017]	[0.017]	[0.016]	[0.016]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.285)	(0.000)	(0.000)	(0.000)
Consumption (log)	-0.097***	-0.048***	-0.015	0.149***	0.028**	-0.012	0.114***	-0.128***	-0.083***
	[0.010]	[0.011]	[0.010]	[0.010]	[0.011]	[0.014]	[0.014]	[0.013]	[0.013]
	(0.000)	(0.000)	(0.111)	(0.000)	(0.010)	(0.392)	(0.000)	(0.000)	(0.000)
N	3219	8731	9674	7966	9652	5409	5412	5412	5412
R^2 including θ	0.513	0.168	0.117	0.237	0.022	0.005	0.037	0.136	0.136
R^2 excluding θ	0.510	0.167	0.112	0.226	0.021	0.003	0.035	0.132	0.129
Mean	22.612	22.945	0.401	0.969	0.121	0.105	0.074	0.789	0.829
S.D	4.868	6.308	0.611	1.139	0.350	0.307	0.261	0.408	0.377

p-values in parentheses. *** p<0.01, ** p<0.05, * p<0.10

Definitions. Habits: smoking, drinking and chewing coca leaves. **Diseases**: Tuberculosis, yellow fever, pneumonia, influenza, cholera, malaria, hepatitis, typhoid.

Estimations. All the estimates are based on linear regressions of the outcome on the estimated individual coefficient of absolute risk aversion and the propensity to choose at random of the decision maker and the covariates included in Table A.3.

Table 8: Relation between the preferences of husbands and wives

VARIABLES	(1)	(2)	(3)	(4)
	Wife's θ (CARA coeff.)		Wife's ω (prob. random choice)	
	No covariates	With covariates	No covariates	With covariates
Husbands's θ (CARA coeff.)	0.130***	0.129***		
	(0.000)	(0.000)		
Husband's ω (prob. random choice)			0.170***	0.165***
			(0.000)	(0.000)
Observations	3,387	3,387	3,387	3,387

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.
Correlation coefficients between individual preferences of wives and husbands. θ is the estimated coefficient of absolute risk aversion for an individual given the structural estimates and the choices made by the subject. ω is the estimated probability of choosing at random given the structural estimates and the choices made by the subject. The columns "with covariates" present the linear regression coefficient controlling for the exact same regressors as in Table 3.

Table 9: Relation between preferences and Economic Efficiency

VARIABLES	(1) Both members of the household	(2) Head of the household	(3) Couples
θ (CARA coeff.)	-0.072*	-0.034	
	[0.041]	[0.051]	
	(0.075)	(0.509)	
ω (Prob. random choice)	-0.028***	-0.023**	
	[0.008]	[0.011]	
	(0.001)	(0.033)	
Husband's θ (CARA coeff.)			-0.004
			[0.066]
			(0.957)
Wife's θ (CARA coeff.)			-0.085
			[0.067]
			(0.205)
Husband's ω (Prob. random choice)			-0.030**
			[0.014]
			(0.033)
Wife's ω (Prob. random choice)			-0.041***
			[0.014]
			(0.004)
Male	-0.017***	-0.031***	-0.060
	[0.003]	[0.012]	[0.044]
	(0.000)	(0.009)	(0.175)
Age (log)	0.039***	0.036***	0.023
	[0.010]	[0.011]	[0.014]
	(0.000)	(0.001)	(0.106)
Non-Spanish speaker	-0.003	-0.004	-0.023**
	[0.007]	[0.007]	[0.009]
	(0.709)	(0.595)	(0.011)
Non-Catholic	-0.010	-0.013	0.003
	[0.008]	[0.009]	[0.011]
	(0.236)	(0.157)	(0.816)
Years of schooling (log)	0.028***	0.026***	0.033***
	[0.004]	[0.006]	[0.008]
	(0.000)	(0.000)	(0.000)
Consumption (log)	0.006	0.007	-0.001
	[0.005]	[0.005]	[0.007]
	(0.212)	(0.192)	(0.911)
Constant	0.129***	0.157***	0.298***
	[0.048]	[0.054]	[0.080]
	(0.008)	(0.004)	(0.000)
Observations	9,038	5,060	3,168
R-squared	0.010	0.008	0.015

Robust s.e. in brackets, p-values in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table 10: Relation between preferences and (log) value of household assets

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
θ (CARA coeff.)		-1.676***		-1.845***			
		[0.446]		[0.453]			
		(0.000)		(0.000)			
ω (Prob random choose)			0.148	0.214**			
			[0.095]	[0.096]			
			(0.119)	(0.026)			
Number of safe decisions					-0.366***		-0.465***
					[0.105]		[0.109]
					(0.000)		(0.000)
Number of switches						0.229*	0.381***
						[0.117]	[0.122]
						(0.051)	(0.002)
Male	0.197*	0.204*	0.200*	0.208*	0.201*	0.199*	0.204*
	[0.112]	[0.111]	[0.112]	[0.111]	[0.111]	[0.112]	[0.111]
	(0.077)	(0.067)	(0.073)	(0.062)	(0.072)	(0.075)	(0.067)
Age	0.048***	0.047***	0.049***	0.048***	0.048***	0.049***	0.048***
	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age squared	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
	(0.014)	(0.017)	(0.012)	(0.015)	(0.016)	(0.012)	(0.013)
Non-Spanish speaker	-0.946***	-0.940***	-0.934***	-0.922***	-0.946***	-0.930***	-0.919***
	[0.061]	[0.061]	[0.061]	[0.061]	[0.061]	[0.061]	[0.061]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Non-Catholic	0.051	0.041	0.052	0.040	0.037	0.051	0.033
	[0.080]	[0.080]	[0.080]	[0.080]	[0.080]	[0.080]	[0.080]
	(0.523)	(0.612)	(0.519)	(0.616)	(0.645)	(0.521)	(0.678)
Years of schooling (log)	0.163***	0.164***	0.162***	0.164***	0.166***	0.161***	0.165***
	[0.051]	[0.051]	[0.051]	[0.051]	[0.051]	[0.051]	[0.051]
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Gross Income (log)	0.374***	0.371***	0.377***	0.374***	0.370***	0.376***	0.373***
	[0.026]	[0.026]	[0.026]	[0.026]	[0.026]	[0.026]	[0.026]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of children	0.008	0.007	0.008	0.007	0.007	0.008	0.006
	[0.018]	[0.018]	[0.018]	[0.018]	[0.018]	[0.018]	[0.018]
	(0.648)	(0.675)	(0.658)	(0.692)	(0.701)	(0.662)	(0.739)
Zero income	2.629***	2.636***	2.641***	2.653***	2.618***	2.637***	2.629***
	[0.332]	[0.331]	[0.332]	[0.331]	[0.331]	[0.331]	[0.331]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	2.418***	2.418***	2.305***	2.253***	2.621***	2.312***	2.499***
	[0.353]	[0.353]	[0.361]	[0.360]	[0.358]	[0.357]	[0.359]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	4,907	4,907	4,907	4,907	4,907	4,907	4,907
R-squared	0.128	0.131	0.129	0.132	0.130	0.129	0.132

