Risk Aversion and Probability Weighting in Peru*

Francisco B. Galarza†
Department of Agricultural and Applied Economics
University of Wisconsin–Madison
427 Lorch Street, Madison, Wisconsin 53706

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Abstract

We estimate the risk preferences held by small-scale rural producers in Peru. Using a multiple price lottery design, we find evidence of moderate risk aversion under various specifications considered. Our results also show that subjects overweight small probabilities and underweight large ones; such non-linear probability weighting is consonant with (cumulative) prospect theory. When we allow for preference heterogeneity via the estimation of a two-component mixture model, we report that the majority of farmers behave as prospect theory decision makers, while only a small fraction of them behave as expected utility maximizers. In either case, the most important individual characteristic correlated with risk preferences is higher education, a result that suggests a connection between cognitive abilities and behavior towards risk.

Keywords: risk aversion, probability weighting, mixture models, experimental economics, Peru.

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†Please address correspondence to: fbgalarza@uwalumni.com.

1 Introduction

We investigate how small-scale rural producers in Peru take decisions under risk. Using the results from a multiple price list lottery design, we find that they exhibit risk averse preferences and they use a probability weighting scheme in their choices under risk. We also report evidence of heterogeneity in risk preferences, with a larger proportion of subjects showing a behavior consistent with probability weighting and a smaller proportion of them behaving as expected utility decision makers. Furthermore, the most salient individual characteristic correlated with risk preferences is higher education, a result that hints a connection between cognitive abilities and behavior towards risk.

The analysis of decisions under risk has been one of the main subjects in economics since at least Arrow (1971). From an economic development perspective, risk aversion has been considered a major factor that may hinder the adoption of financial and production innovations (Feder 1980; Feder et al. 1985), thus losing the opportunity to benefit from potentially profitable investments. Experimental evidence from China (Liu 2009) and India (Binswanger et al. 1980) supports this claim. This problem of lagged technological advancement is more detrimental when it results in a suboptimal accumulation of assets that then translates into in a deterioration of people's ability to cope with large shocks in the long term.

While risk aversion has been largely an assumption in classical microeconomics, recent experimental evidence from the laboratory (e.g., Hey and Orme 1994; Holt and Laury 2002) and the field (e.g., Harrison and Rutström 2007; Harrison et al. 2009; Liu 2009; Schechter 2007; Tanaka et al. 2009) does show that subjects are, in general, risk averse over the gains domain.[1] Several experimental methods to measure risk preferences have been proposed (see Cox and Harrison 2008 for a review), with the multiple price listing (MPL) being one of the most commonly used. In the MPL format, choices across several decision rows are binary lotteries and the "prices" are given by the probability structure associated with each lottery. Subjects get to choose a lottery in each row, knowing the probability of winning the bigger and the lower prizes. The main attractive feature of the MPL is its simplicity to explain, implement, and elicit true valuations, a trait that is especially important for our case, where a large proportion of our experimental subjects have low levels of schooling. The MPL design has also been found to yield less noise than alternative methods that attempt to elicit certainty equivalents (see Hey et al. 2009 for details).

On the flip side, however, MPL allows for multiple switching between lotteries, a behavior that is not expected from fully "rational" players. Multiple switching behavior (MSB) has been reported by previous studies that use some variation of the MPL format (e.g., Andersen et al. 2006; Bruner et al. 2008; Eckel and Wilson 2004; Holt and Laury 2002; Jacobson and Petrie 2009).[2] While such

[1] On exception is by Henrich and McElreath (2002), who find that while Tanzanian peasants appear risk averse, Chilean peasants seem risk loving.

[2] Andersen et al. (2006) find that 5.8 percent of their subjects switch multiple times when allowing for indifference between lotteries. In Bruner et al. (2008), such proportion is 20 percent; in Eckel and Wilson (2004), 12.9 percent; in Holt and Laury (2002), 13.2 percent in hypothetical choices; and in Jacobson and Petrie (2009), 55 percent.

behavior has been attributed to indifference between the two lotteries (e.g., Andersen et al. 2006) or to the lack of salience in the lottery prizes (e.g., Bruner 2007),[3] it could also be due to confusion or to an incomplete understanding of the experiment rules (in this case, we would expect to find large calculation errors).

The typical solution for the multiple switching observed in the MPL designs has been to discard these observations under the premise that there is little to learn from those seemingly irrational choices or *mistakes*. While this solution can certainly be justifiable when the proportion of such inconsistent choices is small (as is found in most of the previously mentioned studies), we believe that when such proportion is large (as we found in this paper) a more constructive approach would be to examine more closely whether those inconsistent choices can be rationalized under a particular framework, as we do in this paper.

We exploit data gathered in Peru, where we conducted an *artefactual* field experiment to estimate the risk preferences held by 378 small-scale cotton producers. We used a MPL-like design popularized by Holt and Laury (2002), with a relatively safe and a relatively risky lottery, and considered only positive prizes. Subjects' task is to choose their preferred lottery along ten decision rows. As mentioned earlier, we keep in our sample the subjects who made multiple switches (52 percent), with the tenet that those choices reflect subjects' preferences and that the MSB could be explained by the use of nonlinear probability weighting in the presence of large random mistakes. Our econometric estimation considers the Expected Utility Theory (EUT) framework and then generalizes EUT to assess the magnitude of such probability weighting in the choices made; in particular, we use Tversky and Kahneman's (1992) Cumulative Prospect Theory (CPT).[4]

Our main results are the following. We find that on average subjects exhibit a moderate degree of relative risk aversion; risk estimates are somewhat similar regardless of the decision model governing the preferences (EUT *or* CPT). Moreover, when we allow the data to be explained by EUT *and* CPT via the estimation of mixture models, we find that 76 percent of the subjects behave as prospect theory decision makers (i.e., they make subjective distortions to the underlying probabilities in their decisions under risk), while 24 percent of them behave as expected utility decision makers; within both models, there is evidence of risk averse preferences. Given the novelty of the experiment and the low levels of schooling attained in our sample, it is not surprising to find that subjects made large random errors when they calculated the values of the lotteries. Furthermore, the main individual characteristic that predicts risk preferences is higher education (higher educated individuals are more likely to take risks); while age and gender do not play a statistically significant role in predicting risk aversion. Lastly, contrary to our expectation, we find that the existence of probability weighting and large calculation errors cannot fully explain the extent of the multiple switching observed in our data.

[3] In a setting where game instructions are written and displayed on computers, Bruner (2007) finds that verbally reinforcing that earnings for the experiment would be determined *only* [added emphasis] by one decision row, significantly reduces the proportion of multiple switches.

[4] Given that our lottery prizes involve only gains, CPT is equivalent to Quiggin's (1982) Rank-Dependent Expected Utility Theory. We use CPT in this paper.

In the remainder of this paper we present the experimental procedures followed in the field and the data used in the empirical analysis (Section 2); explain the analytical framework used to estimate the relevant parameters under the framework of EUT, CPT, and mixing both models (Section 3); discuss the estimation results and examine the role of subjective probability weighting, made in the presence of large calculation errors, in explaining MSB (Section 4). We then restrict the analysis to the subset of subjects who correctly chose the higher prize lottery in the tenth decision row (Section 5), and draw the main conclusions (Section 6).

2 Experimental Procedures

This section describes the sampling design, reports the main characteristics of our experiment participants, and discusses the procedures followed to implement the risk experiment. Using the terminology coined by Harrison and List (2004), our experiment is an artefactual field experiment because we used tools from a conventional laboratory experiment, but the experiment was conducted with farmers, a nonstandard subject pool.

