Understanding the risk preferences of the poor

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Abstract

We investigate the extent to which economic experiments and choice models can characterize individual preferences in the presence of decision error and/or confusion. To do this, we use standard experimental methods to collect choices over risky outcomes in a representative sample of over 9,600 poor rural Peruvians, including couples and single individuals. Standard methods are challenging to implement in these populations because of low literacy and numeracy, but choice-based modelling can help purge these biases. Estimates of preferences that account for these biases are significantly correlated with field behavior across several domains (e.g. participating in formal or informal credit markets, agricultural production decisions, timing of first pregnancy) and personal characteristics while naive measures that ignore measurement error are not. We also find that a participant's propensity to choose at random predicts field behavior and is less frequent among those experiencing recent, bad shocks. The risk preferences of husbands and wives are positively and significantly correlated and both are correlated with the field behavior of the household. Our study highlights the importance of repeated individual measures of preferences and accounting for decision error.

JEL codes: XX, YY, C91

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1 Introduction

According to the World Bank, in 2013, almost 11% of the world population, or 767 million people, lived in poverty. It is important to gain a deeper understanding of how the poor make decisions and how that impacts life outcomes. Preferences and a lack of attention when making decisions can interact to produce suboptimal choices. In this paper, we use experimental methods to investigate this further by examining the way individuals make decisions involving risk. In particular, we use experiments to measure both risk preferences and consistency of behavior in a large and representative sample of 9,600 people living in poverty and extreme poverty in Peru. We demonstrate the empirical relevance of both risk preferences and consistency of behavior by showing their ability to predict actual field behavior. Importantly, we find that quality of decision making, as measured by the propensity to choose consistently, improves after experiencing recent bad events. Our study therefore demonstrates not only the empirical relevance of the quality of decision making, but also its responsiveness to environmental conditions.

Evidence from experimental economics 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). Moreover, several experimental studies show evidence consistent with elicitation method bias. The evidence is not conclusive due to the fact that different methods are not directly comparable. In particular, some methods allow subjects to act inconsistently while others do not. For instance, a subject might be asked to choose one out of six lotteries, varying their means and variances. A researcher observing a uniform distribution of choices over lotteries cannot distinguish if subjects choose completely at random or if preferences themselves are distributed uniformly. Worse yet, a researcher cannot use past studies to guide her inferences if these studies themselves are biased. To obtain robust evidence on the patterns of inconsistent behavior, our study elicits preferences using different methods. It does not force subjects to choose consistently in any of them. This design feature helps not only to better understand the biases in elicitation methods, but also to have robust individual measures of inconsistent behavior.

Identifying preferences and random behavior separately requires making structural assumptions. The statistical model we estimate has been used previously by von Gaudecker et al. (2011) and it is a version of the constant error model originally introduced in experimental research by Harless and Camerer (1994). The model allows for two sources of inconsistency: random utility and a propensity to choose at random. While simple by construction, the model is able to capture the basic patterns in our data.[1] We do not propose a new preference elicitation method, but rather exploit the potential biases of existing methods

[1]The data generated from our experiments are not rich enough to explore other models. While some authors disagree with the empirical relevance of the constant error model (Loomes, 2005), the model does provide a simple approach to inconsistency in behavior and can be applied to our data.

to better understand drivers behind observed behavior in experiments. The question we address is to what extent the combination of structural assumptions and existing experimental designs helps us minimize biases and deepens our understanding of the empirical relevance of inconsistency and preferences proper in decision making.

In our study, we have three main components. (1) We collect experimental measures on 9,600 individuals from a random sample of 12,000 poor and extremely poor Peruvian couples. (2) We randomly assign two elicitation tasks.[2] The use of a multiple price list (MPL), despite its ex-ante tendency to perform poorly in populations with lower levels of education, is a necessity to identify why preference elicitation methods that vary probabilities tend to be noisier. By design, the only difference in elicitation methods is whether prizes or probabilities vary. The MPL also varies whether all payoffs are positive or not. While the list of options within an MPL is held constant, the order in which the MPLs are presented is random. In the experiment, we randomly assign one of six combinations of MPLs to a participant. We also randomize whether lotteries were paid or not and the gender of the enumerator. Finally, because random assignment to elicitation tasks creates variation in the expected range of payments, we are able to test whether minimum payments for participation themselves affect the willingness to complete the experiment. To avoid contamination of the preference measurement of husbands and wives, couples made decisions in separate spaces and with different enumerators. (3) We adjust elicitation techniques to allow the researcher to observe the propensity of participants to choose at random. In our design we use relatively complex elicitation instruments. This provides a stress test of the approach we use in dealing with measurement error and bias.

The advantages of our approach are twofold. First, collecting data from a representative sample of the target population allows us to directly test the external validity of our study. Second, since different elicitation tasks should capture the same underlying preferences of the population, by randomly assigning elicitation methods and conditions to participants we can separate preferences from biases introduced by the elicitation method itself. This is our main identification strategy. While we can only identify the existence and size of the bias across methods, this approach identifies which methods are more prone to generate noisy behavior.

We have several key findings. First, measured preferences and the reliability of the measures are affected by the way preferences are elicited. Consistent with Holt and Laury (2002), participants in the paid condition behave more risk aversely than in the non-paid condition. The effect is equivalent to 14% of the standard deviation of the coefficient of relative aversion. Estimates of risk aversion are affected by whether the instrument has mixed payoffs (gains and losses) or not. Participants in mixed payoff lotteries are less risk averse than in all gain lotteries (7% percent of a standard deviation). Participants are

[2] In our study, each participant is asked to voluntarily complete two multiple price lists (MPL) with either 7 or 10 options. Each MPL varies either the lottery prizes and keeps the probability constant or varies the probability and keeps the prize constant.

more risk averse in gain lotteries that vary prizes but keep probabilities constant (95% of a standard deviation).

Second, we identify significant differences in the level of random behavior by whether options are presented with varying probabilities or varying prizes. Choices are noisier with varying prizes – the probability that a participant chooses at random when presented with a lottery with constant probabilities (and varying prizes) is 8.9 percentage points larger than with constant prizes. This argues against the notion that preferences are more likely to be revealed in instruments that prevent participants from making inconsistent choices.[3] There is random behavior in all elicitation tasks, and taking this noise into account can change conclusions about preferences. For example, in our sample, gender differences in risk aversion disappear once we account for the fact that women are more likely to choose at random than men.

Once the source of bias in the elicitation of preferences is identified, it is possible to estimate the posterior expected value of an individual's coefficient of relative risk aversion with a participant's actual choices and the elicitation task. That is, structural estimates allow us to diminish measurement error caused by the elicitation process and extract a measure of risk aversion. Note that this method takes advantage of the fact that the population level estimates reveal the ways preferences relate to the measurement instrument used.

The naive measures of risk preferences constructed from the experimental data tend to underestimate the correlation in individual preferences across experiments. Our method, by construction, allows us to test if preferences rather than the propensity to choose at random is what explains correlation in choices across experiments. With knowledge of the distribution of preferences, the propensity to choose at random in the population, and knowledge of the choices of a participant in two different instruments, we have two measures of individual preferences. While the naive measures of risk preferences are not significantly correlated, these constructed measures are.

Third, we find that the posterior estimate of an individual's coefficient of risk aversion is significantly correlated with a large range of field behavior including: time of first pregnancy; participation in social organizations and credit markets; production decisions and prevalence of unhealthy habits.[4] Some of the effects are large. For instance, a one SD increase in the coefficient of risk aversion is equivalent to over a two-fifths of a standard deviation decrease in the participation in credit markets. This finding demonstrates the empirical relevance of individual risk preferences on field behavior.

We test the robustness of our results using alternative methods to deal with noisy behav-

[3]It might be argued that we cannot conclude that estimates of preferences will be biased had consistency been enforced. We did not randomly assign participants to equivalent protocols in which consistency was enforced. However, we have collected direct evidence that behavior across elicitation tasks, each of which do not allow inconsistent choices, is no more likely to produce consistent behavior overall. Results are available from the authors upon request.

[4]By posterior estimate, we mean, the estimate of a parameter given the structural estimates, the prior, and the actual choices of the subject

ior. For instance, simply counting the number of risk averse decisions as a measure of risk preferences reproduces similar results, but they are not always significant. Similar results hold if we correct this naive estimate using instrumental variables (Gillen et al., 2015). The results improve once we treat decisions as a noisy measure of preferences. However, they are not as precise as the method we propose. This illustrates that the correlation between our proposed measures and field behavior is not simply due to the availability of a large sample. Other approaches, using the same data, do not correlate as strongly with field behavior.

Fourth, not only is our posterior estimate of risk preferences correlated with field behavior, so is the propensity to choose at random. The propensity to act randomly is higher among women, relatively less educated and older participants. Importantly, we find that those who had recently experienced a bad shock (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 these shocks affect preferences directly.

Finally, our study design 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. A permutation test of this correlation at the district level shows that this correlation is never significantly higher than the estimated ones. The preferences of couples in our sample are positively correlated.[5] In terms of field behavior, the preferences of husbands and wives are both relevant in decision making.

Our contribution lies in the random assignment of different elicitation instruments to different individuals of the same population and using an instrument that does not force participants to choose consistently. This procedure generates data that can be used to identify not only the propensity to choose at random, but also the biases introduced by different elicitation techniques. Ex-ante, it is unclear how these biases might affect the estimation of individual preferences or its relation to field behavior since previous designs do not allow a direct comparison between elicitation methods. Our paper is related to Kimball et al. (2006) and von Gaudecker et al. (2011). Kimball et al. (2006) show how structural estimation can be used to recover individual preference parameters. In their study, they estimate the level of error in the population as a whole and derive posteriors from estimated preference parameters and individual observed choices in hypothetical lotteries. We adopt their estimation approach in our paper to correct regression estimates using constructed individual preferences measures. von Gaudecker et al. (2011) propose a model of individual decision making that allows for decision error in addition to random utility, and we follow

[5] Our data, however, is not rich enough to determine if this is the result of sorting or co-habitation.

the same modelling approach.

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 and field behavior. Section 6 concludes.

2 Data collection

2.1 Experimental Design

To measure risk preferences we use 4 alternative multiple price lists (MPL). Two MPL keep the lottery prizes constant and vary the probabilities (Holt and Laury, 2002) and two MPL keep the lottery probabilities constant and vary the prizes (Binswanger, 1980).[6] Each type of lottery is further subdivided into lotteries with positive prizes and lotteries with positive and negative prizes. Table 1 shows the assignment of instruments to participants. In our study, we randomize whether the lottery was paid or not, the gender of the interviewer, and the combination of instruments to be used. Table 1 shows an uneven distribution of measurement conditions. This is due to two main reasons. First, with 4 different measurement instruments the total possible combinations of instruments and presentation orders is 24 ($4(instruments) \times 3 \times 2(orders)$). For practical reasons, we restricted the number of combinations to only 6. The second reason is that, due to budget limitations, only a subset of non-paid lottery combinations was implemented in the latter part of the survey collection.

Data collection required a series of steps. First, a pair of one male and one female enumerator is assigned to a set of households to be visited. Two enumerators per household were available thanks to the fact that husbands and wives responded to two different household surveys. Prior to visiting households a random assignment of measurement conditions is made. To maximize comparability within households, both husband and wife responded under the same experimental conditions. Upon arrival to a household, the enumerators flip a coin to determine who would interview the husband or wife. The gender of the enumerator is duly recorded.[7] Once the gender of the interviewer of the husband and wife is determined, couples are invited to participate in the experiment. A sample script, including instructions to enumerators, reads as follows:

{...
The text in brackets [] must not be read to participants
[Lotteries must be implemented before the household survey]

[6] Our design builds on the original design by Dave et al. (2010)

[7] Enumerators were trained in this task to secure that randomization was performed correctly.

[Before arriving to the household, the enumerators should flip a coin. If heads, the male enumerator implements the experiment with the husband and the female enumerator implements the experiment with the wife. If tails, the male enumerator implements the experiment with the wife and the female enumerator implements the experiment with the husband.]

"We would like to ask you a few questions about how you make decisions about money and risk. One in each 20 people responding to these questions will be compensated. The payment will depend on your answers but, on average, are around S/. 40 with a minimum 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].

Would you like to participate? Yes ☐ No ☐"

[If the answer is yes, implement the experiment. If the answer is no, continue with the household survey.]