Robust s.e. in brackets, p-values in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

A Appendix

A.1 Supplemental Figures and Tables

Figure A.1: Fixed probabilities & variable prizes (Non-negative payoffs)

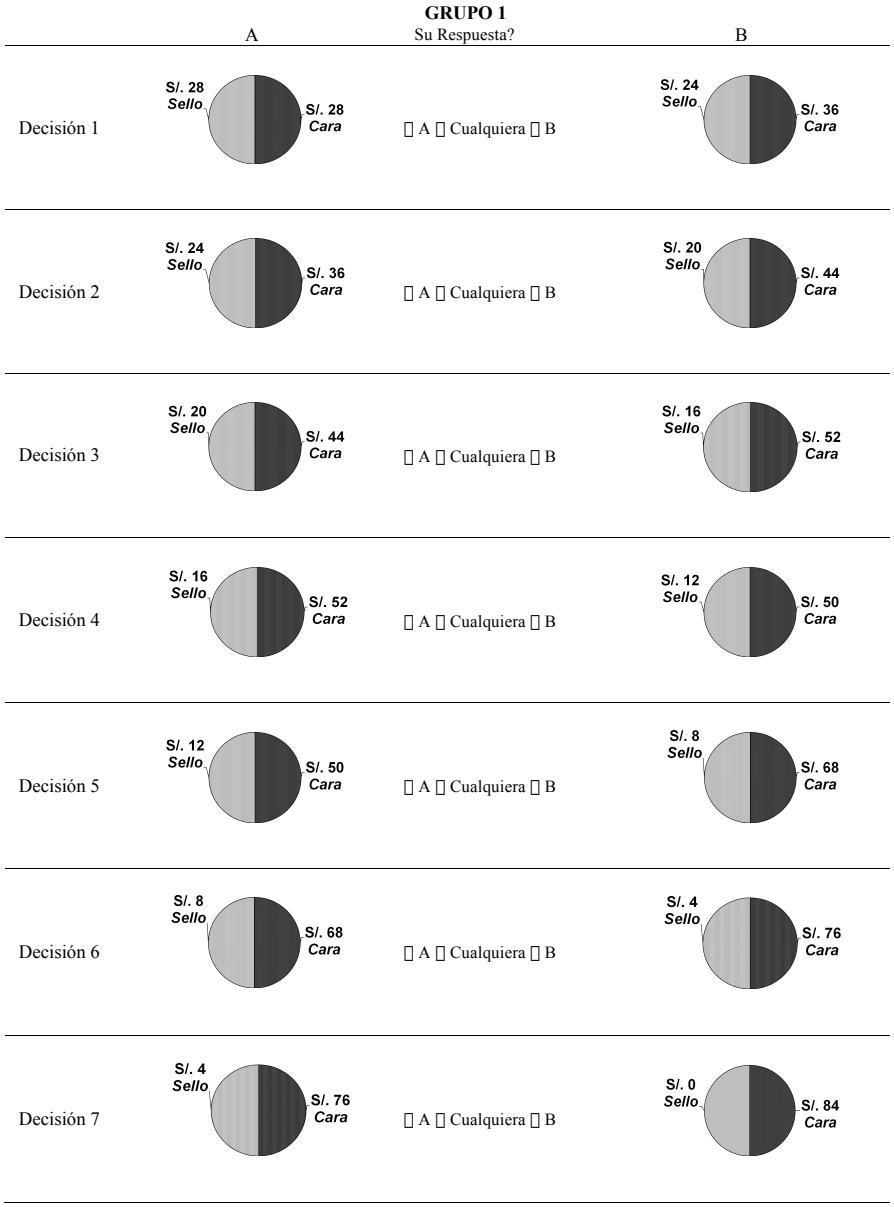


Figure A.2: Fixed probabilities & variable prizes (Mixed payoffs)