2.1 Recruitment of Subjects

The experimental sessions were held in several zones of the Province of Pisco, a valley located in the Department of Ica, in coastal Peru.[5] With a total of 3,600 producers, owning 24,000 hectares, the agricultural activity in Pisco is heavily concentrated in the production of cotton. This crop exploits about 45 percent of the total sown area in Pisco and involves about 80 percent of all Pisco agricultural producers. The average size of a cotton parcel is 3.8 hectares, and a typical farm comprises 6.6 hectares in total (figures as of 2007-2008). This small-scale production is mostly the result of the Peruvian Agrarian Reform carried out in the nineteen seventies, where a military government expropriated the land from the landlords and redistributed it to farming households.

We conducted 24 experimental sessions in 12 different locations across the Pisco valley. These sessions were held in locations where electricity was available and a room to host 25-30 persons was ensured. In all of the cases, farmers were familiar with the locations chosen—public schools, private houses, a church eatery, and municipal auditoriums. Whenever possible, we chose locations that were focal points to the majority of the selected farmers. However, we had to hold several sessions in zones with very scattered households, and with very little or no access to public transportation.

Our sampling strategy relies on information from the *Junta de Usuarios* of Pisco, an entity that operates as the superintendent of water administration in the valley. We selected our subjects using a two-stage stratified sampling. In the first stage, we constructed 23 *conglomerates* out of the 40 Irrigation Blocks in which the valley is geographically divided, with the following criteria: to involve a minimum of 600 hectares and a maximum of 1,500 hectares of cotton in total, and to be

[5] The political division of Peru includes: regions, departments (akin to a U.S. state), provinces, and districts. The Peruvian territory comprises 24 departments and a Constitutional Province, Callao.

geographically adjacent. We then randomly chose 13 conglomerates, having a total of 1,604 farmers. In the second stage, to carry out the individual-level randomization, nearest-neighbor farmers with respect to farm size were broken down into pairs within each of those 13 conglomerates, and one member of each pair was randomly chosen to participate in our experiment. The final sample size consisted of 804 farmers.

Invitations to attend the experimental sessions were sent out for all of those farmers, 745 of whom were reached by our messengers.[6] Invitations were personalized and included the location, date, and time of the experimental sessions, the promise of 7 Soles (the local currency) for just showing up,[7] and an estimate of their *total* winnings for participating in the sessions (between 10 and 30 Soles, or between \$3.6 and \$10.7). We should mention that this risk experiment was conducted after running a farming experiment aimed at measuring the willingness to buy an innovative crop insurance contract (results from this experiment are analyzed in Galarza 2009).[8] All session were conducted in Spanish. Farmers were asked to bring their invitations to the session as a way of checking their identity. We had 410 experimental subjects come to the sessions, 399 of whom stayed until the end.[9] The core of our analysis is based on 378 subjects for whom we have information on most of the variables examined.

2.2 Characteristics of Participants

Participants in our experimental sessions are on average older than 50, mostly male, and have typically completed only elementary school (which takes six years in Peru) (see Appendix A). In terms of the farming activity, subjects report extensive experience managing their own agricultural parcels (an average of 24 years). They own almost 6 hectares in total—a figure that is slightly smaller than the valley average size of a farm (6.6 hectares)—and cultivated 5 of them in the 2007-2008 farming season. Moreover, 83 percent of experimental subjects planted cotton, obtaining an average yield of 47 quintals (or 2,162 Kilograms) per hectare.[10] Compared to subjects who did *not* attend but were invited to the sessions, participants do not show statistically significant differences in terms of the total owned area, total sown area, or area sown with cotton,[11] a result that provides

[6]In order to deliver the invitations, we hired the *sectoristas de riego*, persons in charge of the water administration and use in their respective zone, because of their familiarity with farmers (where they have parcels and live).

[7]In most of the cases, this fee was sufficient to pay for round-trip travel from subjects' houses to the locations where sessions were held. As mentioned earlier, however, in some instances no public transportation was available, and producers could only ride their own motorcyles, horses, or walk, to get to the sessions.

[8]Each experimental session included four parts, conducted in the following order: entry survey, farming experiments, risk experiment, and exit survey.

[9]Explanations for this seemingly low participation rate include: scattered households, poor explanation of the incentives for participating, higher opportunity cost (probably non-pecuniary), unclear explanation or comprehension of the benefits from attending the sessions. Farmers in this valley have low participation rates for any meeting organized by local organizations.

[10]According to official statistics, the valley-wide average yield in 2005 and 2006 was 47 and 42 quintals per hectare, respectively. No official statistics for 2007 were reported at the time of writing this paper. One *quintal* is equivalent to 46 Kilograms.

[11]These are the only variables available to look for selection in the sample who showed up for the experiments. This comparison was done using information from the Junta de Usuarios de Riego de Pisco for the 2007-2008 farming

evidence that no sample selection would seem to exist.

Furthermore, our sample is mainly composed of poor farmers, judging by the self-reported value of their assets (house and land): 20,000 Soles (roughly US$7,000); such value reduces to 7,430 Soles when we consider only land,[12] and to 15,920 Soles when we consider the value of the house alone. In addition to their limited of access to any type of commercial insurance (life or accident insurance), the majority of individuals in our sample (61 percent) report having access to credit markets. This access to credit is concentrated in the formal sector (38 percent), followed by the informal sector (34 percent), and the cotton gins (28 percent).

2.3 Experimental Sessions

In all of our 24 conducted sessions, participants were randomly assigned to numbered seats upon arrival, and received a binder containing the experiment worksheets and a pencil to record their choices. We divided the participants into a maximum of four "valleys" with a minimum of 3 members in each one. Splitting the experimental subjects into several valleys allowed us to have closer monitoring and to accelerate the tasks. Two persons were in charge of each valley. A senior assistant, well versed in the experiment rules and procedures, recorded the choices of players; and a helper assisted with the implementation of the randomizing device used to pick the decision for play (dice rolling). The experiment instructions were read aloud to all participants as a group. To ensure that farmers understood the mechanics and rules of the games, we allowed them to ask questions during the presentation of the instructions. Winnings from the risk experiment, which typically lasted half hour, averaged 3 Soles.[13]

2.4 The Experiment

We used a relatively simple design, in which players chose between a relatively safe lottery (which we called option *Sol*) and a relatively risky lottery (which we called option *Luna*) along ten decision rows. In this design, lotteries' characteristics in row t are as follows (prizes are expressed in Soles): *Sol*: (t/10,1800; 1400), and *Luna*: (t/10,3500; 90). That is, as shown in Table 1, in the first row (i.e., for $t = 1$), subjects choosing lottery *Sol* have a 10 percent chance ($p = 1/10$) of getting 1,800 Soles and a 90 percent ($[1 - p] = 9/10$) chance of getting 1,400 Soles. Similarly, if they choose lottery *Luna*, there is a 10 percent chance of getting 3,500 Soles, and a 90 percent chance of getting 90 Soles. In the second row, there is a 20 percent chance of getting the higher prize in each lottery, and so on.

Note that in this design, prizes are held constant across the decision rows and we vary only the probabilities of the higher and smaller prizes in each row. Also, the probabilities of each

season.

[12] Farmers were asked to self-report their rental value of land, which can be considered a lower bound of the land value.

[13] The total winnings from this and the farming experiment averaged 20 Soles ($7.2). These winnings compare well with the going *daily* unskilled wage.