[Enumerator:Read the following example and show the illustrations]

...}

Appendix A has a translation of all the instruments used in the experiment. We note that the minimum expected payment was a random variable since it depended on the instrument assigned to the couple. That means that, in principle, we could consider testing the effect of minimum payments on selection into experiments. In the hypothetical condition, participants were told the following,

{...

"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.

Would you like to participate? Yes ☐ No ☐"

[If the answer is yes, implement the experiment. If the answer is no, continue with the household survey.]

[Enumerator:Read the following example and show the illustrations]

...}

Figures 1 through 6 reproduce the options presented to participants. Note that Figures 1 through 3 are equivalent to Holt and Laury (2002) and Figures 1 & 2 are MPL versions of the design in Binswanger (1980). We do this to be able to evaluate the possibility that multiple option instruments hide noisy behavior. This design feature also allows us to compare both instruments on a similar footing.

Figure 1 shows the lottery with fixed probabilities, variable prizes and non-negative payoffs. Participants were asked to reveal whether option A or B was preferred or to reveal whether they were indifferent between the options. In this condition, lotteries start at a sure payment option (S/.28) and increase the mean and variance by subtracting S/.4 to the smallest prize and adding S/.8 to the highest prize. If the lottery was presented as a multiple choice condition, a participant would have to choose one out of 8 options. This condition would be an MPL representation of a multiple choice except for the fact that question 4 is modified to allow for the existence of a first order, stochastically dominated lottery. In decision 4, option A provides higher payoffs in all states of the world. Most theories of decision under risk exclude this possibility. Note, however, that this is a weak test of dominance since payoffs are relatively close. Figure 2 shows the lottery with mixed payoffs. In this condition the safest lottery pays nothing and successive lotteries are constructed by decreasing the lowest prize by -S/.3 and increasing the highest payoffs by S/.9. Figures 3-4 and Figures 5-6 show the lotteries with constant prizes and variable probabilities. Note that in both of these lotteries, the last decision corresponds to an obviously dominated option (B).

Participants in the paid conditions were informed that one of the decisions would be chosen at random to calculate payments. Depending on the instrument these could be 14, 17 or 20 separate lottery questions. Participants were shown the randomizing devices to be used in the selection of the question to be used for payment, the randomizing devices to resolve the lotteries, and the randomizing devices to resolve indifference if the participant expressed it.

An advantage of our design is that we obtain multiple measures of risk preferences for each individual. We show that this feature can be exploited to separate noisy behavior from preferences in the econometric model section. Each of the measurement instruments can identify a different range of utility parameters. For instance, let θ be the coefficient of absolute risk aversion of a participant. The instrument with fixed prizes, variable probabilities and non-negative payoffs can identify $\theta \in [-0.047, 0.0597]$, the instrument with fixed prizes, variable probabilities and mixed payoffs can identify $\theta \in [-0.0449, 0.0618]$, the instrument with fixed probabilities, variable prizes and non-negative payoffs can identify $\theta \in [0.000, 0.1205]$ and the instrument with fixed probabilities, variable prizes and mixed payoffs can identify $\theta \in [0.000, 0.2033]$.

2.2 Sample Selection

The experiment is part of a representative sample of Peruvian poor rural households. Thirteen thousand and 153 individuals were contacted of whom 12,576 (95.6%) were present. Table 2 provides descriptive statistics of the sample. Fifty-five percent of the sample are non-

Spanish speakers and 18.3 percent non-Catholic. The average number of years of schooling is 4.6 years, which is less than complete primary education. 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 have a source of water within the household and 78 percent cook using wood fire. Table 2 shows that participants are unlikely to take credit either formally (7.2 percent) or informally (9.6 percent). This confirms 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. We should remark that the decision to participate in the experiment was individual based since husbands and wives were recruited by separate enumerators. Table 3 presents marginals corresponding to probit regressions on whether the target participant was present and whether the participant agreed to participate in the experiment. Important for us, we observe that the decision to participate in the experiment is not independent on the characteristics of the participant or the instrument.

Male participants are almost 5 percentage points more likely to participate in the experiments. Non-Spanish speakers, non-Catholic participants, participants with no schooling, and poor participants 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. We, however, notice that some differential participation by instrument. We consider this to be a result of the fact that, in Northern Sierra departments, only 2 of the 6 possible instruments were used due to budgetary restrictions.[8] We find that the parameter associated with this instrument is half as large once those departments are excluded.

3 Theoretical Framework and Empirical Model

3.1 Utility Specification

We assume that individuals follow expected utility theory (EUT) when choosing among risky alternatives. Following von Gaudecker et al. (2011), we consider an exponential utility function.[9] The utility function is:

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

Where $x \in \mathbb{R}^+$ is the lottery prize and $\theta \in \mathbb{R}$ is the coefficient of absolute risk aversion

[8]The instrument using constant probabilities and variable prizes was implemented with 6,446 participants, the instrument using constant prizes and variable probabilities was implemented with 5,224 participants. The remaining 3,365 participants faced an instrument with constant probabilities and variable prizes and an instrument with constant prizes and variable probabilities. All the prizes in this last case were non-negative.

[9]we show in Appendix 7 that a power utility specification does not fit the data as well as an exponential utility specification.

(CARA). In the experiments, we assured individuals that they were never going to earn negative payoffs. Thus, we assume in this paper that individuals integrate the participation fee with the lottery outcomes. This implies that $x \in \mathbb{R}_+$. While this is immaterial in the case of 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 any 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, in the absence of any type of optimization errors:

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

To allow for stochastic decision-making we consider the possibility that individuals make two kinds of optimization errors. The first type of errors are modeled using the so-called "Fechner's error" specification (Loomes, 2005; Wilcox, 2008). In this specification, an individual's computation of subjective 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} are independent of each other and also of the random coefficients in utility specification.

The second type of optimization error we model 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. We model the propensity of an individual to choose randomly in any given task using a "trembling hand" parameter ω (Harless and Camerer, 1994; Moffatt and Peters, 2001; Wilcox, 2008). Figure 7 illustrates the stochastic decision making process of individuals.

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 the parameters. Given this specification of the decision making process, the likelihood of observed 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} of an individual i in choice situation j 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:

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

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

We have used a transformation using the cumulative logistic distribution function in the case of ω to restrict it to the interval $[0,1]$. 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. We assume 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 using simulations. We 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 simulated log-likelihood of the sample. Genetic algorithms are very effective in searching many peaks of the likelihood function based on a rich "population" of solutions, and thus reduce the probability of being trapped into a local maximum. Since they do not require the computation of gradients, they are computationally very efficient for a global search of the parameters.

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, evaluated on the simulated maximum likelihood estimates. Standard errors for transformed parameters are calculated using the delta method.

3.4 Posteriors

For a given individual, $F(\theta_i|X_i, \hat{\beta}^{\theta}, \hat{\Sigma})$ represents the population level distribution of 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 available information about a given individual's risk aversion parameter. We use the expected value of such posterior distribution of risk aversion to predict an individual's field behavior.

The expectation of posterior distribution is computed using 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 expectation of posterior of random choice propensity 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 Estimation Results

In this section we present the estimation results as described in the previous section. We first discuss the main patterns in the data and then discuss the parametric estimates and robustness of the results to alternative econometric specifications.

4.1 Main Patterns

We first assess the consistency of behavior across instruments. To do this, we measure the proportion of patterns that follow a threshold strategy given all patterns of behavior possible per elicitation instrument. A threshold strategy requires for the participant to switch between option A and B at most once. To make this concept implementable, we introduce the concept of a run. Table 4 presents the number of runs in the data. A run is a maximal sub-sequence of all left or all right choices. For example, say a participant chose AAABABBAAB when presented with 10 different lotteries. In this sequence, there are 6 runs: AAA,B,A,BB,AA,B. In all our experiments, behavior consistent with expected utility theory requires a minimum of 1 run and a maximum of 2 runs. More than 2 runs indicates the presence of optimization errors. The larger the number of runs the larger the magnitude of decision errors. We note, however, that one or two runs does not necessarily indicate a behavior consistent with expected utility and, thus, absence of optimization error. For instance, in a fixed-probability, variable prizes lottery a responder should not follow threshold strategies that switch from risk averse behavior to risk taking behavior. To make optimization error measured in number of runs comparable across different measurement instruments, we report normalized number of runs by dividing observed number of runs by maximum possible number of runs in a given instrument. The maximum possible number of runs is equal to the length of the MPL. Table 4 shows that the number of runs is larger in paid lotteries and for Spanish speakers. We also observe that fixed probabilities, variable prizes lotteries have relatively more runs than fixed prizes and variable probabilities lotteries.

Figure 8 shows the distribution of the distance to expected utility by instrument. We see that a sizable proportion of participants need none or one change to be consistent with expected utility. We also see that in each instrument there is a large portion of participants with a large number of inconsistent choices. For instance, we see that in the lotteries with fixed prizes, variable probabilities and non-negative payoffs over 50 percent of participants make decisions that need at most to change one choice to be consistent with expected utility. This proportion increases to almost 60 percent when the payoffs are mixed (upper right hand corner panel in Figure 8). Regarding lotteries with variable prizes, fixed probabilities and non-negative payoffs we see that almost 60 percent of participants need at most one choice to change to be consistent. A similar number is necessary in the corresponding lotteries with mixed payoffs. This suggests that a sizable portion of the population is close to rational, but another sizable portion of the population is close to random behavior.

Figure 9 presents the proportion of participants choosing option B by measurement instrument for all participants and Figure 10 presents the proportion of participants choosing option B by measurement instrument for the participants with at most 1 inconsistent choice. To understand these graphs, recall that decision 1 in the lotteries with fixed prizes start with a risky choice 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. In the lotteries with fixed probabilities, the first decision starts with the comparison of a sure payment and a lottery with larger mean and variance. As decisions progress, decisions 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 (permanently) to option A. This means that we should expect the proportion of options B chosen to decrease as decisions progress. This is the pattern we observe in the aggregate data. To test the presence of a trend in the probability of choosing option B, 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 fixed prizes, non-negative payoffs instrument; -0.025 (p-value<0.0001) for the fixed prizes, 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).

Figure 10 shows that these patterns of behavior are sharper in the population of participants that had at most 1 inconsistent choice.[10] Importantly, it shows that these participants recognized more frequently that option B in decision 4 in the fixed probability, non-negative payoffs instrument was dominated. Option B is chosen much less frequently in decision 4. For completeness, 11 shows the probability of choosing option B by those participants that had at least 2 inconsistencies. We observe that the pattern of behavior of these participants is not consistent with expected utility theory and closer to random.[11] This evidence supports our modelling assumption that participants either make decisions based on their preferences or choose at random.

[10]The trend is significant in each of the instruments: (-0.052 (p-value<0.0001) for the fixed prizes, non-negative payoffs instrument; -0.049 (p-value<0.0001) for the fixed prizes, 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).

[11]The trend is significant in each of the instruments: (0.007 (p-value<0.0001) for the fixed prizes, non-negative payoffs instrument; 0.009 (p-value<0.0001) for the fixed prizes, mixed payoffs instrument; 0.002 (p-value = 0.356) for the fixed probabilities, non-negative payoffs instrument; and 0.011 (p-value<0.0001) for the fixed probabilities, mixed payoffs instrument).

4.2 Parametric estimates

Table 5 presents the parametric estimates of the model with constant absolute risk aversion. The estimates of the coefficient of absolute risk aversion are presented under the heading θ and the estimates of the propensity to choose randomly are presented under the heading ω. Table 5 presents 2 versions of the model, *Minimal* estimates a mixed logit model without covariates and *Instrument* allows parameters θ and ω to depend on the 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 agree with the overall patterns of behavior in the data. As observed in the previous section, a sizable portion of participants do not seem to respond to preferences when deciding on what lotteries to choose.

Random assignment of elicitation instruments to participants allows us to identify biases in the measurement of preferences. Model *Instrument* present these results. We note that the estimated distribution of preferences is economically and statistically significantly affected by the elicitation instrument used. In 5, BW equal 1 if the lottery used keeps probabilities constant, GL equals 1 if the lotteries have mixed payoffs (positive and negative) and BW$\times$GL equals 1 if the lottery keeps the probabilities constant and uses mixed payoffs. This means that the omitted category is the lottery that varies probabilities and uses non-negative payoffs.

Table 5 shows that, depending of the instrument, a person can be estimated to be risk averse or risk taking. The difference in the coefficient of absolute risk aversion of a person in a fixed prize lottery is measured to be 0.095 larger than if measured with a fixed probability instrument. Consistent with loss aversion, we also find that a person will appear more risk averse in a mixed payoff lottery than in a non-negative payoff lottery (coefficient = 0.0068). This effect, however, does not seem to be uniform across measurement instruments. A person facing mixed payoffs instead of non-negative payoffs in a fixed probability condition will behave *less* risk averse (coefficient = -0.051). These effects are large.