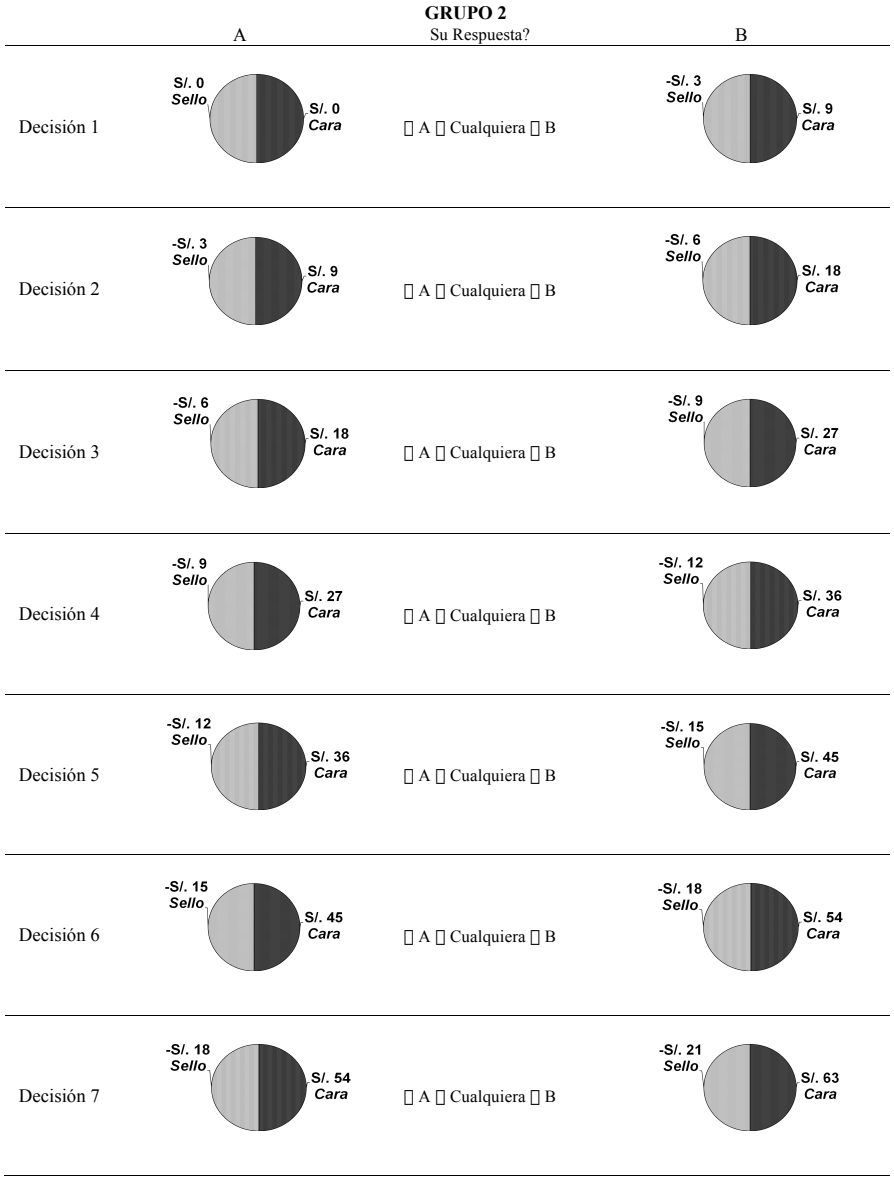


Figure A.3: Variable probabilities & fixed prizes (Non-negative payoffs)

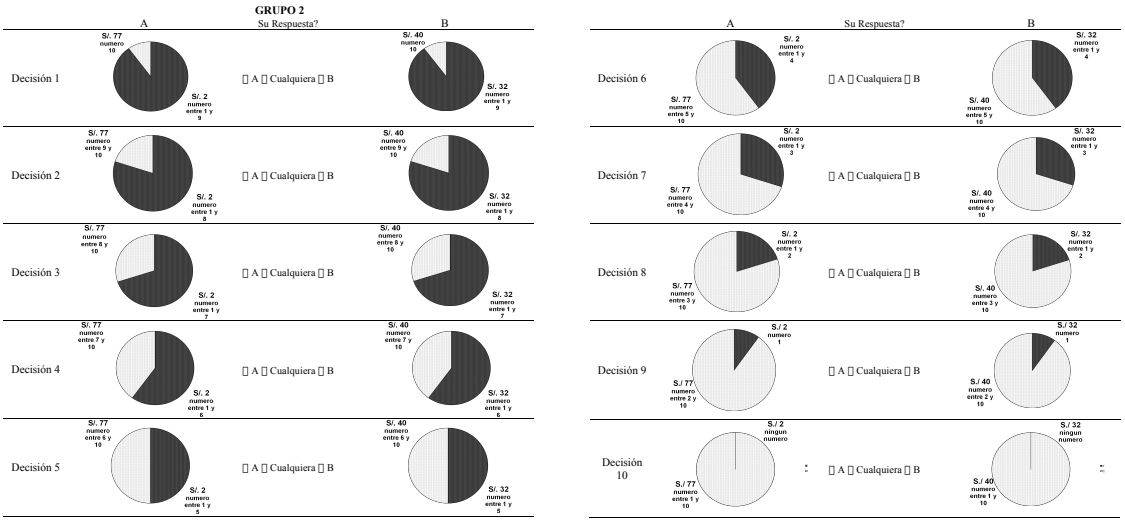


Figure A.4: Variable probabilities & fixed prizes (Mixed payoffs)