Table 1: Matrix Payoff in the Risk Experiment

	Sol				Luna				$EV^S - EV^L$	CRRA interval	Risk Preference
Row	p	Prize	1-p	Prize	p	Prize	1-p	Prize		if switches to **L**	Classification
1	0.1	1800	0.9	1400	0.1	3500	0.9	90	1009	$-\infty$, -1.61	Extremely RL[1]
2	0.2	1800	0.8	1400	0.2	3500	0.8	90	708	-1.61, -0.88	Highly RL
3	0.3	1800	0.7	1400	0.3	3500	0.7	90	407	-0.88, -0.43	Very RL
4	0.4	1800	0.6	1400	0.4	3500	0.6	90	106	-0.43, -0.10	RL
5	0.5	1800	0.5	1400	0.5	3500	0.5	90	-195	-0.10, 0.18	RN[2]
6	0.6	1800	0.4	1400	0.6	3500	0.4	90	-496	0.18, 0.44	Slightly RA[3]
7	0.7	1800	0.3	1400	0.7	3500	0.3	90	-797	0.44, 0.69	RA
8	0.8	1800	0.2	1400	0.8	3500	0.2	90	-1098	0.69, 0.98	Very RA
9	0.9	1800	0.1	1400	0.9	3500	0.1	90	-1399	0.98, 1.38	Highly RA
10	1.0	1800	0.0	1400	1.0	3500	0.0	90	-1700	1.38, $+\infty$	Extremely RA

Note: The last four columns were not shown to experimental subjects.
[1] RL: risk loving; [2] RN: risk neutral; [3] RA: risk averse. This classification is based on the mid-CRRA intervals.

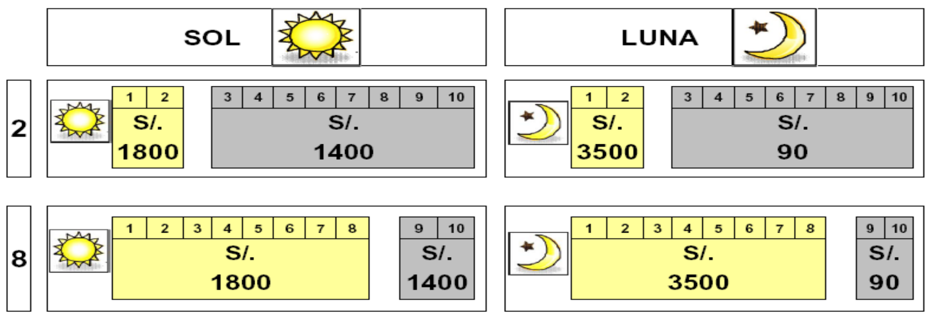
prize in a given row are the same for both lotteries, so that subjects would focus on the changes in probabilities (the higher prize in each lottery increases its related probability) across rows. As a result, the difference in the expected values of the lotteries (*Sol* minus *Luna*) decreases as subjects move down in the decision rows, as seen in column 10 of Table 1. We also show the risk intervals associated with switches made at every decision row (columns 11-12) and the risk categories associated with each interval (column 13), which are based on the mid-point interval in each row. Thus, only risk loving subjects would choose the lottery *Luna* in the first decision rows, while only risk averse subjects would choose the lottery *Sol* in the last decision rows. In turn, risk neutral subjects would switch from choosing lottery *Sol* to lottery *Luna* in row 5, where the expected values of both lotteries are about the same. This switching point from the safe to the risky lottery provides an estimate of subjects' degree of risk aversion (the farther they switch in the rounds, the higher the risk aversion, as shown above). In this design, subjects *could* start by choosing the lottery *Luna* in the first row (if they were highly risk seeking) and stick to it until the last row (in which case they would be infinitely risk seeking), or switch to lottery *Sol* before the tenth row. Note that this design does not prevent switching back and forth (from *Sol* to *Luna* or viceversa).[14]

The experiment was implemented as follows (the experiment instructions are provided in Ap-

[14] Two other critiques to this MPL format follow (Harrison et al., 2005a): it only elicits intervals of risk aversion, and it can be vulnerable to framing issues, since subjects may be drawn to some *focal* choice picking (e.g., switching at the middle of the table). Although refinements have been suggested to overcome those potential obstacles—offering more choices to subjects withing each interval, and randomizing the order of the lottery choices—such methodological improvements may have come at a high cost: most likely, the resulting higher complexity would have overwhelmed our subjects.

pendix B): we first showed subjects the prizes associated with each lottery, the task involved (i.e., choose one of those lotteries along ten decision rows), and the way they could win those prizes. We next showed the prizes in decision row 2, putting emphasis on the probabilities associated with each of the prizes for *both* lotteries. Then, we showed the prizes in decision row 8 and proceeded likewise. We then displayed rows 2 and 8 together in order to show the symmetry in probabilities of the bigger and smaller prizes: while in row 2, there is a 20 percent chance of getting the higher prize in each lottery, in row 8 such odds are 80 percent. Figure 1 shows the slide shared with our experimental subjects at this point.

Figure 1: Risk Experiment: Characteristics of Rows 2 and 8



We next projected a slide containing all the decision rows, and showed subjects the pattern of increasing probability of getting the higher payoffs and the resulting decreasing probability of getting the lower prizes in both lotteries as one goes down in the table. The explanation of the experiment ended with a mention of the last row, when the monitor said that subjects will get the higher prize for certain in each lottery, so that the choice would be between 1,800 if they choose *Sol* and 3,500 if they choose *Luna*. Appendix C shows a sample worksheet used in the experiment.

In sum, the main factors we asked farmers to consider in their decisions were the minimum and maximum prizes within each lottery, and the likelihood of those prizes in each decision row. Also, by showing them all the decision rows rather than one by one sequentially, we wanted them to see the decreasing (and increasing) probability pattern of the lower (higher) prize within each lottery. Despite the fact that we explained this, a large proportion of subjects (105 out of 378) chose the safe lottery (lottery *Sol*) in the last round, which clearly denotes lack of attention or understanding of the experiment. Fatigue could also explain those mistakes, since the risk experiment was played after an intensive section of farming experiments.

After the explanation of the experiment procedures and rules, we conducted the experiment with hypothetical payoffs. Subjects selected their preferred lotteries along ten decision rows and learned how to calculate their winnings in Soles, but did not earn money in cash. They thus learned that their winnings would be determined by only one decision row, chosen at random in *each* valley by rolling a ten-sided die (row "for play"), and that their specific winnings would correspond to the prize associated, in the option chosen in the row for play, with the number resulting in a second, individual die roll. In other words, if, for example, the first die roll for the valley of certain subject landed on the number 5 (i.e., the fifth row will be played), and if this subject's second die roll landed on the number 6, she would win 1,400 Soles if she chose lottery *Sol* in row 5 and 90 Soles if she selected lottery *Luna*.

Immediately after this hypothetical payoffs round, we conducted the experiment *for real*, following the same rules indicated above, and having an exchange rate of 1 Sol in cash for every 600 Soles of lottery winnings.