The model *Instrument* also shows that the measurement error varies systematically across instruments. We observe that fixed probability lotteries are noisier (a 10 percent increase in the probability of choosing at random). This suggests that the multiple option version of this elicitation instrument might produce less reliable estimates of preferences. In other words, the simplicity of multiple option instruments might be less attractive if repeated measures are necessary to correct for measurement error. Finally, we see that mixed payoff lotteries dramatically reduce the level of noise in behavior. While this is a positive finding, we remark that allowing for losses might require the estimation of additional preference parameters. We will discuss this issue in more detail in the robustness section below.

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 also that collecting multiple measures of the same instrument also allows to separately identify the propensity of an instrument to generate random choice. To put this in perspective, while repeated measures of the same elicitation instrument allows us to identify the level of measurement error associated with a particular instrument, it is the collection of repeated measures of alternative measurement instruments that allows us to identify the biases on the measurement of preference parameters. In our design, we observe that the multiple price list presentation rather than the use of varying probabilities what explains noisy behavior. This, of course, does not imply that noisy behavior is absent in multiple choice instruments. Rather, we cannot detect it.

Table 6 shows that individual characteristics are related to the coefficient of risk aversion and to the probability of choosing randomly. This table presents regression results of the posterior estimates of the coefficient of absolute risk aversion and the propensity to make mistakes on individual characteristics. Older, richer and non-Catholic participants are relatively less risk averse and non-Spanish speakers and those in the paid lotteries are relatively more risk averse. This last result is consistent with the findings of Holt and Laury (2002).

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

Recent research in behavioral economics suggests that the quality of decision making might be affected by the level of scarcity experienced by an agent (Mullainathan and Shafir, 2013; Shah et al., 2015). Our study can look at this question directly. The experiments were part of a large study evaluating barriers to escape from poverty and collected a rich data set on individuals and their circumstances. We make two observations. First, non-Spanish speakers, by far the most disadvantaged population in Peru,[12] are significantly less likely to make decisions at random. 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 bad shock and it holds even when we restrict the estimation to those shocks that are not under the control of the agent.[13]

[12]Non-Spanish speakers in our sample are less educated (t-test = 11.7386, p-value < 0.0001), hold fewer assets (t-test = 11.7386, p-value < 0.0001), experience more negative shocks (t-test = -8.0245, p-value < 0.0001) and more bad acts of nature (t-test = -16.2603, p-value < 0.0001).

[13]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.

4.3 Robustness Checks

Table 19 presents the estimates of the model under the assumption that preferences over lotteries can be represented by a constant relative risk aversion (CRRA) utility function. We observe that the model with CRRA preferences has a poorer fit than the model with CARA preferences.[14] 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 worse than with a CARA, Table 19 reproduces most of the qualitative findings using a CARA utility function. Table 19 shows that participants appear more risk averse in constant probability and variable prizes instruments than in constant prizes and variable probability instruments. We also find that participants are less likely to choose at random in lotteries with mixed payoffs than in non-negative payoffs lotteries. The model using CRRA, however, shows that noisier behavior is more likely in the constant probability and variable prizes instrument than in the constant prizes and variable probabilities instrument.

4.4 Comparison with von Gaudecker et al. (2011)

Table 7 and Figure 12 present a comparison of our estimates in a sample of poor Peruvian rural households and the estimates of a similar model in a random sample of the urban population of the Netherlands. The two populations are comparable regarding the estimated parameter of absolute risk aversion. The Peruvian sample is less risk averse, but 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 larger propensity to choose at random. However, we should remark von Gaudecker et al. (2011) find that the propensity to choose at random for low income and wealthy participants is 40 percent at the median. Our sample is clearly composed of poor and low educated participants.

5 Evaluating structural estimates

In this section, we evaluate the structural estimates according to the ability to detect within person correlation of behavior across instruments, correlation with field behavior and correlation within couples.

[14] The difference in log likelihoods is 3690 for the *Minimal* and 4123 for the *Instrument* model. This represents about 4 percent changes in the likelihood functions. These differences are significant (Voung test, p-value < 0.01).

5.1 Within person correlation across instruments

We begin by evaluating the question of 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. Table 8 shows the correlation between measures of risk preferences across measurement instruments. The first four columns correlate the coefficients of absolute risk aversion based on only one measurement instrument with other estimates of the coefficient of absolute risk aversion using other measurement instruments and with the number of (consistent) safe decisions.[15] These correlations therefore show the relationship between alternative measures of preferences at the individual level. The last four columns repeat the analysis using the number of safe decisions as a measure of risk preferences.

The first thing to notice is that all the correlations in Table 8 are positive and significant (p-value < 0.001). However, the correlations vary greatly across instruments. First, holding constant whether probabilities or lottery prizes vary, we find that using mixed payoffs (gains and losses) reduces the correlation by over 60 percentage points in both instruments. Second, comparing fixed payments, variable probabilities and variable payments, fixed probability instruments produces an even lower correlation between instruments. This suggests that using fixed or variable probabilities have a larger impact on the measurement of preferences than the use of all gains or mixed payoff lotteries.

Table 8 highlights the importance of having repeated measures of preferences. One way to read these results is that we might 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. (2013) 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 8 shows the correlations between measures of risk attitudes based on the number of safe decisions. 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 sample sizes common in laboratory experiments. This highlights the benefits of accessing large samples in the presence of measurement error and instrument biases.

Finally, the bottom left-hand panel of Table 8 shows the correlation between the structural estimates and the number of safe decisions. If the number of safe decisions provides an unbiased estimate of individual preferences, we would expect that these correlations be close to 1. We observe that is not always the case and that in some cases correlations are far from 1. Overall, these results show that the number of safe decisions, while correlated with underlying preferences, does not completely eliminate measurement error. It would be

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

interesting to test 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.

5.2 Differences by gender

In this section we briefly review the evidence of gender difference in risk attitudes using different approaches. Table 9 shows average decisions of male and female participants according to different measures. The first row shows the percent of decisions that are consistent with risk neutrality. Fifty four percent of females decisions are consistent with risk neutrality while 55 percent of male decisions are consistent with risk neutrality. This difference is significant. The number of risk neutral decisions ignores that some participants are inconsistent with expected utility theory. 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 (as in the previous section). Using this alternative measure, we find that 52.73% of choices made by female participants are consistent with risk neutrality while 53.76% 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 9 shows the difference in the estimate coefficient of absolute risk aversion (parameter θ in Table 5). We observe no gender difference in this coefficient. This is similar to the results in Table 6. Importantly, the fourth row in Table 9 shows that there is a significant difference in the propensity of male and female participant to choose at random. Female participants are more likely to choose at random.

To test whether propensity to make mistakes 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. We find no gender difference in risk attitudes in the sample of participants with at most one decision not consistent with expected utility, while we 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 the table 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 to make decisions at random. We observe that female participants with relatively lower propensity to make decisions at random are less risk averse than male participants while the opposite is true for participants with relatively higher propensity to make decisions at random.

This simple exercise shows that the propensity to make mistakes can be confounded with the detection of gender differences in individual preferences. In our particular case, if the propensity to make decisions at random is correlated with individual characteristics and the propensity to make mistakes is correlated with the measurement of individual preferences, differences in the propensity to choose at random might be attributed to differences in individual preferences. Our estimation, however, shows that once this propensity to choose at random is taken into account, a clearer view of gender differences in risk attitudes can be obtained. The method, of course, is agnostic to whether these differences exist or not.

5.3 Field behavior

In this section 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 data independently from husbands and wives. We will first look at behavior at the individual level and later we will look at the behavior of couples. As in the previous section, the analysis uses as regressors the estimated posterior expected value of the parameter θ (see section 3.4).

Table 10 has descriptive statistics of the field behaviors we consider. As the Table 10 shows, not all these variables vary much across households. This is true for age of marriage and age at first pregnancy as well as production decisions. This might be a reflection of the fact that many of these households share similar backgrounds.

Table 11 presents linear regressions of several field behaviors on the estimated coefficient of absolute risk aversion of the person making a decision. That is, for decisions involving credit and production, the regressions are restricted to the person listed as the head of the household. To reduce the possibility of selecting only variables for which there is a significant relationship between risk parameters 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 5. Kimball et al. (2008) show how to use the GMM estimation method to eliminate the potential bias created by the correlation between the prediction error of the model of preferences and the included covariates. Table 11 uses consistent estimates of these regressions and provides corrected R-squared estimates.[16]

We find that the estimate of the individual coefficient of absolute risk aversion, θ, is correlated to several field behaviors and individual characteristics. Females that are relative more risk averse tend to have pregnancies at an earlier age. More risk averse individuals marry later, are less likely to participate in social groups, less likely to engage in unhealthy habits, less likely to suffer from diseases, less likely to ask for credit and more likely to use purchased seeds and fertilizer.[17]

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

[17] 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

All the variables in Table 11 are standardized and the last row in the table provides the 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. We observe that while the estimates of θ explain a small portion of the observed variables, the actual effect can be quite large. For instance, one S.D. 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 capture the same field behavior as the posteriors obtained from structural estimates. This is important since parametric estimates make identifying assumptions that might not be appropriate. Table 13 presents estimates with number of safe decisions as an alternative measure of risk aversion. To account for the possibility of errors in decision making, we consider the maximum number of safe decisions that are consistent with expected utility and minimize the distance between this pattern of behavior and the actual choices of participants. That is, we consider the maximum number of safe decisions that rationalize the data according to expected utility. We readily see that the results using this measure of risk aversion coincide with those already presented. However, we find that this measure of risk aversion is less likely to be statistically significant. This suggests that ad-hoc measures of risk aversion might not always account for measurement error. This result is consistent with Castillo et al. (2014) who show that structural estimates of childrens risk preferences outperform naive measures of risk aversion in predicting field behavior.

A recent alternative approach to deal with 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. This approach is clearly an improvement over a naive measure of risk aversion in that it deals directly with the measurement problem.

Table 14 presents results using the proposed method by Gillen et al. (2015). For the estimations, we count the number of risk neutral decisions chosen in each instrument separately. Since each participant answered two lottery questions, each participant has two independent measures of risk preferences. We observe that 14 reproduces the patterns of behavior already observed in Table 11 and Table 13. These estimates are less precise.

Perhaps more importantly, both alternative approaches do not directly deal with the fact that correlation between measures might be due to noisy behavior rather than due to underlying preferences. For instance, two instruments might over or underestimate risk aversion of a person choosing randomly. Correlation between measures might be due to the presence of a tendency to make mistakes rather than risk aversion. Depending of the context, this tendency to make mistakes might or might not be consistent with risk aversion.

is not the case 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.

The structural estimation, by construction, attempts to separate random decisions from preferences.

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 of an individual are given their choices in the experiment and the structural estimates of the model in the population.

Table 15 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 included covariates are the same as in Table 5.

We observe that the preference parameters of husbands and wives are positively and significantly correlated. Risk averse women are married[18] to relatively more risk averse men and women more likely to choose at random are married to men more likely to choose at random. One possible reason for this correlation is assortative matching based on economic characteristics. Research shows that people match in terms of income and abilities. This correlation might be therefore due to the fact that those marrying are likely to have similar backgrounds and face similar conditions. Table 15 shows that the positive correlation between the preference parameters of husbands and wives persists after including individual and household characteristics.[19] Both parameter estimates are barely changed. To test the robustness of the relationship between husbands' and wives' preferences, we reproduce the analysis in Table 15 under the assumption of constant relative risk averse preferences. Table 21 presents these results and demonstrates that the correlation between the parameters of preferences of husbands and wives are robust to functional form assumptions.

We can test if husbands and wives have correlated θ's and ω's simply because they share similar background by estimating the correlation of a man and woman paired at random. This permutation test shows that none out of 500 trials produces a correlation coefficient that exceeded the actual correlation between the preferences of husbands and wives. This result holds even if we restrict random matches to live in the same district of our sample.

We look now at the relationship between the preferences of husbands and wives on their field behavior. As mentioned before, husbands and wives participated in the experiment

[18] We include non-legal unions in this definition as well.

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

independently and in isolation.[20] We can then see to what extent their individual and group behavior is affected by each others preferences. Table 16 reproduces the analysis of 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. We remark 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.