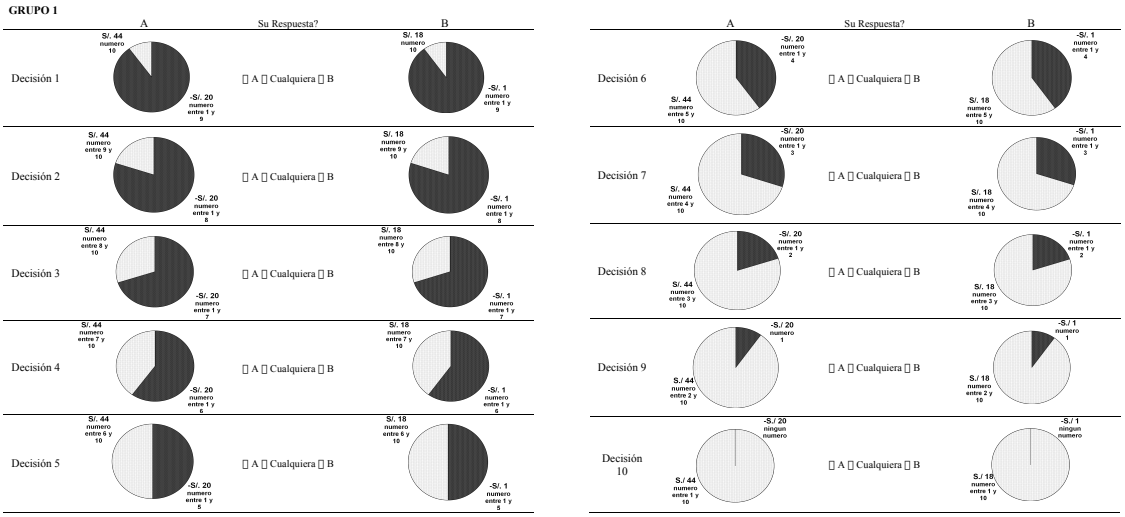


Figure A.5: Decision tree

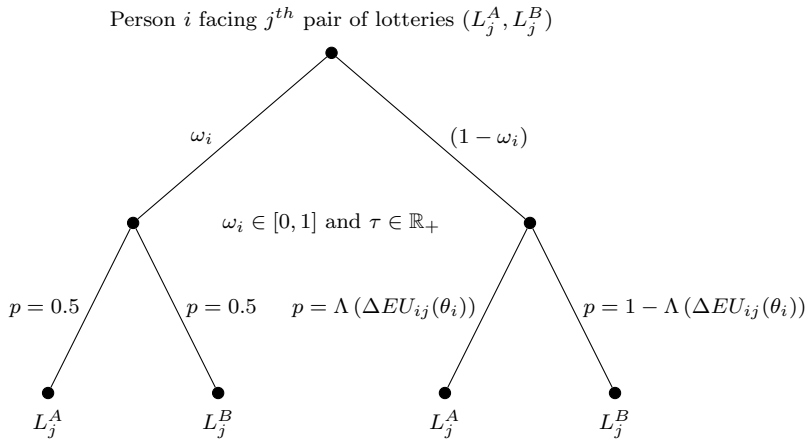
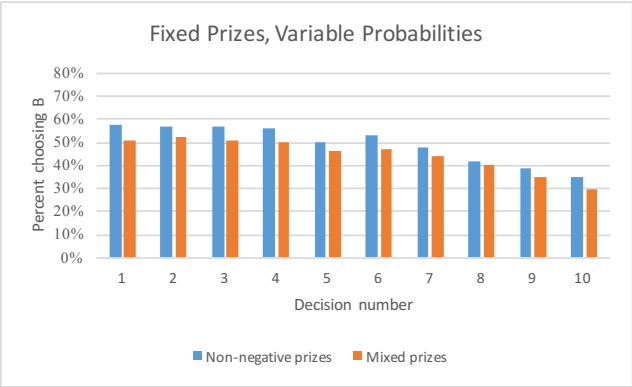
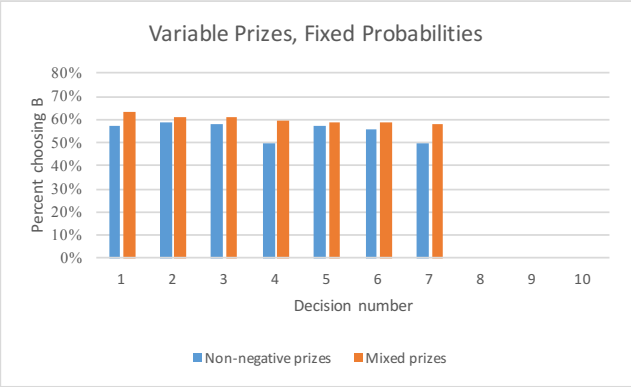


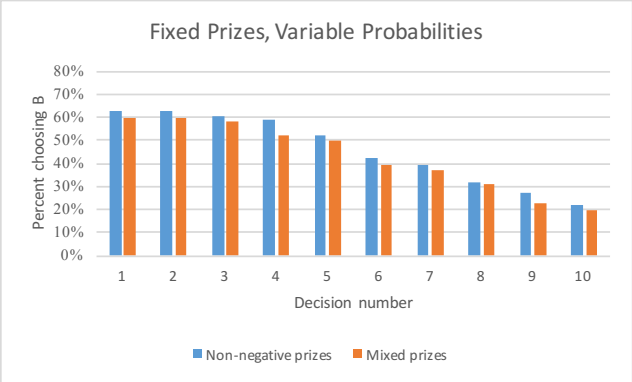
Figure A.6: Proportion choosing option B by instrument

(a) All participants





(b) At most one inconsistent choice



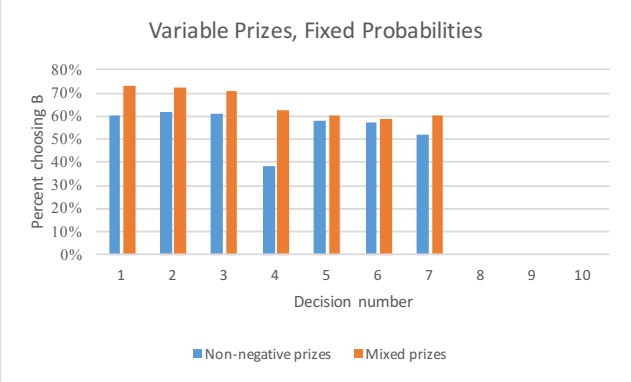


Figure A.7: Comparing θ and ω of Rural Peru and Urban Dutch

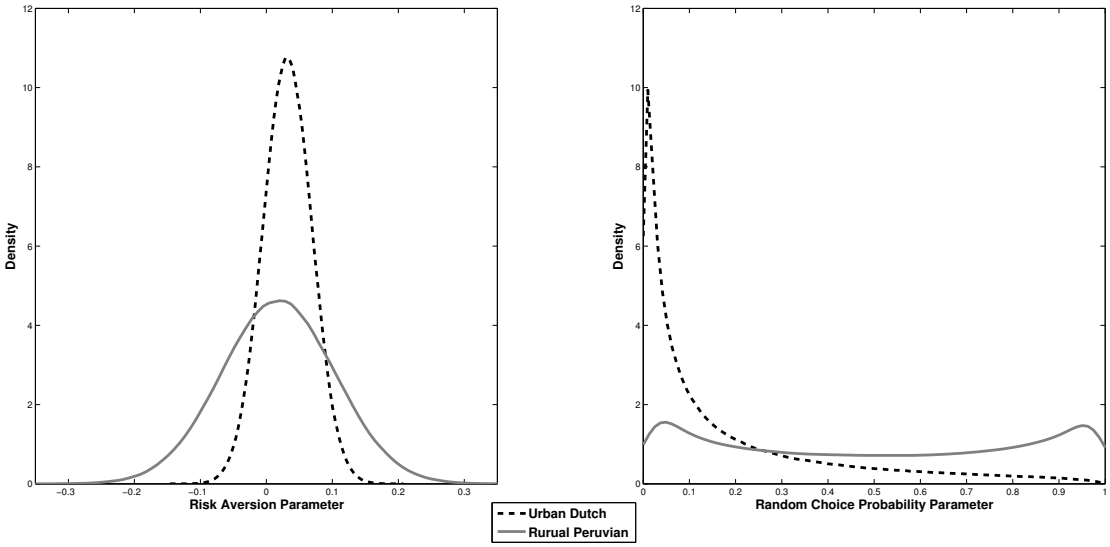


Table A.1: Probit regression on participation in the experiment - Marginals

VARIABLES	(1) Present at time of survey	(2) Participated in experiment
Non-Spanish speaker	-0.021***	-0.049***
	(0.000)	(0.000)
Non-Catholic	0.008**	-0.061***
	(0.034)	(0.000)
Male	-0.016***	0.048***
	(0.000)	(0.000)
Age in years (log)	-0.001	-0.110***
	(0.861)	(0.000)
Consumption (log)	0.016***	0.060***
	(0.000)	(0.000)
Years of schooling (log)	-0.002	0.035***
	(0.336)	(0.000)
Paid lottery	-0.113***	0.034***
	(0.000)	(0.004)
Male interviewer	0.005	-0.005
	(0.307)	(0.638)
Male responder×Male interviewer	-0.001	-0.018
	(0.910)	(0.257)
Instrument (mixed instruments omitted)		
Fixed probabilities & variable prizes	0.013***	0.103***
	(0.000)	(0.000)
Variable probabilities & fixed prizes	-0.003	-0.023**
	(0.355)	(0.023)
Observations	13,145	12,568
pseudo-R^2	0.0873	0.0731