3 Structural Estimation of Risk Parameters

The estimation of the risk preferences performed below assumes first that the data are entirely generated by a single model (either Expected Utility Theory [EUT] or Cumulative Prospect Theory [CPT]). We then estimate a two-component mixture model that allows for the estimation of the proportion of subjects whose choices are best explained by EUT and the proportion best explained by CPT, in addition to the risk parameters under each model. The estimation in all the cases was done using the maximum likelihood method,[15] and the standard errors are corrected for clustering at the individual level, in order to account for the possibility that choices made by the same individual are correlated across decision rows. We will analyze 378 subjects' decisions made over monetary gains along 10 decision rows, which makes a total of 3,780 choices.[16]

3.1 Assuming Expected Utility Theory

As is typical under EUT, we will assume that the utility of income from outcome $j \in \{1, 2\}$ in lottery $k \in \{Sol\ (S), Luna\ (L)\}$ that individual $i \in \{1, ..., N\}$ gets, denoted by $M_i^{k,j}$, is defined by the following Constant Relative Risk Aversion (CRRA) preferences:

$$U(M_i^{k,j}) = \frac{\left(M_i^{k,j}\right)^{1-r_i{}^{\mathrm{EU}}}}{1 - r_i^{\mathrm{EU}}} \quad , \quad r_i^{\mathrm{EU}} \neq 1, \tag{1}$$

Note that since the prizes are constant across rows in every lottery (see Table 1 above), no row index is needed for M_i. In this specification, risk aversion is completely determined by the curvature parameter, r_i^{EU}, with $r_i^{\mathrm{EU}} = 0$ denoting risk neutrality; $r_i^{\mathrm{EU}} > 0$, risk aversion; and $r_i^{\mathrm{EU}} < 0$, risk seeking behavior. Recall that in the experiment, each lottery k in row m has two possible outcomes, with probabilities p_m^j and $(1 - p_m^j)$. Then, when confronted with a binary lottery, subjects are

[15]The estimation was done in STATA. The algorithm used was the BFGS (Broyden, Fletcher, Goldfarb, Shanno). The codes were graciously shared by Glenn Harrison from the University of Central Florida (UCF).

[16]However, when we include individual characteristics as covariates, the sample size shrinks to 365 subjects with 3,650 choices, due to missing information.

assumed to make the following expected utility (EU) calculation at every decision row, m:

$$EU^k_{i,m} = \sum_{j=1}^{2} p^j_m * U(M^{k,j}_i), \tag{2}$$

and to choose, either lottery *Sol* or *Luna*, according to the value of the following latent index or choice rule:

$$\Delta EU_{i,m} = EU^S_{i,m} - EU^L_{i,m} + \mu_i, \tag{3}$$

where μ_i denotes the errors made by subject i (as a result of carelessness, hurry, or insufficient motivation) in the process of calculating the expected utilities,[17] which will be assumed to be white noise (i.e., with mean zero and constant variance). This additive error was first proposed by Fechner (1860/1966), was used by Hey and Orme (1994), and we will refer to it as "Fechner error." The previous function can be interpreted as the *perceived* advantage of lottery S over lottery L, while such function excluding the error term represents the *true* advantage of lottery S over lottery L. Appealing to the Central Limit Theorem, we can assume that μ_i is also normally distributed:

$$\mu_i \sim N(0, \sigma^2_{\mu_i}). \tag{4}$$

We will further assume that errors are uncorrelated across decision rows. In this Fechner error story, a careful individual i would have a relatively small error or noise,[18] represented by a small standard deviation (σ_{μ_i}), in her decisions. On the other hand, when σ_{μ_i} becomes large, her decision would respond less to the differences in subjective values and more to randomness.

For estimation purposes, under the assumption made in eqn.[4], we will use a probit linking function to transform the latent index given by eqn.[3] (which takes values between $\pm\infty$) into a binary variable that denotes the observed choices. Thus, the probability that S is chosen over L will be given by:

$$\begin{aligned} \Pr(EU^S_{i,m} - EU^L_{i,m} + \mu_i &> 0) = \Pr(\frac{\mu_i}{\sigma_{\mu_i}} > -\frac{EU^S_{i,m} - EU^L_{i,m}}{\sigma_{\mu_i}}) \\ &= 1 - \Phi(-\frac{EU^S_{i,m} - EU^L_{i,m}}{\sigma_{\mu_i}}) = \Phi(\frac{EU^S_{i,m} - EU^L_{i,m}}{\sigma_{\mu_i}}), \end{aligned} \tag{5}$$

where the expression in the last parenthesis has a standard normal distribution, and will be referred to as the stochastic expected utility indicator (ΔSEU):

$$\Delta SEU_{i,m} = \frac{EU^S_{i,m} - EU^L_{i,m}}{\sigma_{\mu_i}}. \tag{6}$$

[17] For a discussion of the different stages at which randomness can play a role in the decision making in lotteries, see Loomes et al. (2002).

[18] The terms *noise*, *error*, and *mistake* are used interchangeably throughout the text.

Thus, $\Phi(\Delta SEU_{i,m})$ denotes the probability of choosing lottery S, and $[1-\Phi(\Delta SEU_{i,m})]$ represents the probability of choosing lottery L. By the symmetry of the normal distribution, the last expression is equivalent to $\Phi(-\Delta SEU_{i,m})$. To be clear, lottery S should be chosen when $\Delta EU_{i,m} > 0$ or $\Phi(\Delta SEU_{i,m}) > 0.5$; otherwise, lottery L should be selected. We will use the previous eqn. in the optimization routine implemented to estimate the risk parameter, r_i, and the standard deviation of the noise, σ_{μ_i}. The individual $i's$ contribution to the model's likelihood can be written as:

$$L_i^{\text{EU}}(r_i^{\text{EU}}, \sigma_{\mu_i}; I_i^m, X_i) = \prod_{m=1}^{10} \left[\Phi(\Delta SEU_{i,m})^{I_{i,m}}\right] * \left[\Phi(-\Delta SEU_{i,m})^{1-I_{i,m}}\right], \quad (7)$$

where $I_{i,m}$ is an indicator variable of the choice made by individual i in row $m \in \{1, ..., 10\}$, which takes the value of 1 when lottery S is chosen in row m, and 0 otherwise. X_i is a vector of individual $i's$ characteristics. The model's log-likelihood would then be the logarithm of the product of L_i^{EU} over all the individuals i:

$$l^{\text{EU}} = \sum_{i=1}^{N} \ln L_i^{\text{EU}}(r_i^{\text{EU}}, \sigma_{\mu_i}; I_i^m, X_i) = \sum_{i=1}^{N}\sum_{m=1}^{10} \left[\ln(\Phi(\Delta SEU_{i,m})^{I_i^m}) + \ln(\Phi(-\Delta SEU_{i,m})^{1-I_i^m})\right]. \quad (8)$$

Note that the inclusion of a vector of covariates (X_i) in the likelihood functions above allows the estimation of subject specific parameters (including the standard deviation of the error, σ_{μ_i}), where we consider the parameter to be a linear function of the covariates. Doing so permits to unveil the existence of heterogeneity at the parameter level, in contrast to other sources of heterogeneity, such as heterogeneity at the preference functional level, which is analyzed in section 3.3, via the estimation of mixture models.

In particular, individual-specific risk parameter estimates, $\widehat{r}_i$, will be estimated as a linear function of dummy variables of gender, age, education, and geographic location whenever it is possible in this specification and in the other specifications considered later on (prospect theory and mixture models). We label this as the *heterogeneous subjects* case: $\widehat{r}_i = \widehat{r}(X_i)$:

$$\widehat{r}_i = \widehat{r}_0 + \widehat{r}_{age} * Age_i + \widehat{r}_{gender} * Gender_i + \widehat{r}_{edu} * Education_i + \widehat{r}_{geog} * Geog.Location_i, \quad (9)$$

Clearly, not including individual characteristics in the above equation would yield estimates only for a representative subject in the sample, which we label as the *homogeneous subjects* case: $\widehat{r}_i = \widehat{r}_0$. Similarly, we will estimate heteroskedastic random errors below, but with a restricted set of individual characteristics; and again when no covariates are included in the errors regression, we would be estimating an aggregate standard deviation of the errors for the entire sample: $\widehat{\sigma}_{\mu_i} = \widehat{\sigma}_0$.