16 shows that the timing of the first pregnancy is significantly related to the preferences of the wife rather than the husband. The direction reproduces that presented in Table 11. We observe that the preferences of both husbands and wives are important in production decisions. Table 16 presents estimates that control for the propensity to choose completely at random. We find that, in general, the estimates of these variables are similar in sign to the estimates on the coefficient of risk aversion. This is consistent with the hypothesis that the level of noisy behavior is in itself informative. Evidence of this has been provided in another developing context by Jacobson and Petrie (2009). Regarding the relative importance of the preferences of husbands and wives, they are both estimated to be important in the decisions of the household once the propensity to choose at random is controlled for.

6 Conclusion

In this paper, we assess the ability of experimental methods to accurately capture the risk preferences of poor populations and their relationship with actual field behavior. To do this, we take advantage of a unique data set that combines exogenously assigned experimental elicitation methods and survey data on households. The experimental tasks were designed to detect several potential sources of biases in the elicitation of preferences in the field and were careful to allow participants to express any desire to choose at random.

We find that while elicitation instruments can have measurement error and introduce biases, structural estimation methods can be successfully used to identify and correct for them. Without accounting for decision error and biases, naive measures of risk preferences are not informative in explaining field behavior. However, once error and biases are accounted for, individual estimates of risk preferences parameters do significantly explain field behavior. The estimated preferences of husbands and wives are significantly and positively correlated, and the preferences of husbands tend to dominate those of wives in household as well as individual decisions. The alternative approaches we tried that do not explicitly model the possibility of random decisions tend to underestimate the importance of risk preferences in field behavior and the correlation between repeated measures of individual preferences.

Our study shows that by preventing participants from expressing their desire to choose

[20] According to the reports by the enumerators, in many cases husbands were in the field while wives were at home.

randomly, researchers might lose a potentially rich alternative source of information on individual decision making. Variations in individual levels of optimization might be not only malleable but also predictive of behavior.

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7 Appendix

7.1 Empirical Identification & Specification Diagnostics

7.1.1 Empirical Identification of Minimal Model

To investigate the empirical identification of the econometric model we used in the Results section, we set up a Monte Carlo experiment. Following the procedure outlined in Cherchi and de Dios Ortúzar (2008), we simulated a collection of data sets following the decision making process outlined in Section 2. Ideally, we would like to simulate data sets involving 9,676 participants as in the original experimental data set. However, estimating the model over 50 large data sets would be prohibitive in terms of computational times. To keep computational time tractable, we simulated data sets of 900 individuals. Our original experimental data set involved individuals responding to 4 alternative MPLs. Two MPLs keep the lottery prizes constant and vary the probabilities (Holt and Laury, 2002) and two MPLs keep the lottery probabilities constant and vary the prizes (Binswanger, 1980). Each type of lottery is further subdivided into lotteries with positive prizes and lotteries with positive and negative prizes. Figures 1 through 6 reproduce the options presented to participants. Denote the instrument with variable prizes, fixed probabilities and positive prizes as VGG and the instrument with variable prizes, fixed probabilities and mixed payoffs as VGL. Similarly, Denote the instrument with fixed prizes, variable probabilities and positive prizes as FGG and the instrument with fixed prizes, variable probabilities and mixed payoffs as FGL.

We have used parameter estimates obtained using the minimal model estimation without any co-variates in Table 5 to generate artificial data sets. Monte Carlo procedure is as follows:

- **For each data set** i **in** [1..50]

  1. Assign VGG-VGL instrument combination to first 300 individuals, VGG-FGG to next 300 individuals and FGG-FGL to the last 300 individuals.
  2. **for each individual** j **in** [1...900]
     - Draw θ_j and ω_j from distributions specified by original parameters
     - Depending on instrument combination, generate corresponding series of choice situations involving binary lotteries
     - In each choice situation
       * compute expected utilities of two binary lotteries using θ_j
       * Add EV1 error to expected utility of each lottery and call it observed utility

* Draw a random number r from Uniform[0,1]. if $r < (1 - \omega_j)$ choose the lottery with higher observed utility. Otherwise, choose each lottery with equal probability.

3. Run estimation as outlined in Section 3.3 and collect the estimated parameters.

Table 17 summarizes results from the Monte Carlo experiment outlined above. It can be seen that the original parameters used in generating data are recovered very closely. However, in two instances, σ_θ and μ_ω, the recovered parameters seem to be statistically significantly different from true parameter values. While the t-tests show that we can reject the true parameter being the mean of the distribution represented by recovered parameters, we can observe that MSE ($bias^2 + variance$) is quite small in both cases. A possible explanation for these small deviations in the recovered parameters could be the size of the artificial data sets we used in the Monte Carlo experiment. With larger data sets, like the one we used in estimations in Section 2, that are of sizes ten times larger than artificial data sets these deviations may disappear.

7.1.2 Model Specification Diagnostics

In the previous subsection we outlined results from a Monte Carlo experiment that showed that true parameters of the data generating process can be recovered quite closely in the estimations.

The flexibility of mixed logit models also means that model misspecification errors are difficult to diagnose Revelt and Train (2000). Revelt and Train (2000) discuss a way to examine model misspecification in mixed logit models using individual-specific distributions of parameters. If a model is correctly specified and estimated, the conditional distributions of parameters, aggregated over all sampled participants, equals the population distributions of parameters. To see why this would be the case, let the true parameters be κ^* and the true frequency of responses y conditional on explanatory variables be $m(y|\kappa^*)$. If the model is correctly specified and consistently estimated $P(y|\hat{\kappa})$ approaches $m(y|\kappa^*)$ asymptotically, where $\hat{\kappa}$ is the empirical estimate of κ^*. Then, conditional on explanatory variables, the expected value of individual specific posterior distribution of parameters conditioned on data $h(\beta|y, \hat{\kappa})$ would be:

$$E_y h(\beta|y, \hat{\kappa}) = \sum_y \frac{P(y|\beta).g(\beta|\hat{\kappa})}{P(y|\hat{\kappa})} \rightarrow \sum_y P(y|\beta).g(\beta|\hat{\kappa}) = g(\beta|\hat{\kappa})$$

Thus if the average of the conditional distributions of the parameter are aggregated over all sampled participants and the population distributions of parameters are similar, it would indicate that model is correctly specified and accurately estimated. A large discrepancy would indicate specification error. The discrepancy between these distributions can also arise if the sample log-likelihood converged to a local maximum, which is also quite commonly observed in mixed logit model estimations. As discussed in the estimation section, we used a hybrid approach of maximization, combining genetic algorithm search and BFGS method to avoid convergence to local maximum of sample log-likelihood.

Table 18 summarizes posterior distributions of θ, ω conditioned on individual level choices. The mean of individual level $E(\theta)$ is very close to the population mean which is 0.01752. Also, its standard deviation is 0.05085, indicating that conditioning on individual specific choices captures more than half of the variability across individuals that is estimated at the population level. This, added with the average standard deviation of the individual level posterior θ distribution adds up close to the estimated population level variability. Similarly, the mean of the individual $E(\omega)$ is very close to the population mean which is 0.4900. Standard deviation of $E(\omega)$ across individuals combined with the average standard deviation of individual level posterior ω distribution adds up to reflect the population level standard deviation of ω very closely. These results indicate that there is no significant specification error involved with the model and that the estimation is accurate.

7.2 Alternative Utility Specification

$$U(x;\theta) = \frac{x^{1-\theta}}{1-\theta} \tag{12}$$

Estimating the unbounded distribution of θ using a normal distribution specification runs into numerical problems as the estimated standard deviation of θ was big. Following von Gaudecker et al. we constrained $|\theta| < 1$. This was achieved by using $\theta_i = 2(\Lambda(X_i^\theta \beta^\theta + \xi_i^\theta)) - 1$, where Λ is logistic transformation.

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

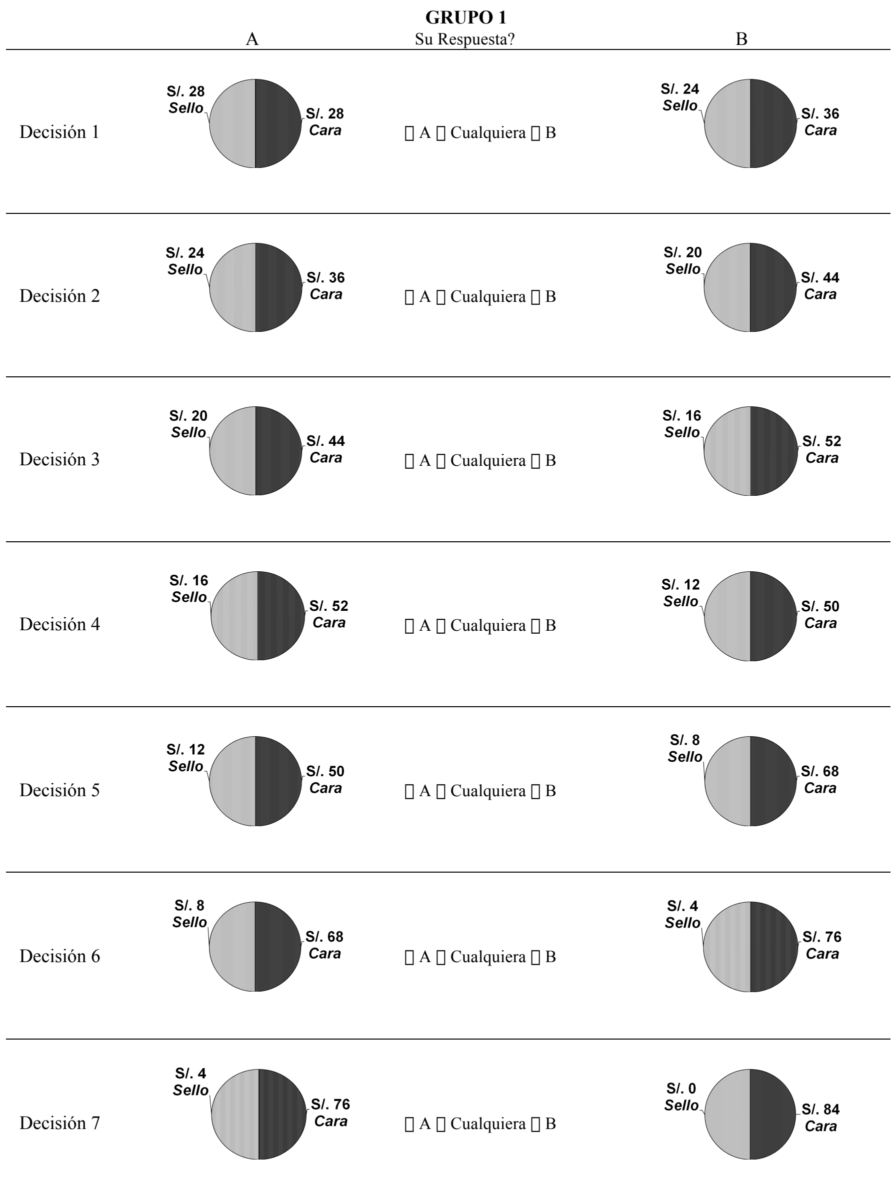


Figure 2: Fixed probabilities & variable prizes condition (Mixed payoffs)