p-values in parentheses. *** p<0.01, ** p<0.05, * p<0.10

Table A.2: Average number of runs over maximal number of runs

	Variable Probabilities Fixed Prizes		Fixed Probabilities Variable Prizes	
	Non-negative payoffs	Mixed payoffs	Non-negative payoffs	Mixed payoffs
Male	0.35	0.33	0.43	0.40
Female	0.38	0.36	0.45	0.42
Paid	0.48	0.46	0.54	0.51
Unpaid	0.33	0.31	0.42	0.39
Spanish Speaker	0.42	0.39	0.46	0.43
Non-Spanish Speaker	0.33	0.32	0.41	0.39
Catholic	0.36	0.35	0.44	0.41
Non-Catholic	0.37	0.34	0.44	0.41
Age (< 26)	0.36	0.35	0.45	0.43
Age (26-35)	0.37	0.34	0.43	0.41
Age (36-45)	0.36	0.34	0.43	0.39
Age (> 45)	0.37	0.36	0.43	0.40
No schooling	0.36	0.36	0.43	0.42
$1-6$ Years of schooling	0.36	0.34	0.44	0.41
> 6 Years of schooling	0.37	0.35	0.44	0.41
1st Consumption quartile	0.34	0.32	0.42	0.39
2nd Consumption quartile	0.34	0.33	0.43	0.40
3rd Consumption quartile	0.37	0.35	0.44	0.42
4th Consumption quartile	0.42	0.40	0.46	0.42
Total	0.36	0.35	0.44	0.41

Table A.3: Determinants of individual preferences

	Coefficient of absolute risk aversion (θ)				Propensity to choose at random (ω)			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Male	-0.001	-0.001	-0.001	-0.001	-0.014**	-0.013**	-0.014**	-0.014**
	[0.001]	[0.001]	[0.001]	[0.001]	[0.007]	[0.007]	[0.007]	[0.007]
	(0.684)	(0.680)	(0.684)	(0.684)	(0.036)	(0.039)	(0.033)	(0.034)
Age (log)	-0.002	-0.002	-0.002	-0.002	-0.019*	-0.019*	-0.018	-0.018
	[0.002]	[0.002]	[0.002]	[0.002]	[0.011]	[0.011]	[0.011]	[0.011]
	(0.334)	(0.330)	(0.335)	(0.334)	(0.078)	(0.084)	(0.103)	(0.109)
Non-Spanish speaker	0.005***	0.005***	0.005***	0.005***	-0.028***	-0.027***	-0.025***	-0.024***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.007]	[0.007]	[0.007]	[0.007]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Non-Catholic	-0.004*	-0.004*	-0.004*	-0.004*	0.003	0.004	0.003	0.003
	[0.002]	[0.002]	[0.002]	[0.002]	[0.009]	[0.009]	[0.009]	[0.009]
	(0.055)	(0.053)	(0.055)	(0.055)	(0.755)	(0.681)	(0.703)	(0.700)
Years of schooling (log)	-0.000	-0.000	-0.000	-0.000	-0.021***	-0.021***	-0.020***	-0.020***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.005]	[0.005]	[0.005]	[0.005]
	(0.819)	(0.816)	(0.820)	(0.818)	(0.000)	(0.000)	(0.000)	(0.000)
Consumption (log)	-0.001	-0.001	-0.001	-0.001	0.003	0.004	0.003	0.003
	[0.001]	[0.001]	[0.001]	[0.001]	[0.005]	[0.005]	[0.005]	[0.005]
	(0.438)	(0.417)	(0.438)	(0.438)	(0.636)	(0.492)	(0.585)	(0.612)
Paid lotteries	0.013***	0.013***	0.013***	0.013***	0.103***	0.096***	0.094***	0.094***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.009]	[0.010]	[0.010]	[0.010]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of bad shocks^{+}		0.000				-0.011***		
		[0.001]				[0.003]		
		(0.544)				(0.000)		
Acts of nature (drought,			-0.000				-0.023***	
frost & mudslides)			[0.001]				[0.005]	
			(0.982)				(0.000)	
Acts of nature (0-1)				0.000				-0.032***
				[0.001]				[0.007]
				(0.962)				(0.000)
Constant	-0.011	-0.011	-0.011	-0.011	0.644***	0.647***	0.647***	0.648***
	[0.011]	[0.011]	[0.011]	[0.011]	[0.052]	[0.052]	[0.052]	[0.052]
	(0.332)	(0.327)	(0.332)	(0.332)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	9,674	9,674	9,674	9,674	9,674	9,674	9,674	9,674
R-squared	0.006	0.006	0.006	0.006	0.022	0.023	0.024	0.024

Robust s.e. in brackets, p-values in parentheses. *** p<0.01, ** p<0.05, * p<0.10

$^{+}$Sources of loss: death of family member, stealing, drought, pests, mudslides, disease, social engagements, fire, job loss, loss of income, local festivities and others.