3.2 Assuming Cumulative Prospect Theory

Unlike EUT, where the risk preferences are entirely defined by the curvature of the utility function, when income is defined over the gains domain, in Tversky and Kahneman's (1992) (henceforth TK) Cumulative Prospect Theory (CPT), risk preferences are also defined by psychological factors that create distortions in the probabilities information when evaluating risky prospects.[19] Another distinctive feature of CPT is that the utility function, renamed by TK as *value function*, is defined over *gains* and *losses*, not over terminal wealth. Gains and losses are, in turn, defined with respect to a *reference point*, which is usually assumed to be the status quo, or the current level of wealth. We will adopt this approach, thus defining gains as a situation that is better than the *status quo* and losses, as a situation that is less favorable than the *status quo*. Further, we will continue to assume CRRA preferences, with r^{PT} denoting the risk parameter, for ease of comparison with the EUT risk parameter, r^{EU}:

$$U(M_i^{k,j}) = \frac{\left(M_i^{k.j}\right)^{1-r_i^{\text{PT}}}}{1-r_i^{\text{PT}}}, \quad r_i^{\text{PT}} \neq 1. \tag{10}$$

In CPT, instead of probabilities, we have *decision weights*, $\mathbf{dw}^j(p)$, associated with each of the two outcomes in lottery k. Defined over the cumulative probabilities, these decision weights reflect the subjective distortion of probabilities that has been found by several previous studies (e.g., Camerer and Ho 1994; Gonzalez and Wu 1999; Starmer 2000; Tversky and Kahneman 1992), and which can explain why the same subjects can be risk averse over some prospects (i.e., buying insurance), while being risk loving over some others (e.g., gambling). In this context, when given a binary lottery k to choose, subjects are now assumed to make the following *Cumulative* Prospect Utility (CPU) calculation:

$$CPU_{i,m}^k = \sum_{j=1}^{2} \mathbf{dw}_m^j(p) * U(M_i^{k,j}) = \mathbf{dw}_m^1(p)U(M_i^{k,1}) + \mathbf{dw}_m^2(p)U(M_i^{k,2}), \tag{11}$$

where $\mathbf{dw}_m^j(p)$ at every decision row is given by:

$$\mathbf{dw}_m^j(p) = \begin{cases} 1-\mathbf{w}(p_m^2), & \text{for } j=1 \\ \mathbf{w}(p_m^2), & \text{for } j=2 \end{cases}, \tag{12}$$

and the weighting function, $\mathbf{w}(p_m^j)$, will be represented by:

$$\mathbf{w}(p_m^j) = \frac{(p_m^j)^\gamma}{\left[(p_m^j)^\gamma + (1-p_m^j)^\gamma\right]^{1/\gamma}}, \qquad \gamma > 0 \quad (j=1,2), \tag{13}$$

where $\mathbf{w}(0) = 0$ and $\mathbf{w}(1) = 1$. This one-parameter weighting function was proposed by Quiggin

[19] A second feature, known as *loss aversion*, is included when losses are also considered: the notion that losses are more heavily felt than gains of similar magnitude.

(1982) and popularized by TK. Looking at eqns.[11] and [12] we see that CPU^k is the sum of two rank-dependent outcomes, where different weights are given to different utilities of outcomes. Note also that the decision weights in eqn.[12] add up to one, since this function is defined over the *cumulative* probability distribution. This specification overcomes the potential problem that (nonlinear) probability weighting can cause violations of stochastic dominance (Fox and Poldrack 2009) that affected the original version of Kahneman and Tversky's (1979) Prospect Theory.

Further note that those probability distortions (subsumed in the one-parameter probability weighting function) create a new source of risk aversion (Tversky and Kahneman 1992). Thus, for a given curvature of the value function, risk aversion is reinforced by underweighting of middle to large probabilities and offset by overweighting of small probabilities (Fox and Poldrack 2009). We will explain what we mean by overweighting and underweighting next, when we examine the different shapes that TK's weighting function can yield, depending on the value of the curvature and elevation parameter, γ:[20]

(i) If $0 < \gamma < 1$, then $\mathbf{w}(p)$ would have an inverse S-shape, implying that subjects overweight small probabilities (see the concave section, where $\mathbf{w}(p) > p$) and underweight large probabilities (convex section, where $\mathbf{w}(p) < p$).[21] Examples of this case are depicted by the solid ($\gamma = 0.33$), the dot-dashed ($\gamma = 0.54$), and the dashed ($\gamma = 0.78$) curves in Figure 2.

(ii) If $\gamma = 1$, then $\mathbf{w}(p) = p$, and we would be back to the EUT framework with linear probabilities. This case is represented by the 45° degree line in Figure 2.

(iii) If $\gamma > 1$, then $\mathbf{w}(p)$ will have a S-shape, with convexity for small and moderate probabilities and concavity for larger probabilities. An example of this case ($\gamma = 1.40$) is depicted by the dotted curve in Figure 2.

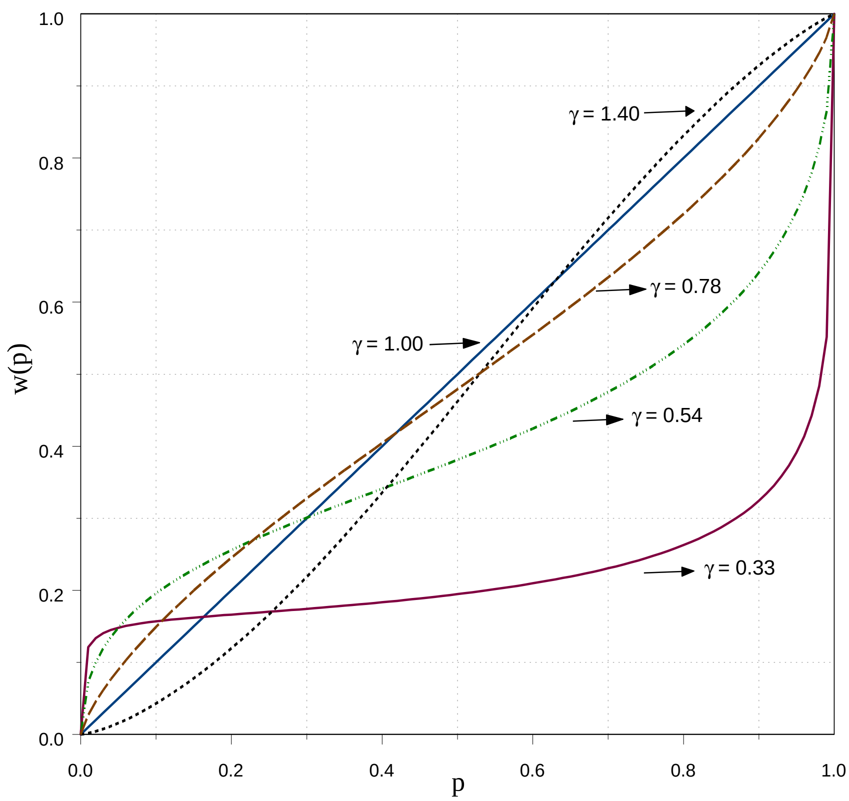
While TK's weighting function has shown to fit well the data by several empirical studies, it is not without drawbacks. In particular, it is not increasing in p for small values of γ (such a function is partially decreasing for $\gamma \leq 0.278$, as shown by Rieger and Wang 2006), and it does not have axiomatic foundations. While the former limitation does not represent a practical problem for us (since we generally find estimates of γ greater than 0.3, as we will see in the next section), the latter implies that TK's function, as well as other *ad hoc* functions, such as Lattimore et al.'s (1992), could not fit data from subjects who reduce simple compound lotteries (Luce 2000).[22] In any case, this function serves well our purpose of showing the existence of probability distortions in the data.