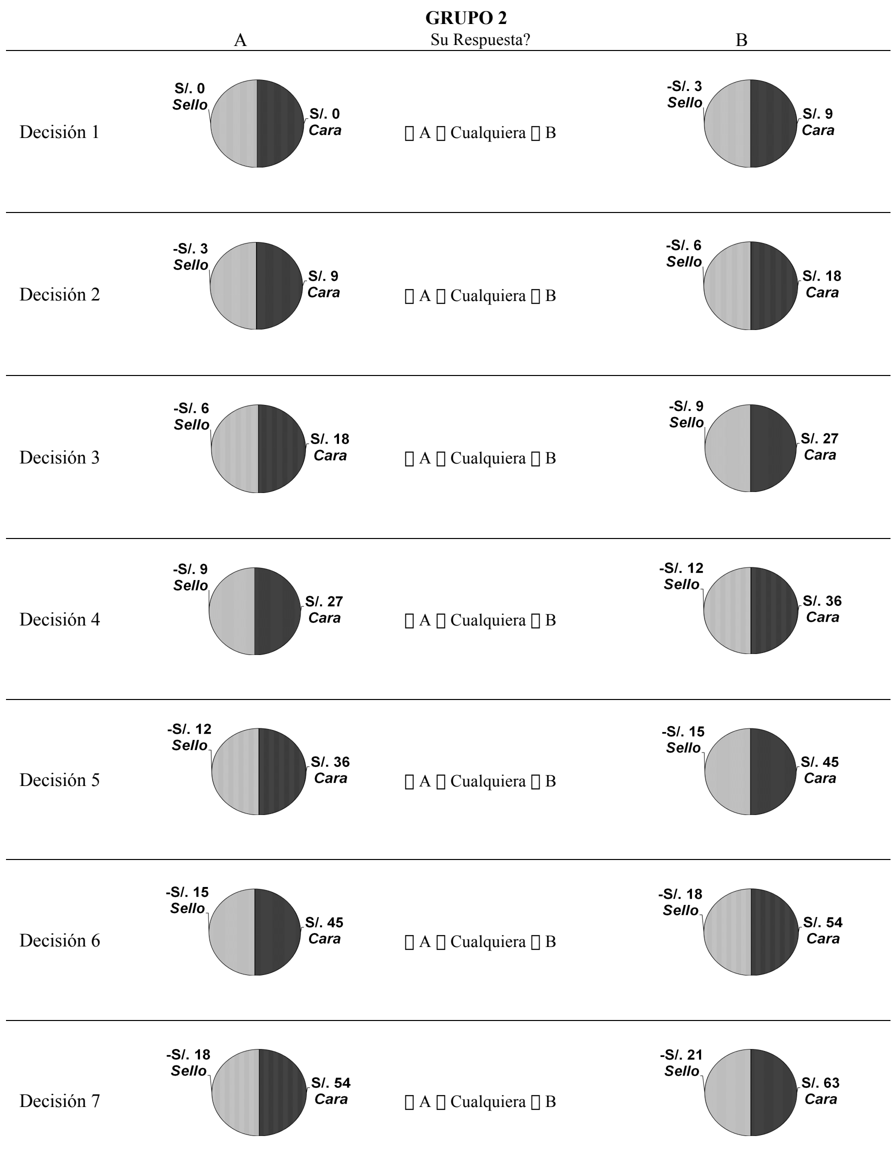


Figure 3: Fixed prizes & variable prob. condition (Non-negative payoffs)

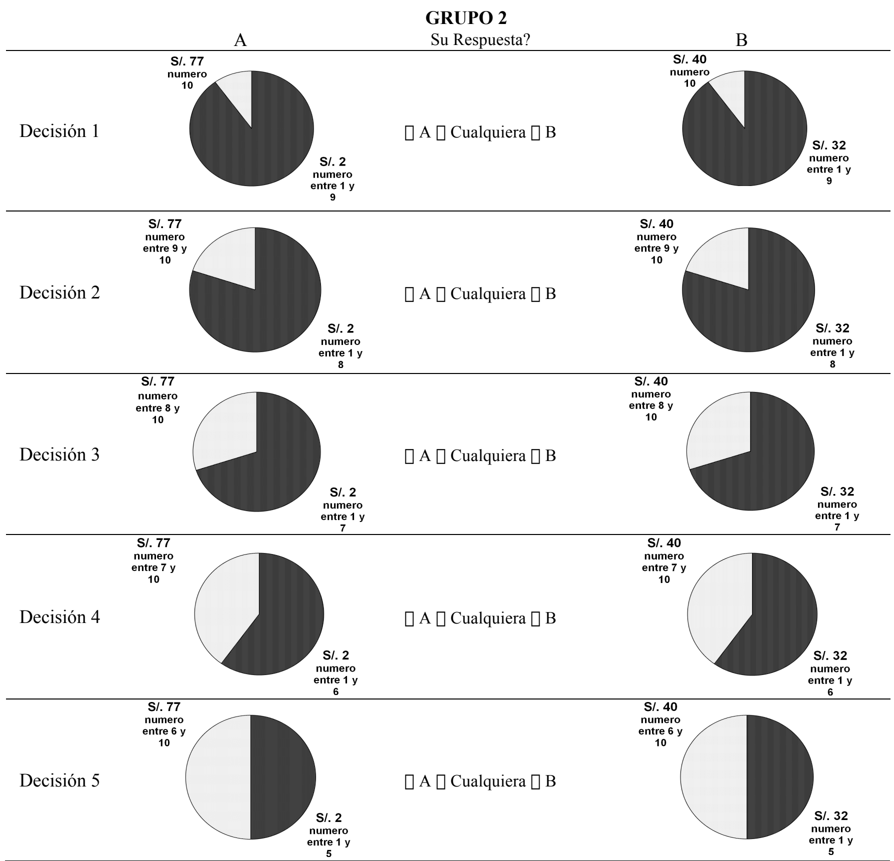


Figure 4: Fixed prizes & variable prob. condition (Non-negative payoffs)

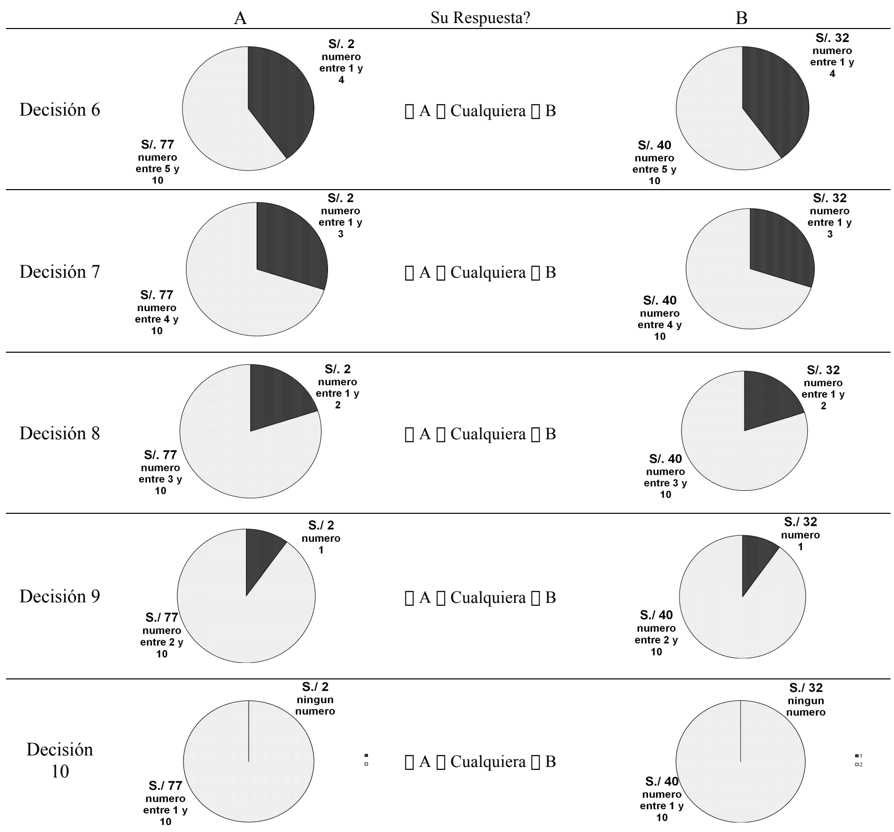


Figure 5: Fixed prizes & variable prob. condition (Mixed payoffs)

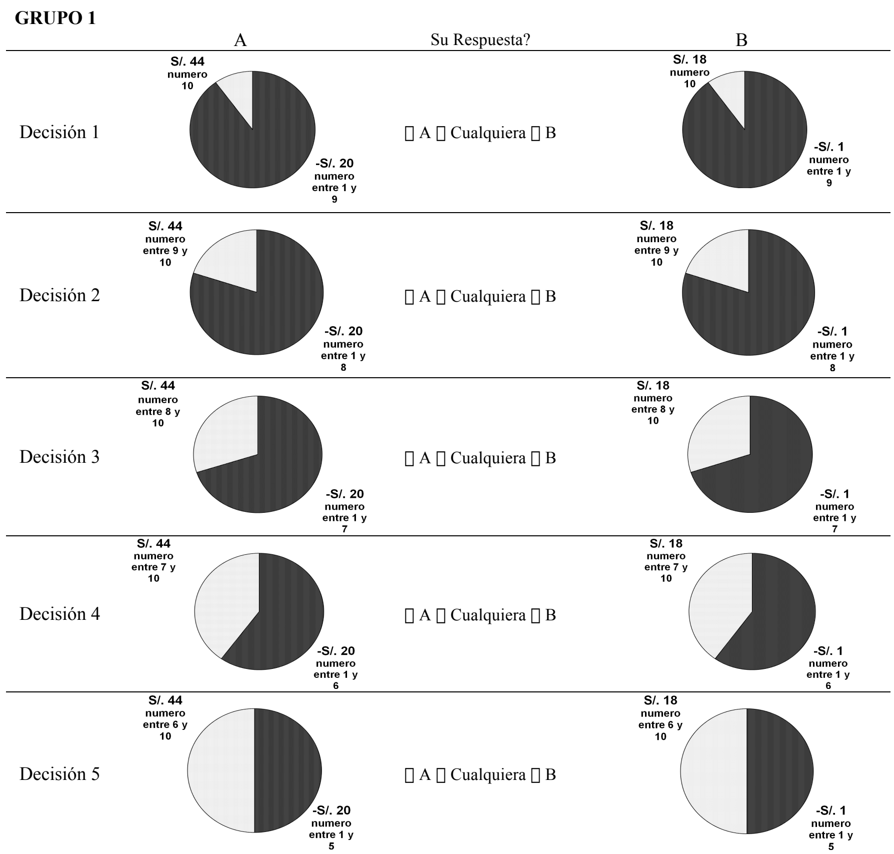


Figure 6: Fixed prizes & variable prob. condition (Mixed payoffs)