Table A.4: Determinants of individual preferences (using inverse probability weights to account for selection)

	Coefficient of absolute risk aversion (θ)				Propensity to choose at random (ω)			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Male	-0.001	-0.001	-0.001	-0.001	-0.017**	-0.017**	-0.014**	-0.014**
	[0.002]	[0.002]	[0.002]	[0.002]	[0.007]	[0.007]	[0.007]	[0.007]
	(0.354)	(0.354)	(0.355)	(0.356)	(0.021)	(0.021)	(0.033)	(0.034)
Age (log)	-0.001	-0.001	-0.001	-0.001	-0.013	-0.012	-0.018	-0.018
	[0.003]	[0.003]	[0.003]	[0.003]	[0.014]	[0.013]	[0.011]	[0.011]
	(0.840)	(0.834)	(0.833)	(0.823)	(0.343)	(0.381)	(0.103)	(0.109)
Non-Spanish speaker	0.005***	0.005***	0.005***	0.005***	-0.025***	-0.024***	-0.025***	-0.024***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.008]	[0.008]	[0.007]	[0.007]
	(0.004)	(0.004)	(0.004)	(0.005)	(0.001)	(0.002)	(0.000)	(0.001)
Non-Catholic	-0.002	-0.002	-0.002	-0.002	0.002	0.003	0.003	0.003
	[0.002]	[0.002]	[0.002]	[0.002]	[0.010]	[0.010]	[0.009]	[0.009]
	(0.306)	(0.301)	(0.305)	(0.303)	(0.824)	(0.739)	(0.703)	(0.700)
Years of schooling (log)	-0.000	-0.000	-0.000	-0.000	-0.021***	-0.021***	-0.020***	-0.020***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.006]	[0.006]	[0.005]	[0.005]
	(0.976)	(0.974)	(0.971)	(0.964)	(0.000)	(0.000)	(0.000)	(0.000)
Consumo (log)	-0.001	-0.001	-0.001	-0.001	0.003	0.004	0.003	0.003
	[0.001]	[0.001]	[0.001]	[0.001]	[0.007]	[0.007]	[0.005]	[0.005]
	(0.370)	(0.362)	(0.369)	(0.369)	(0.676)	(0.549)	(0.585)	(0.612)
Paid lotteries	0.011***	0.011***	0.011***	0.011***	0.094***	0.087***	0.094***	0.094***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.011]	[0.011]	[0.010]	[0.010]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of bad shocks^{+}		0.000				-0.012***		
		[0.001]				[0.003]		
		(0.765)				(0.000)		
Acts of nature (drought, frost & mudslides)			0.000				-0.023***	
			[0.001]				[0.005]	
			(0.850)				(0.000)	
Acts of nature (0-1)				0.001				-0.032***
				[0.002]				[0.007]
				(0.673)				(0.000)
Constant	-0.014	-0.014	-0.014	-0.014	0.622***	0.624***	0.647***	0.648***
	[0.012]	[0.012]	[0.012]	[0.012]	[0.060]	[0.060]	[0.052]	[0.052]
	(0.259)	(0.258)	(0.259)	(0.258)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	8,036	8,036	8,036	8,036	8,036	8,036	9,674	9,674
R-squared	0.004	0.004	0.004	0.004	0.017	0.019	0.024	0.024

Robust s.e. in brackets, p-values in parentheses. *** p<0.01, ** p<0.05, * p<0.10.
$^{+}$Sources of loss: death of family member, stealing, drought, pests, mudslides, disease, social engagements, fire, job loss, loss of income, local festivities and others.
Note: Weights calculated from the model estimated in column 2 in Table A.1.

Table A.5: Comparison of Estimated Preferences of Rural and Urban Samples

	Rural Peruvian Sample		Urban Dutch Sample	
	θ^a	ω^b	θ^a	ω^b
μ	0.018***	0.49***	0.032***	0.083***
	(0.0011)	(0.011)	(0.0010)	(0.0082)
$\sigma^\dagger$	0.086***	2.25***	0.037***	1.96***
	(0.0020)	(0.061)	(0.001)	(0.090)

$^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$

^{a} Coefficient of absolute risk aversion

^{b} Probability of choosing at random

† Standard deviation of untransformed variable

Table A.6: Field behavior - Descriptive statistics

	N	Mean	SD
Age of Marriage	8,731	22.94	6.31
Age at first pregnancy	4,046	24.21	6.87
No. Social organizations	9,674	0.40	0.61
Asked informal credit (percent)	5,409	0.11	0.31
Asked formal credit (percent)	5,412	0.07	0.26
No. of bad habits	7,966	0.97	1.14
No. of diseases	9.652	0.12	0.35
Purchased seeds (percent)	5,412	0.79	0.41
Purchased fertilizer (percent)	5,412	0.83	0.38

Table A.7: Relation between preferences and field behavior (Naive measure)

Variable	Age of first pregnancy	Age of marriage	No. soc. organizations	No. unhealthy habits	No. diseases	Asked for informal credit	Asked for formal credit	Used purchased seeds	Used purchased fertilizer
Number of safe decisions	-0.005	0.003	-0.029***	-0.065***	0.011	0.006	-0.012	0.033***	0.042***
(closest consistent pattern)	[0.009]	[0.010]	[0.010]	[0.010]	[0.010]	[0.014]	[0.013]	[0.013]	[0.013]
	(0.585)	(0.744)	(0.002)	(0.000)	(0.287)	(0.680)	(0.368)	(0.009)	(0.001)
Age (log)	0.536***	0.363***	0.021**	-0.024**	0.114***	-0.045***	0.056***	0.110***	0.131***
	[0.010]	[0.011]	[0.011]	[0.011]	[0.011]	[0.015]	[0.014]	[0.014]	[0.014]
	(0.000)	(0.000)	(0.047)	(0.024)	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)
Non-Catholic	0.003	-0.003	0.263***	-0.133***	0.028***	0.012	0.038***	-0.013	0.000
	[0.009]	[0.010]	[0.010]	[0.010]	[0.010]	[0.014]	[0.013]	[0.013]	[0.013]
	(0.742)	(0.791)	(0.000)	(0.000)	(0.006)	(0.395)	(0.005)	(0.328)	(0.989)
Non-Spanish speaker	-0.007	-0.016	-0.073***	-0.219***	-0.047***	-0.026*	-0.076***	0.280***	0.297***
	[0.010]	[0.010]	[0.010]	[0.011]	[0.011]	[0.014]	[0.014]	[0.013]	[0.013]
	(0.475)	(0.113)	(0.000)	(0.000)	(0.000)	(0.071)	(0.000)	(0.000)	(0.000)
Years of schooling (log)	0.046***	0.115***	0.071***	-0.179***	-0.037***	0.016	0.082***	0.205***	0.202***
	[0.009]	[0.011]	[0.011]	[0.012]	[0.012]	[0.017]	[0.017]	[0.016]	[0.016]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.342)	(0.000)	(0.000)	(0.000)
Consumption (log)	-0.087***	-0.047***	-0.017*	0.148***	0.028***	-0.011	0.113***	-0.128***	-0.083***
	[0.010]	[0.011]	[0.010]	[0.011]	[0.011]	[0.014]	[0.014]	[0.013]	[0.013]
	(0.000)	(0.000)	(0.093)	(0.000)	(0.009)	(0.449)	(0.000)	(0.000)	(0.000)
Male		0.159***	0.171***	0.366***	0.017	0.006	-0.024	-0.093***	-0.091***
		[0.011]	[0.010]	[0.011]	[0.011]	[0.015]	[0.014]	[0.014]	[0.014]
		(0.000)	(0.000)	(0.000)	(0.126)	(0.674)	(0.103)	(0.000)	(0.000)
N	3657	8731	9674	7966	9652	5409	5412	5412	5412
R^2	0.451	0.167	0.112	0.23	0.021	0.003	0.035	0.134	0.131