[20] The notion of elevation in the weighting functions becomes relevant with the estimation of two-parameter functions. In such a case, elevation refers to the attractiveness to gambling (or a higher weight assigned to the larger prize in our context). For more details, see Gonzalez and Wu (1999). Popular weighting functions include Rieger and Wang's (2006), Prelec's (1998), and Lattimore et al.'s (1992).

[21] Underweighting (overweighting) happens when subjects behave as if the chances of occurring a given outcome are lower (greater) than they actually are.

[22] Reduction of compound lotteries states that an individual should be indifferent between two lotteries with the same probability of winning and the same prize for winning. In notational terms, $((x, p; y), q; y) \sim (x, pq; y))$, where x and y are prizes and p and q are probabilities.

Figure 2: Tversky and Kahneman's (1992) Subjective Weighting Function



Analogously to the EUT case, in order to get estimates of the risk and weighting function parameters under CPT, we will maximize the following log-likelihood function:

$$l^{\text{PT}} = \sum_{i=1}^{N} \ln L_i^{\text{PT}}(r_i^{\text{PT}}, \gamma_i, \sigma_{\mu_i}; I_i^m, X_i) = \sum_{i=1}^{N} \underbrace{\left\{ \sum_{m=1}^{10} \left[\ln(\Phi(\Delta SPU_{i,m})^{I_i^m}) + \ln(\Phi(-\Delta SPU_{i,m})^{1-I_i^m}) \right] \right\}}_{\ln L_i^{\text{PT}}(\cdot)}, \tag{14}$$

where the new choice rule, $\Delta CPU_{i,m}$, is given by the sign of the following expression:

$$\Delta CPU_{i,m} = CPU_{i,m}^S - CPU_{i.m}^L + \mu_i, \tag{15}$$

and the stochastic prospect utility indicator, SPU, used in the maximization algorithm, is given by:

$$\Delta SPU_{i,m} = \frac{CPU_{i,m}^S - CPU_{i,m}^L}{\sigma_{\mu_i}}. \tag{16}$$

To account for individual heterogeneity at the parameter level, we will estimate the parameters

r_i^{PT} and γ_i, whenever is possible, as linear functions of individual characteristics, included in the vector X_i, using the specification shown in eqn.[9]. We will proceed similarly with the estimation of σ_{μ_i} when we consider the heteroskedastic case (section 4.1.1).

3.3 Mixture Model Specification

In this section, we will move one step forward towards a more accurate depiction of the true but unknown underlying risk preferences, by allowing for the presence of heterogeneity at the functional form level. So far, we have assumed that a single decision model, either EUT *or* CPT, explains the preferences of *all* subjects. While such homogeneity in preferences has been commonly imposed in most of the studies, it is plausible to think that the preferences of different groups of subjects may be explained by distinct underlying decision models.[23] In order to verify the existence of this type of heterogeneity in risk preferences, we will estimate *a two-component mixture model*,[24] which will allow us to estimate the proportion of subjects whose choices are consistent with utility maximization with linear probabilities (labeled as EUT-type) and that whose choices are consistent with nonlinear probability weighting (labeled as CPT-type).

Thus, in order to estimate a two-component mixture model, we sum the likelihood of each type, denoted by $L_i^{\text{EU}}(\cdot)$ and $L_i^{\text{PT}}(\cdot)$ and shown in eqns.[7] and [14]), multiplied by its respective *mixing* proportion, θ^{EU} and $\theta^{\text{PT}} = 1 - \theta^{\text{EU}}$. These proportions denote the probability that the EUT (CPT) model is the correct specification for a given observation. We could think of θ^{EU} as the unobservable proportion of subjects who do not distort probabilities when making risky choices, while θ^{PT} captures the unobservable proportion of subjects distorting probabilities in a nonlinear way. And what the mixture model estimation does is to cluster the observations into two groups within which the behavior is homogeneous. Then, as a result of maximizing the following weighted log-likelihood function,

$$l^{\text{MIXED}} = \sum_{i=1}^{N} \ln L_i^{\text{MIXED}}(r_i^{\text{EU}}, r_i^{\text{PT}}, \gamma_i, \theta^{\text{EU}}, \sigma_{\mu_i}^{\text{EU}}, \sigma_{\mu_i}^{\text{PT}}; I_i^m, X_i) = \sum_{i=1}^{N} \ln\left[(\theta^{\text{EU}} * L_i^{\text{EU}}(\cdot)) + ((1-\theta^{\text{EU}}) * L_i^{\text{PT}}(\cdot))\right], \tag{17}$$

the mixing proportions are estimated together with the risk and weighting parameters and the noise associated to each model.[25] The econometrics behind the mixture models is similar to that of the unobserved exogenous regime switching models, with the (unobserved) probability of belonging to either one of those regimes being exogenous to the calculation errors. Note that in our case, although one regime (the EUT model) is nested in the other (the CPT model), the way that probabilities are

[23] Harrison and Rutström (2009), Conte et al. (2008), and Bruhin et al. (2007), provide evidence supporting heterogeneity in preferences using these mixture models.

[24] While we could have estimated the number of groups that behaves according to different models, there is little to gain from doing so, given that our sample size is relative small. The reader interested in learning this method may consult McLachlan and Peel (2000).

[25] It is worth mentioning that we are estimating an *aggregate* noise here for each model. We could also work on a heteroskedastic specification, but given our sample size it is likely that the estimation will not converge. Estimating a common noise for both models yields similar risk estimates, but with a smaller weighting function parameter estimate.

perceived and *assessed* under those models or regimes is markedly different. It should be therefore clear that this estimation method is *not* equivalent to assuming that CPT explains *all* the data and then to simply estimate the weighting function parameter, γ_i, for every individual i and test whether such estimate is equal to 1 or not: while in the mixture model specification we assume that the population is composed of two homogeneous subpopulations (EUT-type and CPT-type subjects), here we would be assuming that the population is composed only of CPT-type subjects.

In an analogous way as we did for the heteroskedastic errors case estimated earlier (i.e., when $\sigma_{\mu_i} = \sigma_\mu[X_i]$), we could also estimate the unobservable mixing proportions as a linear function of individual characteristics (i.e., $\theta_i = \theta[X_i]$), provided that the optimization algorithm will converge. (Indeed we do so in section 4.2.1.) It is precisely in this case where the similarity of mixture models with the switching regression models becomes more transparent.[26]

4 Risk Estimation Results

In this section, we discuss the maximum likelihood estimates of the risk preferences under EUT and CPT (sections 4.1 and 4.2) and then examine to which extent nonlinear probability weighting and large random mistakes can explain the multiple switching behavior observed in our data (section 4.3).