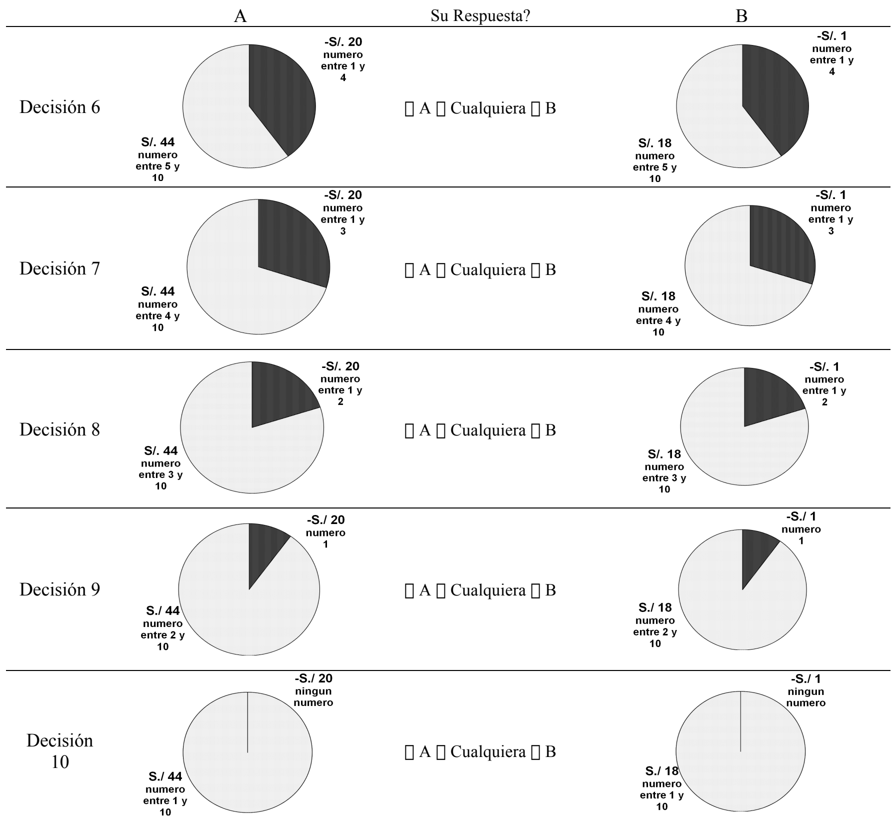


Figure 7: Decision tree

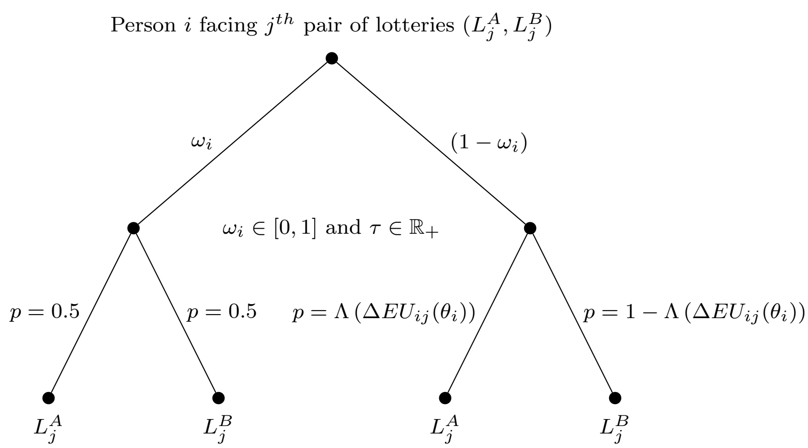


Figure 8: Distribution of inconsistent choices by instrument

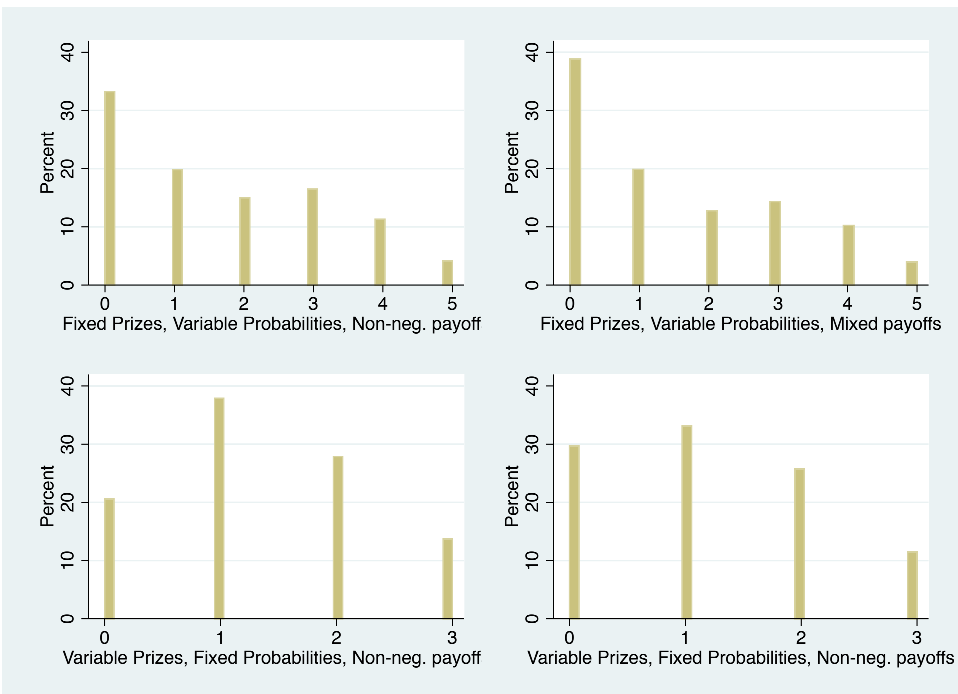


Figure 9: Proportion choosing option B by instrument - All participants

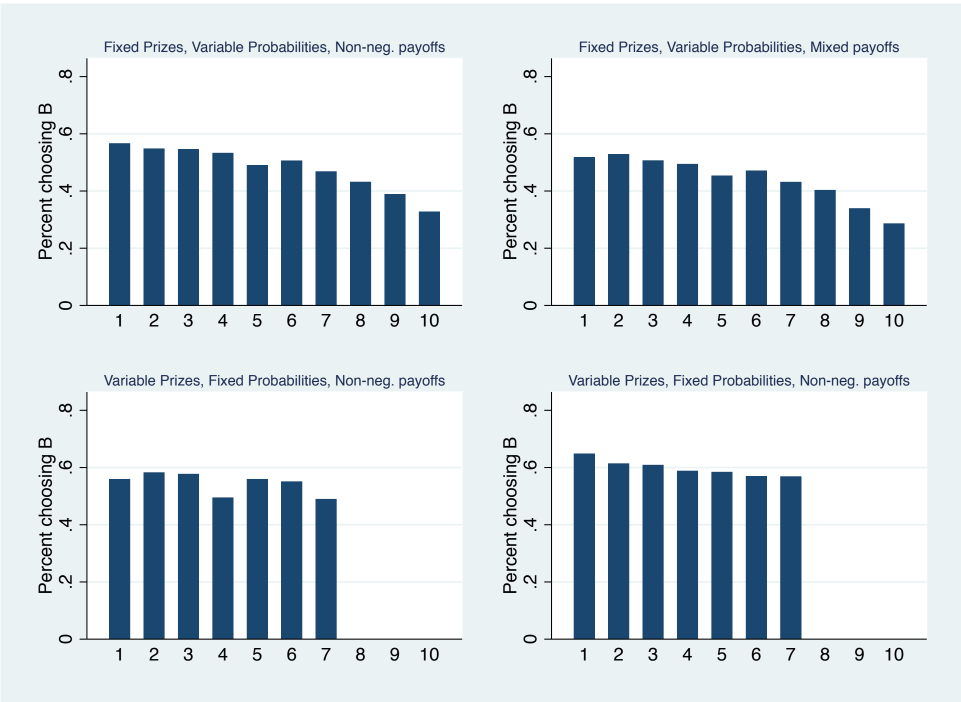


Figure 10: Proportion choosing option B by instrument - At most 1 inconsistency

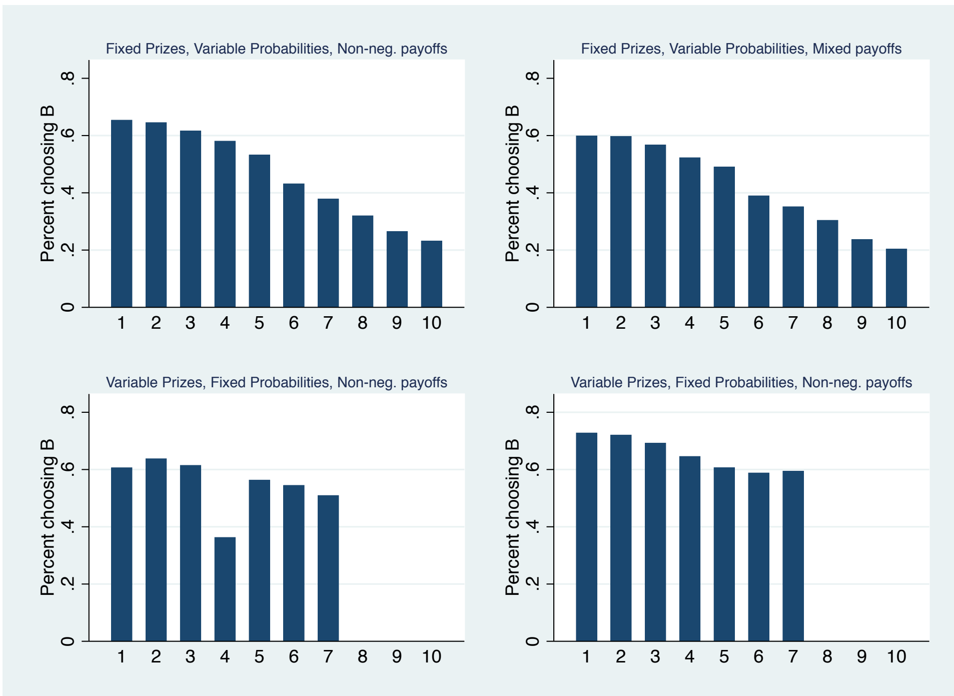
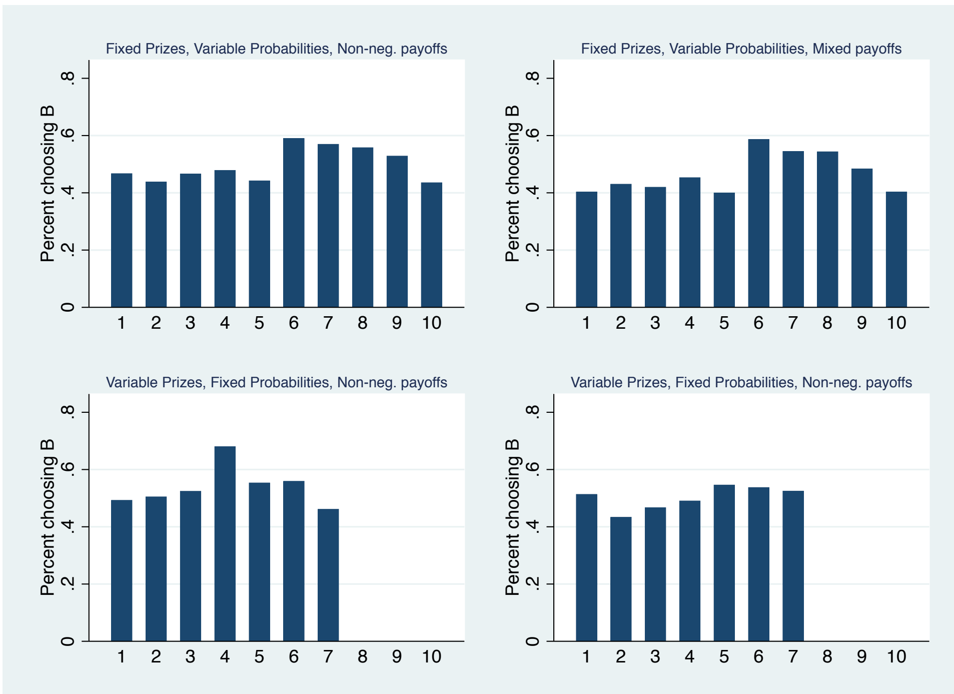


Figure 11: PROPORTION CHOOSING OPTION B BY INSTRUMENT - AT LEAST 2 INCONSISTENCIES



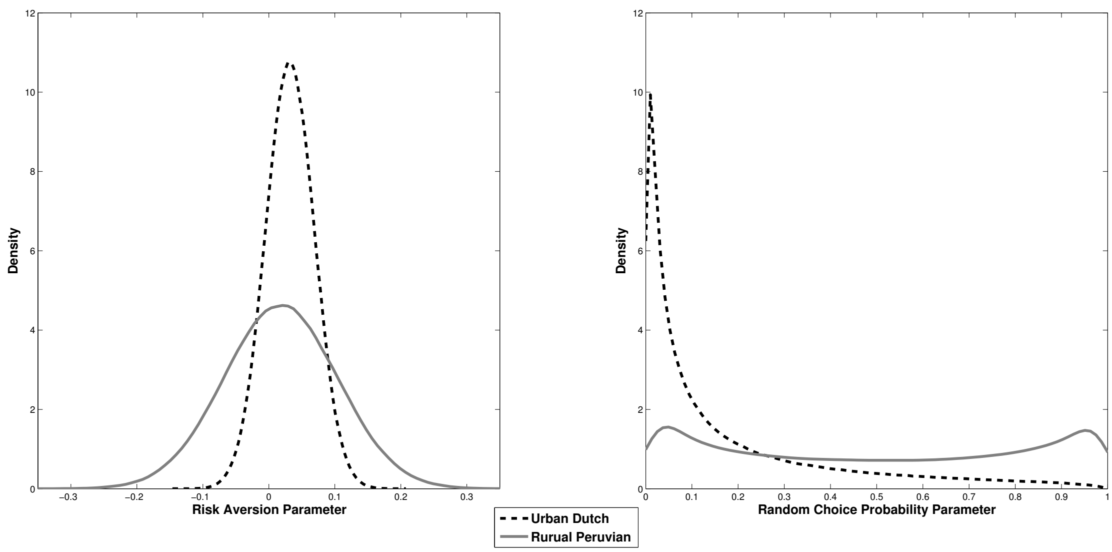


Figure 12: Comparing θ and ω of Rural Peru and Urban Dutch

Table 1: Measurement conditions assignment

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

Table 2: Descriptive statistics

	Mean	S.D.
Male	0.502	0.500
Age in years	43.742	14.766
Years of schooling	4.624	3.383
Non-Spanish speaker	0.5459	0.498
Non-Catholic	0.1830	0.387
Consumption (Monthly)	354.3	256.2
Age of marriage	23.09	6.67
Age of first pregnancy	24.51	7.10
Rooms	3.50	1.41
Adobe walls	0.884	0.320
Dirt floors	0.907	0.290
Water in house	0.252	0.434
Cooks with wood	0.784	0.412
Solicited informal credit	0.096	0.295
Solicited formal credit	0.072	0.258
Present at the time of interview	0.956	0.205
Agreed to participate in the experiment	0.770	0.421