Robust s.e. in brackets, p-values in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Unhealthy habits: smoking, drinking and chewing coca leaves. **Diseases**: Tuberculosis, yellow fever, pneumonia, influenza, cholera, malaria, hepatitis, typhoid.

Estimations. All the estimates are based on linear regressions of the outcome on the estimated individual coefficient of absolute risk aversion of the decision maker and the covariates included in Table A.3.

Table A.8: Relation between preferences and field behavior (using inverse probability weights to account for selection)

Variable	Age of first pregnancy	Age of marriage	No. soc. organizations	No. unhealthy habits	No. diseases	Asked for informal credit	Asked for formal credit	Used purchased seeds	Used purchased fertilizer
Number of risk averse decisions	-0.034	0.060**	-0.084***	-0.083***	-0.042	-0.028	-0.069*	0.036	0.103**
	[0.022]	[0.027]	[0.027]	[0.032]	[0.029]	[0.037]	[0.040]	[0.039]	[0.040]
	(0.122)	(0.027)	(0.002)	(0.010)	(0.156)	(0.445)	(0.083)	(0.351)	(0.011)
Male		0.159***	0.170***	0.367***	0.016	0.017	0.007	-0.142***	-0.127***
		[0.008]	[0.009]	[0.009]	[0.010]	[0.023]	[0.021]	[0.021]	[0.020]
		(0.000)	(0.000)	(0.000)	(0.124)	(0.459)	(0.740)	(0.000)	(0.000)
Age (log)	0.379***	0.365***	0.020*	-0.027**	0.113***	-0.043***	0.059***	0.105***	0.128***
	[0.011]	[0.013]	[0.011]	[0.012]	[0.011]	[0.015]	[0.014]	[0.014]	[0.014]
	(0.000)	(0.000)	(0.072)	(0.026)	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)
Non-Spanish speaker	0.003	-0.018	-0.072***	-0.218***	-0.046***	-0.025*	-0.074***	0.280***	0.295***
	[0.009]	[0.012]	[0.012]	[0.013]	[0.012]	[0.014]	[0.014]	[0.014]	[0.014]
	(0.751)	(0.152)	(0.000)	(0.000)	(0.000)	(0.069)	(0.000)	(0.000)	(0.000)
Non-Catholic	0.001	-0.002	0.263***	-0.131***	0.027**	0.011	0.038***	-0.014	-0.001
	[0.008]	[0.012]	[0.013]	[0.011]	[0.011]	[0.014]	[0.015]	[0.013]	[0.013]
	(0.929)	(0.866)	(0.000)	(0.000)	(0.017)	(0.425)	(0.009)	(0.288)	(0.934)
Years of schooling (log)	0.056***	0.117***	0.069***	-0.183***	-0.037***	0.016	0.081***	0.206***	0.203***
	[0.009]	[0.013]	[0.011]	[0.012]	[0.012]	[0.017]	[0.017]	[0.016]	[0.016]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.328)	(0.000)	(0.000)	(0.000)
Consumption (log)	-0.057***	-0.048***	-0.017	0.150***	0.028**	-0.012	0.112***	-0.125***	-0.082***
	[0.009]	[0.013]	[0.011]	[0.012]	[0.011]	[0.014]	[0.014]	[0.013]	[0.013]
	(0.000)	(0.000)	(0.108)	(0.000)	(0.015)	(0.414)	(0.000)	(0.000)	(0.000)
Observations	6,438	17,462	19,348	15,932	19,304	10,818	10,824	10,824	10,824
R-squared	0.301	0.166	0.109	0.223	0.020	0.003	0.033	0.133	0.125

Robust s.e. in brackets, p-values in parentheses. *** p<0.01, ** p<0.05, * p<0.10.
Definitions. Habits: smoking, drinking and chewing coca leaves. **Diseases**: Tuberculosis, yellow fever, pneumonia, influenza, cholera, malaria, hepatitis, typhoid.
Estimations. All the estimates are based on linear regressions of the outcome on number of safe decisions of the decision maker and the covariates included in Table A.3.

Table A.9: Relation between preferences and field behavior (Couples)