4.1 EUT and CPT Estimates

Table 2 reports the relative risk estimates assuming that choices are *entirely* explained by EUT (using eqn.[8]), and considering that such risk estimate is a linear function of selected individual characteristics. We find a moderate degree of risk aversion (average $\widehat{r}^{\text{EUT}} = 0.45$) and evidence of a large degree of randomness in choices, as indicated by the big standard deviation of the random mistakes, $\widehat{\sigma}_\mu = 2.79$. To put this figure in context, such value is 5 percent lower than the expected utility obtained by subjects who chose lottery *Luna* (average across all decision rows), and 12 percent lower than the expected utility obtained by those choosing lottery *Sol* (average across all rows). Moreover, our proxy variable for cognitive abilities—education—appears negatively correlated with risk aversion; in particular, higher educated individuals (indicated by the variable *skilled*) tend to be more likely to take risks. While this result needs further investigation before concluding any robust correlation between cognitive abilities and risk preferences, it goes in line with findings by other studies (e.g., Benjamin et al. 2006; Burks et al. 2009; Dohmen et al. 2007; Frederick 2005). The indicators of age and gender do not appear to predict risk preferences, though all the variables

[26] Note the similarity between expressing the problem in the terms indicated above and in context of the exogenous switching regression (Maddala 1983):

Regime 1: $y_i = X_{1i}\beta_1 + \mu_{1i}$ with probability θ_i

Regime 2: $y_i = X_{1i}\beta_2 + \mu_{2i}$ with probability $(1-\theta_i)$,

with $\mu_{1i} \sim N\left[0, \left(\sigma^{\text{EUT}}_{\mu_i}\right)^2\right]$ and $\mu_{2i} \sim N\left[0, \left(\sigma^{\text{CPT}}_{\mu_i}\right)^2\right]$, where y_i is a binary variable, and β_1 (β_2) denotes the parameter estimate under EUT (CPT).

included in the regression are jointly significant (*p-value* < 0.001).

Table 2: Expected Utility Estimates with Fechner Normal Errors
Heterogeneous Subjects Case

Coefficient	Variable	Estimate	Std.Error	*p-value*	95% Conf.	Interval
r_i^{EUT}	Intercept	0.44	0.16	0.00	0.13	0.75
	Female	0.02	0.12	0.87	-0.22	0.26
	Young (Age < 40)	-0.18	0.18	0.31	-0.53	0.17
	Middle (Age: [50-60])	0.05	0.16	0.77	-0.26	0.36
	Old (Age > 60)	0.11	0.19	0.56	-0.26	0.48
	Illiterate	-0.33	0.28	0.24	-0.87	0.21
	Some secondary	-0.23	0.15	0.13	-0.54	0.07
	Skilled (> sec. educ.)	-0.53	0.20	0.00	-0.92	-0.14
	Low Pisco (lower zone)	0.19	0.13	0.14	-0.06	0.44
	High Pisco (upper zone)	0.45	0.42	0.28	-0.38	1.28
Predicted r^{EUT} at average values		*0.45*				
σ_u	Intercept	2.79	0.25	0.00	2.31	3.27
N		3,650				

Notes: S.E. clustered at the individual level. The omitted category for *age* is for those aged between 40-50. The omitted category for *education* is for those with some primary education.

Turning to the CPT maximum likelihood estimates resulting from estimating eqn.[14]), we observe a relatively high degree of risk aversion, $\widehat{r}^{\text{PT}} = 0.74$ (top panel of Table 3).[27] The results also show a significant subjective probability weighting, given that the parameter estimate, $\widehat{\gamma} = 0.54 < 1$ is significantly different from 0 or 1 (*p-values* in both cases < 0.001). This estimate of γ is pictured by the dot-dashed curve in Figure 2 above, where we see that subjects overweight probabilities (i.e., $\mathbf{w}(p) > p$) until $p = 0.3$, and thereafter they underweight (i.e., $\mathbf{w}(p) < p$) middle and large probabilities. In addition to this *nonlinear probability weighting* pattern, the relative magnitude of the noisiness in the choices made is found to be smaller than under EUT: the estimated standard deviation of the calculation mistakes, $\widehat{\sigma}_\mu = 1.38$, represents 29.0 percent of the expected utility obtained by subjects who chose lottery *Luna* (average across all decision rows), and 27.6 percent of the expected utility obtained by those choosing lottery *Sol* (average across all rows). Furthermore, we continue to find that higher educated subjects are more likely to take risks.[28] Other individual characteristics, such as age and gender, do not enter the regression with statistically significant coefficients.

Let us consider now the bottom panel of Table 3, where we show the variables correlated with

[27] The correlation coefficient between the risk estimates under EUT and CPT (heterogeneous cases) is 0.82.

[28] In order to further the analysis of the effect of higher education on the risk estimates, in an auxiliary regression (not included in this paper), we estimated the risk and weighting function parameters including *female*, *age* (in years), and *education* (in years) as covariates. We found that having 10 more years of education would decrease the risk estimate by between 0.3 (under EUT) and 0.5 (under CPT); the respective coefficients resulted barely significant in both cases (*p-values* are 0.08 and 0.10).

Table 3: Cumulative Prospect Theory Estimates with Fechner Normal Errors
Heterogeneous Subjects Case

Coefficient	Variable	Estimate	Std.Error	*p-value*	95% Conf.	Interval
r_i^{CPT}	Intercept	0.85	0.18	0.00	0.50	1.19
	Female	0.15	0.15	0.31	-0.14	0.43
	Young (Age < 40)	-0.07	0.12	0.58	-0.30	0.17
	Middle (Age: [50-60])	0.15	0.13	0.27	-0.11	0.41
	Old (Age > 60)	0.11	0.22	0.63	-0.33	0.54
	Illiterate	-0.28	0.42	0.50	-1.10	0.54
	Some secondary educ.	-0.49	0.16	0.00	-0.80	-0.19
	Skilled (> sec. educ.)	-0.71	0.19	0.00	-1.08	-0.34
	Low Pisco (lower zone)	0.07	0.13	0.57	-0.17	0.32
	High Pisco (upper zone)	0.03	0.22	0.88	-0.40	0.47
Predicted r^{CPT} at average values		*0.74*				
γ_i	Intercept	0.44	0.08	0.00	0.29	0.60
	Female	-0.09	0.06	0.17	-0.21	0.04
	Young (Age < 40)	0.09	0.17	0.59	-0.24	0.43
	Middle (Age: [50-60])	-0.09	0.07	0.15	-0.22	0.03
	Old (Age > 60)	-0.07	0.09	0.47	-0.25	0.12
	Illiterate	0.03	0.13	0.82	-0.22	0.28
	Some secondary educ.	0.22	0.08	0.00	0.06	0.38
	Skilled (> sec. educ.)	0.53	0.29	0.06	-0.03	1.09
	Low Pisco (lower zone)	0.04	0.07	0.50	-0.08	0.17
	High Pisco (upper zone)	0.16	0.15	0.29	-0.14	0.46
Predicted γ at average values		*0.54*				
σ_μ	Intercept	1.38	0.18	0.00	1.02	1.73
N		3,650				

Notes: S.E. clustered at the individual level. The omitted category for *age* is for those aged between 40-50. The omitted category for *education* is for those with some primary education.

the weighting function parameter estimate. Only secondary and higher education are significantly correlated with the shape of the weighting function; the positive signs of the coefficients indicate that highly educated subjects are less sensitive to probability changes. Moreover, the coefficient on the gender variable implies that women display a more curved weighting function: female subjects underweight medium and large probabilities more strongly than males,[29] but the coefficient on the gender indicator is not statistically significant at conventional levels (*p-value* is 0.17).