Table 3: PROBIT REGRESSION ON PARTICIPATION ON 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)		
Prizes variable & probabilities constant	0.013***	0.103***
	(0.000)	(0.000)
Prizes constant & probabilities variable	-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 4: AVERAGE NUMBER OF RUNS OVER MAXIMAL NUMBER OF RUNS

	Fixed Prizes Variable probabilities		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
1^{st} Consumption quartile	0.34	0.32	0.42	0.39
2^{nd} Consumption quartile	0.34	0.33	0.43	0.40
3^{rd} Consumption quartile	0.37	0.35	0.44	0.42
4^{th} Consumption quartile	0.42	0.40	0.46	0.42
Total	0.36	0.35	0.44	0.41

Table 5: Estimation of θ and ω

	θ		ω	
	Minimal	Instrument	Minimal	Instrument
Constant	0.018***	-0.020***	0.49***	0.55***
	(0.0011)	(0.0009)	(0.011)	(0.10)
BW		0.095***		0.10***
		(0.0021)		(0.029)
GL		0.0068***		-0.34***
		(0.0008)		(-0.021)
BW×GL		-0.051***		-0.24***
		(0.0024)		(0.034)
σ	0.086***	0.099***	2.25***	3.01***
	(0.0020)	(0.017)	(0.061)	(0.10)
N	9676	9676	9676	9676
Log-Likelihood	97964	96376	97964	96376

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

Table 6: 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)	(9)	(10)
Male	-0.001	-0.000	-0.000	-0.000	-0.000	-0.014**	-0.013**	-0.013**	-0.013**	-0.013**
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]
	(0.684)	(0.749)	(0.743)	(0.749)	(0.750)	(0.036)	(0.044)	(0.047)	(0.040)	(0.041)
Age (log)	-0.002	-0.002	-0.002	-0.002	-0.002	-0.019*	-0.020*	-0.020*	-0.018*	-0.018*
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]
	(0.334)	(0.448)	(0.444)	(0.447)	(0.444)	(0.078)	(0.073)	(0.076)	(0.095)	(0.100)
Non-Spanish speaker	0.005***	0.005***	0.005***	0.005***	0.005***	-0.028***	-0.027***	-0.026***	-0.024***	-0.023***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)
Non-Catholic	-0.004*	-0.004*	-0.004**	-0.004*	-0.004*	0.003	0.003	0.004	0.004	0.004
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.009]	[0.009]	[0.009]	[0.009]	[0.009]
	(0.055)	(0.052)	(0.049)	(0.052)	(0.052)	(0.755)	(0.707)	(0.634)	(0.659)	(0.653)
Years of schooling (log)	-0.000	-0.000	-0.000	-0.000	-0.000	-0.021***	-0.021***	-0.021***	-0.020***	-0.020***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
	(0.819)	(0.890)	(0.886)	(0.888)	(0.884)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Consumption (log)	-0.001	-0.000	-0.000	-0.000	-0.000	0.003	0.003	0.003	0.003	0.002
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.005]	[0.006]	[0.006]	[0.006]	[0.006]
	(0.438)	(0.895)	(0.867)	(0.894)	(0.896)	(0.632)	(0.648)	(0.552)	(0.623)	(0.666)
Paid lotteries	0.013***	0.013***	0.014***	0.013***	0.013***	0.103***	0.104***	0.097***	0.095***	0.095***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.009]	[0.010]	[0.010]	[0.010]	[0.010]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Household assets (log)		-0.001***	-0.001***	-0.001***	-0.001***		-0.000	0.000	0.000	0.000
		[0.000]	[0.000]	[0.000]	[0.000]		[0.001]	[0.001]	[0.001]	[0.001]
		(0.003)	(0.002)	(0.003)	(0.003)		(0.926)	(0.859)	(0.983)	(0.908)
Number of bad shocks			0.001					-0.011***		
			[0.001]					[0.003]		
			(0.373)					(0.000)		
Acts of nature (drought, frost & mudslides)				0.000					-0.023***	
				[0.001]					[0.005]	
				(0.930)					(0.000)	
Acts of nature (0-1)					0.000					-0.031***
					[0.001]					[0.007]
					(0.831)					(0.000)
Observations	9,674	9,627	9,627	9,627	9,627	9,674	9,627	9,627	9,627	9,627
R-squared	0.006	0.007	0.007	0.007	0.007	0.022	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 7: 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 8: Within person correlation of measures of risk attitudes

	Instruments							
	Variable Payments Fixed Probabilities		Fixed Payments Variable Probabilities		Variable Payments Fixed Probabilities		Fixed Payments Variable Probabilities	
	Gains & Gains	*Gains & Losses*	*Gains & Gains*	*Gains & Losses*	*Gains & Gains*	*Gains & Losses*	*Gains & Gains*	*Gains & Losses*
		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 9: Differences in risk attitudes by gender

	Female ($N = 4722$) Mean (s.e.)	Male ($N = 4952$) Mean (s.e.)	t-test (p-value)
Percent of risk neutral decisions	54.40 (0.31)	55.31 (0.31)	-2.08 (0.0368)
Percent of risk neutral decisions in closest consistent pattern	52.73 (0.41)	53.76 (0.34)	-1.80 (0.0717)
Coefficient of Absolute risk aversion (θ)	-0.020 (0.0009)	-0.020 (0.0010)	-0.05 (0.9598)
Minimum number of switches necessary for consistency	1.92 (0.018)	1.82 (0.017)	3.96 (0.0001)
Propensity to choose at random (ω)	58.63 (0.45)	52.01 (0.45)	10.42 (0.0000)
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)
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)
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)
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 10: 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	5,409	0.11	0.31
Asked formal credit	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	5,412	0.79	0.41
Purchased fertilizer	5,412	0.83	0.38

Table 11: 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.)	-0.022***	0.019**	-0.025**	-0.067***	-0.014	-0.020	-0.027*	0.037***	0.054***
	[0.009]	[0.009]	[0.010]	[0.010]	[0.010]	[0.014]	[0.014]	[0.013]	[0.013]
	(0.009)	(0.049)	(0.014)	(0.000)	(0.184)	(0.147)	(0.050)	(0.003)	(0.000)
Male		0.160***	0.171***	0.366***	0.016	0.006	-0.024*	-0.094***	-0.091***
		[0.010]	[0.010]	[0.011]	[0.011]	[0.015]	[0.014]	[0.015]	[0.015]
		(0.000)	(0.000)	(0.000)	(0.151)	(0.697)	(0.082)	(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)	(0.035)	(0.022)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)
Non-Catholic	0.001	-0.001	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]
	(0.895)	(0.884)	(0.000)	(0.000)	(0.010)	(0.479)	(0.011)	(0.373)	(0.861)
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]
	(0.801)	(0.090)	(0.000)	(0.000)	(0.000)	(0.075)	(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	0.114***	-0.129***	-0.084***
	[0.010]	[0.011]	[0.010]	[0.010]	[0.011]	[0.014]	[0.014]	[0.013]	[0.013]
	(0.000)	(0.000)	(0.081)	(0.000)	(0.009)	(0.434)	(0.000)	(0.000)	(0.000)
N	3219	8731	9674	7966	9652	5409	5412	5412	5412
R^2 including θ	0.512	0.168	0.113	0.236	0.022	0.004	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 of the husband and wife, the estimated individual propensity to choose at random by husbands and wives (not shown) and all the covariates included in Table 6 (not shown).

Table 12: 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.)	-0.022**	0.016*	-0.018*	-0.066***	-0.015	-0.023*	-0.025*	0.039***	0.056***
	[0.009]	[0.010]	[0.010]	[0.010]	[0.010]	[0.014]	[0.014]	[0.012]	[0.013]
	(0.011)	(0.085)	(0.071)	(0.000)	(0.132)	(0.093)	(0.069)	(0.002)	(0.000)
ω (prob. random choice)	-0.003	0.019*	-0.059***	-0.016*	0.016*	0.031**	-0.020	-0.023**	-0.022**
	[0.009]	[0.010]	[0.010]	[0.009]	[0.009]	[0.013]	[0.013]	[0.011]	[0.011]
	(0.744)	(0.057)	(0.000)	(0.084)	(0.095)	(0.021)	(0.126)	(0.035)	(0.035)
Male		0.160***	0.168***	0.366***	0.016	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)	(0.138)	(0.634)	(0.071)	(0.000)	(0.000)
Age (log)	0.505***	0.363***	0.021**	-0.024**	0.114***	-0.045***	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)	(0.035)	(0.022)	(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	0.002
	[0.008]	[0.010]	[0.011]	[0.009]	[0.010]	[0.014]	[0.015]	[0.013]	[0.013]
	(0.898)	(0.863)	(0.000)	(0.000)	(0.011)	(0.480)	(0.011)	(0.373)	(0.860)
Non-Spanish speaker	0.002	-0.016	-0.078***	-0.218***	-0.044***	-0.020	-0.077***	0.275***	0.291***
	[0.009]	[0.010]	[0.010]	[0.011]	[0.011]	[0.014]	[0.014]	[0.014]	[0.014]
	(0.823)	(0.131)	(0.000)	(0.000)	(0.000)	(0.139)	(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)	(0.283)	(0.000)	(0.000)	(0.000)
Consumption (log)	-0.097***	-0.048***	-0.015	0.150***	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)	(0.391)	(0.000)	(0.000)	(0.000)
N	3219	8731	9674	7966	9652	5409	5412	5412	5412
R^2 including $\theta\&\omega$	0.512	0.168	0.117	0.237	0.022	0.005	0.037	0.136	0.136
R^2 excluding $\theta\&\omega$	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 of the husband and wife, the estimated individual propensity to choose at random by husbands and wives (not shown) and all the covariates included in Table 6 (not shown).

Table 13: 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	-0.009	0.006	-0.025**	-0.063***	0.009	-0.001	-0.011	0.039***	0.043***
	[0.009]	[0.010]	[0.010]	[0.010]	[0.010]	[0.014]	[0.013]	[0.013]	[0.013]
	(0.336)	(0.525)	(0.010)	(0.000)	(0.354)	(0.926)	(0.416)	(0.002)	(0.001)
Male		0.159***	0.171***	0.366***	0.017	0.006	-0.023	-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)	(0.682)	(0.104)	(0.000)	(0.000)
Age (log)	0.536***	0.363***	0.021**	-0.024**	0.114***	-0.044***	0.055***	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)	(0.025)	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)
Non-Catholic	0.003	-0.002	0.263***	-0.133***	0.028***	0.011	0.038***	-0.013	0.000
	[0.009]	[0.010]	[0.010]	[0.010]	[0.010]	[0.014]	[0.013]	[0.013]	[0.013]
	(0.745)	(0.799)	(0.000)	(0.000)	(0.006)	(0.407)	(0.004)	(0.330)	(0.999)
Non-Spanish speaker	-0.007	-0.016	-0.074***	-0.219***	-0.047***	-0.026*	-0.076***	0.281***	0.297***
	[0.010]	[0.010]	[0.010]	[0.011]	[0.011]	[0.014]	[0.014]	[0.013]	[0.013]
	(0.461)	(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***	0.017	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)	(0.337)	(0.000)	(0.000)	(0.000)
Consumption (log)	-0.087***	-0.048***	-0.017*	0.149***	0.028***	-0.011	0.114***	-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)	(0.094)	(0.000)	(0.009)	(0.442)	(0.000)	(0.000)	(0.000)
Male		0.159***	0.171***	0.366***	0.017	0.006	-0.023	-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)	(0.682)	(0.104)	(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

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, the estimated individual propensity to choose at random by husbands and wives (not shown) and all the covariates included in Table 6 (not shown).

Table 14: Relation between preferences and field behavior (IV approach)

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 the estimated individual coefficient of absolute risk aversion of the husband and wife, the estimated individual propensity to choose at random by husbands and wives (not shown) and all the covariates included in Table 6 (not shown).

Table 15: Relation between the preferences of husbands and wives

VARIABLES	(1) Wifes θ (CARA coeff.) No covariates	(2) With covariates	(3) Wife's ω (prob. random choice) No covariates	(4) 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 5.

Table 16: Relation between preferences and field behavior for 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, the estimated individual propensity to choose at random by husbands and wives (not shown) and all the covariates included in Table 6 (not shown).