Variable	Age of first pregnancy	Age of marriage	No. soc. organizations	No. unhelathy habits	No. diseases	Asked for informal credit	Asked for formal credit	Used purchased seeds	Used purchased fertilizer
Husband's θ	-0.010	0.010	-0.046***	-0.096***	-0.027**	-0.037**	-0.011	0.035**	0.056***
	[0.010]	[0.011]	[0.012]	[0.013]	[0.012]	[0.018]	[0.018]	[0.017]	[0.018]
	(0.303)	(0.351)	(0.000)	(0.000)	(0.027)	(0.046)	(0.552)	(0.041)	(0.001)
Wife's θ	-0.017*	0.012	0.002	-0.047***	-0.005	-0.027	-0.013	0.035**	0.042**
	[0.010]	[0.011]	[0.012]	[0.012]	[0.012]	[0.018]	[0.018]	[0.016]	[0.017]
	(0.073)	(0.261)	(0.856)	(0.000)	(0.701)	(0.130)	(0.492)	(0.033)	(0.011)
Husband's ω	-0.003	0.023*	-0.027**	0.003	0.012	0.041**	-0.020	-0.026*	-0.028*
	[0.010]	[0.012]	[0.011]	[0.011]	[0.012]	[0.018]	[0.018]	[0.015]	[0.015]
	(0.754)	(0.050)	(0.015)	(0.815)	(0.286)	(0.024)	(0.278)	(0.083)	(0.059)
Wife's ω	0.000	0.002	-0.076***	-0.011	0.010	0.038**	0.011	-0.065***	-0.050***
	[0.010]	[0.011]	[0.012]	[0.011]	[0.011]	[0.018]	[0.018]	[0.015]	[0.015]
	(0.987)	(0.868)	(0.000)	(0.344)	(0.376)	(0.031)	(0.545)	(0.000)	(0.001)
Male	0.000***	0.169***	0.191***	0.361***	0.011	0.031	-0.037**	-0.120***	-0.115***
	[0.000]	[0.011]	[0.012]	[0.013]	[0.013]	[0.019]	[0.017]	[0.019]	[0.019]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.421)	(0.115)	(0.025)	(0.000)	(0.000)
Age (log)	0.507***	0.369***	0.016	-0.024*	0.105***	-0.022	0.061***	0.112***	0.123***
	[0.008]	[0.012]	[0.012]	[0.014]	[0.013]	[0.020]	[0.019]	[0.019]	[0.019]
	(0.000)	(0.000)	(0.165)	(0.077)	(0.000)	(0.268)	(0.001)	(0.000)	(0.000)
Non-Catholic	0.000	0.004	0.254***	-0.145***	0.036***	0.008	0.033*	0.001	0.015
	[0.009]	[0.012]	[0.012]	[0.012]	[0.013]	[0.019]	[0.019]	[0.017]	[0.017]
	(0.994)	(0.709)	(0.000)	(0.000)	(0.004)	(0.668)	(0.078)	(0.931)	(0.389)
Non-Spanish speaker	0.011	0.006	-0.086***	-0.242***	-0.047***	-0.002	-0.090***	0.309***	0.338***
	[0.010]	[0.012]	[0.012]	[0.014]	[0.013]	[0.018]	[0.018]	[0.018]	[0.018]
	(0.278)	(0.606)	(0.000)	(0.000)	(0.000)	(0.921)	(0.000)	(0.000)	(0.000)
Years of schooling (log)	0.096***	0.123***	0.057***	-0.179***	-0.025*	0.016	0.109***	0.216***	0.208***
	[0.010]	[0.014]	[0.012]	[0.014]	[0.014]	[0.024]	[0.022]	[0.023]	[0.023]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.071)	(0.490)	(0.000)	(0.000)	(0.000)
Consumption (log)	-0.102***	-0.041***	-0.014	0.174***	0.023*	-0.041**	0.106***	-0.134***	-0.070***
	[0.011]	[0.012]	[0.012]	[0.014]	[0.013]	[0.019]	[0.020]	[0.019]	[0.019]
	(0.000)	(0.001)	(0.222)	(0.000)	(0.071)	(0.034)	(0.000)	(0.000)	(0.000)
N	2382	6643	6774	5366	6759	3396	3397	3397	3397
R^2 including θ	0.536	0.180	0.136	0.274	0.021	0.011	0.037	0.157	0.158
R^2 excluding θ	0.533	0.178	0.121	0.244	0.019	0.003	0.035	0.148	0.145

Robust s.e. in brackets, p-values in parentheses. *** p<0.01, ** p<0.05, * p<0.10

Definitions. Habits: smoking, drinking and chewing coca leaves. **Diseases**: Tuberculosis, yellow fever, pneumonia, influenza, cholera, malaria, hepatitis, typhoid.

Estimations. All the estimates are based on linear regressions of the outcome on the estimated individual coefficient of absolute risk aversion of the husband and wife and the covariates included in Table A.3.

Table A.10: Relation between couples preferences and (log) value of household assets

	(1)	(2)	(3)	(4)
Husband's θ	-1.242**		-1.443**	-3.304***
	[0.566]		[0.574]	[0.989]
	(0.028)		(0.012)	(0.001)
Wife's θ	-0.271		-0.573	-1.757*
	[0.574]		[0.584]	[1.006]
	(0.636)		(0.327)	(0.081)
Husband's ω		0.172	0.232*	0.362***
		[0.123]	[0.125]	[0.136]
		(0.161)	(0.063)	(0.008)
Wife's ω		0.262**	0.288**	0.373***
		[0.123]	[0.125]	[0.137]
		(0.033)	(0.022)	(0.006)
Husband's $\theta \times$Husband's ω				5.266**
				[2.237]
				(0.019)
Wife's $\theta \times$Wife's ω				3.312
				[2.213]
				(0.135)
Male	-0.472	-0.503	-0.478	-0.483
	[0.393]	[0.392]	[0.392]	[0.392]
	(0.229)	(0.200)	(0.223)	(0.218)
Age	0.043**	0.046***	0.045**	0.046***
	[0.017]	[0.017]	[0.017]	[0.017]
	(0.013)	(0.009)	(0.010)	(0.008)
Age squared	-0.000	-0.000*	-0.000*	-0.000*
	[0.000]	[0.000]	[0.000]	[0.000]
	(0.103)	(0.075)	(0.085)	(0.070)
Non-Spanish speaker	-1.059***	-1.042***	-1.031***	-1.007***
	[0.076]	[0.077]	[0.077]	[0.077]
	(0.000)	(0.000)	(0.000)	(0.000)
Non-Catholic	-0.039	-0.038	-0.048	-0.054
	[0.101]	[0.101]	[0.101]	[0.101]
	(0.698)	(0.709)	(0.637)	(0.594)
Years of schooling (log)	0.095	0.091	0.098	0.089
	[0.067]	[0.067]	[0.067]	[0.067]
	(0.156)	(0.175)	(0.145)	(0.184)
Gross Income (log)	0.388***	0.396***	0.394***	0.392***
	[0.033]	[0.033]	[0.033]	[0.033]
	(0.000)	(0.000)	(0.000)	(0.000)
Number of children	0.005	0.006	0.005	0.003
	[0.023]	[0.023]	[0.023]	[0.023]
	(0.826)	(0.809)	(0.825)	(0.890)
Zero income	2.939***	2.897***	2.913***	2.895***
	[0.458]	[0.458]	[0.458]	[0.458]
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	3.306***	3.011***	2.923***	2.800***
	[0.581]	[0.592]	[0.592]	[0.593]
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3,136	3,136	3,136	3,136
R-squared	0.139	0.140	0.142	0.145

Robust s.e. in brackets, p-values in parentheses. *** p<0.01, ** p<0.05, * p<0.10.