Table 17: Identification Results for Minimal Model

Parameter	True	Recovered†	Bias	T-stat	Cohen's d	MSE
σ_θ	0.0855	0.091	0.0055	3.634***	0.515	0.000146
σ_ω	2.253	2.250	-0.002	-0.0794	-0.011	0.0589
μ_θ	0.0175	0.0185	0.0011	0.990	0.140	5.83e-05
μ_ω	-0.395 (0.490)	0.0681 (0.516)	0.517(0.0268)	4.56***	0.645	0.0395

Notes:
1. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$
2. In brackets transformed median value
3. † These are means of recovered parameters from 50 datasets

Table 18: Expected Values of Parameters Conditional on Individuals' Choices and the Point Estimates of the Population Parameters

Posterior $E(\beta)$:	
Mean	0.01746
Standard Deviation	0.05085
Posterior $SD(\beta)$:	
Mean	0.06549
Posterior $E(\omega)$:	
Mean	0.4917
Standard Deviation	1.3276
Posterior $SD(\omega)$:	
Mean	1.7771

Table 19: Estimation of θ and ω: Power Utility Specification in (9)

	θ		ω	
	Minimal	Instrument	Minimal	Instrument
Constant	0.56***	0.086	0.60***	0.81***
	(0.044)	(0.070)	(0.010)	(0.011)
BW		0.86***		-0.17***
		(0.064)		(0.030)
GL		0.10***		-0.38***
		(0.029)		(-0.019)
BW×GL		-1.013***		0.034**
		(0.063)		(0.016)
σ	6.00***	6.07 ***	1.85***	2.16***
	(0.30)	(0.37)	(0.066)	(0.078)
N	9676	9676	9676	9676
Log-Likelihood	101654	100499	101654	100499

$*p < 0.1, **p < 0.05, ***p < 0.01$
Standard errors are computed using outer product of gradients

Table 20: Determinants of individual preferences - CRRA

	Coefficient of absolute risk aversion (θ)					Propensity to choose at random (ω)				
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Male	-0.016	-0.014	-0.014	-0.014	-0.014	-0.010**	-0.010**	-0.009**	-0.010**	-0.010**
	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
	(0.361)	(0.405)	(0.409)	(0.402)	(0.403)	(0.020)	(0.025)	(0.027)	(0.023)	(0.024)
Age (log)	-0.026	-0.019	-0.019	-0.019	-0.019	-0.015**	-0.015**	-0.015**	-0.014**	-0.014**
	[0.028]	[0.028]	[0.028]	[0.028]	[0.028]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]
	(0.350)	(0.487)	(0.490)	(0.500)	(0.499)	(0.029)	(0.028)	(0.030)	(0.038)	(0.036)
Non-Spanish speaker	0.076***	0.069***	0.070***	0.070***	0.070***	-0.012***	-0.011**	-0.010**	-0.009*	-0.009*
	[0.018]	[0.019]	[0.019]	[0.019]	[0.019]	[0.004]	[0.005]	[0.005]	[0.005]	[0.005]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.009)	(0.019)	(0.031)	(0.058)	(0.056)
Non-Catholic	-0.027	-0.028	-0.027	-0.028	-0.028	0.004	0.004	0.005	0.004	0.004
	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
	(0.234)	(0.222)	(0.232)	(0.226)	(0.226)	(0.487)	(0.456)	(0.392)	(0.418)	(0.427)
Years of schooling (log)	0.004	0.006	0.006	0.006	0.006	-0.013***	-0.013***	-0.013***	-0.013***	-0.013***
	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
	(0.736)	(0.657)	(0.654)	(0.643)	(0.645)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Consumo (log)	-0.010	0.002	0.003	0.002	0.002	0.005	0.005	0.006	0.005	0.005
	[0.014]	[0.014]	[0.014]	[0.014]	[0.014]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
	(0.480)	(0.863)	(0.834)	(0.859)	(0.866)	(0.125)	(0.152)	(0.113)	(0.142)	(0.157)
Paid lotteries	0.195***	0.199***	0.195***	0.196***	0.197***	0.038***	0.039***	0.035***	0.034***	0.035***
	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Household assets (log)		-0.012***	-0.012***	-0.012***	-0.012***		-0.000	0.000	0.000	0.000
		[0.003]	[0.003]	[0.003]	[0.003]		[0.001]	[0.001]	[0.001]	[0.001]
		(0.000)	(0.000)	(0.000)	(0.000)		(0.984)	(0.769)	(0.923)	(0.900)
Number of bad shocks			-0.008					-0.008***		
			[0.008]					[0.002]		
			(0.360)					(0.000)		
Acts of nature				-0.009					-0.014***	
				[0.013]					[0.003]	
				(0.486)					(0.000)	
Acts of nature (0-1)					-0.010					-0.013***
					[0.018]					[0.004]
					(0.598)					(0.003)
Observations	9,674	9,627	9,627	9,627	9,627	9,674	9,627	9,627	9,627	9,627
R-squared	0.008	0.011	0.011	0.011	0.011	0.010	0.010	0.012	0.012	0.011

Robust s.e. in brackets, p-values in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.10$

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

Table 21: Relation between the preferences of husbands and wives - power utility

	(1)	(2)	(3)	(4)
VARIABLES	Wifes θ		Wive's ω	
	No covariates	With covariates	No covariates	With covariates
Husbands's θ	0.1265***	0.1252***		
	(0.000)	(0.000)		
Husband's ω			0.1144***	0.1103***
			(0.000)	(0.000)
Observations	3,387	3,387	3,387	3,387
R-squared	0.022	0.073	0.025	0.096

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 19.

Table 22: Relation between preferences and field behavior - CRRA

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 (CRRA coeff.)	-0.023**	0.014	-0.018*	-0.075***	-0.012	-0.025*	-0.015	0.059***	0.068***
	[0.009]	[0.010]	[0.010]	[0.010]	[0.010]	[0.014]	[0.013]	[0.013]	[0.013]
	(0.010)	(0.151)	(0.081)	(0.000)	(0.237)	(0.073)	(0.253)	(0.000)	(0.000)
ω	0.005	0.009	-0.043***	0.014	0.007	0.036***	-0.034**	-0.046***	-0.032***
	[0.009]	[0.010]	[0.010]	[0.010]	[0.010]	[0.012]	[0.014]	[0.011]	[0.011]
	(0.617)	(0.394)	(0.000)	(0.152)	(0.513)	(0.004)	(0.014)	(0.000)	(0.004)
Male		0.160***	0.168***	0.367***	0.017	0.009	-0.026*	-0.097***	-0.094***
		[0.010]	[0.010]	[0.011]	[0.011]	[0.015]	[0.014]	[0.015]	[0.015]
		(0.000)	(0.000)	(0.000)	(0.137)	(0.557)	(0.053)	(0.000)	(0.000)
Age (log)	0.506***	0.364***	0.020**	-0.024**	0.114***	-0.044***	0.055***	0.110***	0.131***
	[0.008]	[0.011]	[0.010]	[0.011]	[0.011]	[0.014]	[0.014]	[0.013]	[0.013]
	(0.000)	(0.000)	(0.049)	(0.023)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)
Non-Catholic	0.002	-0.002	0.264***	-0.132***	0.027***	0.011	0.038***	-0.013	0.000
	[0.008]	[0.010]	[0.011]	[0.009]	[0.010]	[0.014]	[0.015]	[0.013]	[0.013]
	(0.802)	(0.805)	(0.000)	(0.000)	(0.009)	(0.436)	(0.008)	(0.311)	(0.975)
Non-Spanish speaker	0.003	-0.016	-0.077***	-0.215***	-0.046***	-0.020	-0.080***	0.273***	0.291***
	[0.009]	[0.010]	[0.010]	[0.011]	[0.011]	[0.014]	[0.014]	[0.014]	[0.014]
	(0.753)	(0.121)	(0.000)	(0.000)	(0.000)	(0.142)	(0.000)	(0.000)	(0.000)
Years of schooling (log)	0.101***	0.116***	0.067***	-0.177***	-0.036***	0.020	0.079***	0.201***	0.198***
	[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)	(0.230)	(0.000)	(0.000)	(0.000)
Consumption (log)	-0.098***	-0.048***	-0.014	0.148***	0.028**	-0.013	0.116***	-0.126***	-0.082***
	[0.010]	[0.011]	[0.010]	[0.010]	[0.011]	[0.014]	[0.014]	[0.013]	[0.013]
	(0.000)	(0.000)	(0.142)	(0.000)	(0.010)	(0.359)	(0.000)	(0.000)	(0.000)
N	3219	8731	9674	7966	9652	5409	5412	5412	5412
R^2 including θ	0.511	0.168	0.117	0.231	0.021	0.006	0.039	0.138	0.133
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 of the husband and wife, the estimated individual propensity to choose at random by husbands and wives (not shown) and all the covariates included in Table 20 (not shown).

Table 23: Relation between preferences and field behavior for couples - CRRA

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
Husband's θ	-0.007	0.001	-0.044***	-0.110***	-0.034***	-0.038**	-0.001	0.052***	0.065***
	[0.010]	[0.012]	[0.012]	[0.013]	[0.013]	[0.018]	[0.018]	[0.017]	[0.018]
	(0.462)	(0.940)	(0.000)	(0.000)	(0.007)	(0.039)	(0.969)	(0.003)	(0.000)
Wife's θ	-0.022**	0.021*	-0.004	-0.067***	-0.008	-0.034*	-0.010	0.074***	0.068***
	[0.010]	[0.011]	[0.012]	[0.013]	[0.013]	[0.018]	[0.019]	[0.018]	[0.018]
	(0.029)	(0.055)	(0.720)	(0.000)	(0.505)	(0.063)	(0.582)	(0.000)	(0.000)
Husband's ω	0.003	0.010	-0.017	0.038***	0.008	0.042**	-0.039**	-0.050***	-0.040**
	[0.011]	[0.012]	[0.012]	[0.012]	[0.013]	[0.017]	[0.019]	[0.016]	[0.016]
	(0.786)	(0.365)	(0.162)	(0.001)	(0.536)	(0.015)	(0.041)	(0.002)	(0.012)
Wife's ω	0.010	-0.004	-0.056***	0.013	-0.003	0.034**	0.003	-0.078***	-0.061***
	[0.010]	[0.011]	[0.012]	[0.012]	[0.012]	[0.017]	[0.018]	[0.015]	[0.016]
	(0.310)	(0.748)	(0.000)	(0.274)	(0.813)	(0.039)	(0.871)	(0.000)	(0.000)
Male	0.000***	0.169***	0.192***	0.359***	0.010	0.030	-0.035**	-0.118***	-0.113***
	[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)	(0.430)	(0.128)	(0.035)	(0.000)	(0.000)
Age (log)	0.508***	0.369***	0.014	-0.022	0.105***	-0.019	0.058***	0.106***	0.119***
	[0.008]	[0.012]	[0.012]	[0.014]	[0.013]	[0.020]	[0.019]	[0.019]	[0.019]
	(0.000)	(0.000)	(0.228)	(0.111)	(0.000)	(0.355)	(0.002)	(0.000)	(0.000)
Non-Catholic	0.001	0.004	0.256***	-0.145***	0.037***	0.008	0.036*	0.003	0.014
	[0.010]	[0.012]	[0.013]	[0.012]	[0.013]	[0.019]	[0.019]	[0.017]	[0.017]
	(0.953)	(0.759)	(0.000)	(0.000)	(0.004)	(0.660)	(0.055)	(0.872)	(0.411)
Non-Spanish speaker	0.013	0.005	-0.086***	-0.239***	-0.049***	-0.004	-0.094***	0.305***	0.338***
	[0.011]	[0.012]	[0.012]	[0.014]	[0.013]	[0.018]	[0.018]	[0.018]	[0.018]
	(0.215)	(0.671)	(0.000)	(0.000)	(0.000)	(0.833)	(0.000)	(0.000)	(0.000)
Years of schooling (log)	0.096***	0.123***	0.056***	-0.172***	-0.024*	0.019	0.104***	0.210***	0.205***
	[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)	(0.078)	(0.427)	(0.000)	(0.000)	(0.000)
Consumption (log)	-0.102***	-0.041***	-0.012	0.169***	0.023*	-0.043**	0.107***	-0.128***	-0.066***
	[0.011]	[0.012]	[0.012]	[0.013]	[0.013]	[0.019]	[0.020]	[0.019]	[0.019]
	(0.000)	(0.001)	(0.316)	(0.000)	(0.068)	(0.025)	(0.000)	(0.000)	(0.000)
N	2382	6643	6774	5366	6759	3396	3397	3397	3397
R^2 including θ	0.534	0.179	0.134	0.260	0.020	0.010	0.039	0.165	0.157
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, the estimated individual propensity to choose at random by husbands and wives (not shown) and all the covariates included in Table 20 (not shown).