In order to examine the specific effects of education on the shape of the weighting function, we use the results of an auxiliary regression, with gender, age and education (expressed in years) included as covariates (see page foot 31). We find that five additional years of education are correlated with an increase in $\widehat{\gamma}$ by 0.24, which would be reflected by a substantial reduction in the

[29]The effect of gender on the shape of weighting function was also addressed by Fehr-Duda et al. (2006), who find a similar result to ours.

curvature of the weighting function, especially in the convex, underweighting region. We can see an example of this effect in Figure 2 above, by comparing the curves corresponding to the estimates of $\widehat{\gamma} = 0.54$ (dot-dashed curve) and $\widehat{\gamma} = 0.78$ (dashed curve).

4.1.1 Heteroskedastic Specification of Fechner Errors

The analysis performed thus far has considered that the random calculation errors are homoskedastic; i.e., that the errors have a constant standard deviation across subjects. This assumption seems, however, overly restrictive. In the context of our experiment, we would hypothesize that the variability of the errors is correlated with indicators of ability (higher ability subjects should display lower randomness in their choices). In the following exploratory analysis, we include age and education (both expressed in years)[30] in the equation:

$$\widehat{\sigma}_{\mu_i} = \widehat{\sigma}_0 + \widehat{\sigma}_a Age_i + \widehat{\sigma}_e Education_i. \tag{18}$$

In the case of the expected utility model (see Table 4), the average standard deviation of the mistake thus estimated is large, 3.30, while the predicted risk aversion evaluated at the mean of the regressors is 0.57. We also observe that the significance of the negative correlation between higher education (represented by the variable *skilled*) and risk aversion is robust to this heteroskedastic specification. The regressors on the risk parameter equation are jointly significant at 5 percent.

Furthermore, we find that the standard deviation of the mistakes is positively correlated with age ($\widehat{\sigma}_a = 0.04$) and negatively correlated with education ($\widehat{\sigma}_e = -0.20$). While both variables enter the regression with significant coefficients at 1 percent, only in the latter case, the magnitude of the effect is substantial: a subject who attains five more years of education than another one would exhibit a randomness in choices that is one standard deviation smaller.

[30] Expressing age and education as indicator variables in the regressions did not yield convergence.

Table 4: EUT Estimates Assuming Heterogeneous Agents
With Heteroskedastic Fechner Normal Errors

Coefficient	Variable	Estimate	Std.Error	*p-value*	95% Conf. Interval	
r_i^{EUT}	Intercept	0.45	0.19	0.02	0.08	0.83
	Female	0.10	0.10	0.34	-0.10	0.30
	Young (Age $<$ 40)	-0.0003	0.12	1.00	-0.24	0.24
	Middle (Age: [50-60])	0.04	0.14	0.76	-0.24	0.33
	Old (Age $>$ 60)	0.23	0.27	0.40	-0.30	0.75
	Illiterate	-0.61	0.41	0.14	-1.42	0.20
	Some secondary educ.	-0.22	0.19	0.24	-0.60	0.15
	Skilled ($>$ sec. educ.)	-0.35	0.20	0.08	-0.75	0.05
	Low Pisco (lower zone)	0.15	0.11	0.16	-0.06	0.36
	High Pisco (upper zone)	0.77	0.42	0.07	-0.06	1.60
Predicted r^{EUT} at average values		0.57				
σ_{u_i}	Intercept	2.30	0.68	0.00	0.95	3.64
	Age (years)	0.04	0.01	0.00	0.02	0.06
	Education (years)	-0.20	0.05	0.00	-0.29	-0.11
Predicted σ_μ at average values		*3.30*				
N		3,650				

Notes: S.E. clustered at the individual level. The omitted category for *age* is for those aged between 40-50. The omitted category for *education* is for those with some primary education.

The results for the prospect theory model in this heteroskedastic specification are similar those in the homoskedastic case examined earlier in terms of the risk estimate (Table 3): with an average estimate of 0.67, the same indicators of education (some secondary and higher education) are significant (top panel of Table 5). However, in the case of the weighting function parameter, although there is still evidence of overweighting of small probabilities ($\widehat{\gamma} = 0.86$), the indicator variables for education turn insignificant. Similarly, in the errors equation, *education* has the expected sign ($\widehat{\sigma}_e = -0.08$) but it enters with an insignificant coefficient (*p-value* is 0.16), while age becomes significant at 1 percent. With a positive sign on age ($\widehat{\sigma}_a = 0.03$), this estimate indicates that older subjects appear to be more prone to make mistakes.

Table 5: CPT Estimates Assuming Heterogeneous Subjects
With Heteroskedastic Fechner Normal Errors

Coefficient	Variable	Estimate	Std.Error	*p-value*	95% Conf.	Interval
r_i^{CPT}	Intercept	0.68	0.22	0.00	0.26	1.10
	Female	0.16	0.13	0.23	-0.10	0.42
	Young (Age $<$ 40)	0.10	0.12	0.43	-0.15	0.34
	Middle (Age: [50-60])	0.09	0.13	0.51	-0.17	0.35
	Old (Age $>$ 60)	0.08	0.23	0.74	-0.38	0.53
	Illiterate	-0.03	0.54	0.95	-1.09	1.03
	Some secondary	-0.35	0.19	0.06	-0.72	0.02
	Skilled ($>$ sec. educ.)	-0.54	0.23	0.02	-1.00	-0.08
	Low Pisco (lower zone)	0.05	0.10	0.62	-0.15	0.26
	High Pisco (upper zone)	0.30	0.30	0.32	-0.29	0.89
Predicted r^{CPT} at average values		*0.67*				
γ_i	Intercept	0.55	0.17	0.00	0.23	0.88
	Female	-0.15	0.13	0.25	-0.40	0.10
	Young (Age $<$ 40)	-0.15	0.12	0.19	-0.39	0.08
	Middle (Age: [50-60])	-0.11	0.12	0.38	-0.34	0.13
	Old (Age $>$ 60)	-0.01	0.17	0.97	-0.33	0.32
	Illiterate	3.58	3.56	0.31	-3.39	10.55
	Some secondary	0.19	0.12	0.12	-0.05	0.42
	Skilled ($>$ sec. educ.)	0.39	0.30	0.19	-0.19	0.98
	Low Pisco (lower zone)	0.11	0.13	0.38	-0.14	0.36
	High Pisco (upper zone)	0.47	0.19	0.01	0.10	0.84
Predicted γ at average values		0.86				
σ_{μ_i}	Intercept	0.73	0.76	0.34	-0.75	2.22
	Age (years)	0.03	0.01	0.00	0.01	0.06
	Education (years)	-0.08	0.06	0.16	-0.20	0.03
Predicted σ_μ at average values		*2.11*				
N		3,640				

Notes: S.E. clustered at the individual level. The omitted category for *age* is for those aged 40-50. The omitted category for *education* is for those with some primary education.

4.2 Mixing EUT and CPT: Estimation Results

The maximum likelihood estimation results of the two-component *mixture* model specification, given in eqn.[17], show clear evidence of preference heterogeneity at the functional form level (Table 6). In particular, we see that 76 percent of subjects behave as prospect utility maximizers (i.e., $\widehat{\theta}^{\text{PT}} = 0.76$), overweighting small probabilities and underweighting medium and large probabilities (this pattern is implied by $\widehat{\gamma} = 0.33$), while the remaining 24 percent behave as expected utility maximizers, treating probabilities linearly. These mixing proportions are statistically different from 0.5 or 0 (both *p-values* < 0.05). A direct implication of the statistical significance of the mixing proportions is that aggregation of preferences, that is, assuming that *only* one model governs risk preferences, becomes problematic. In particular, using these risk estimates as correlates of outcomes would lead to biased results.

Furthermore, we continue to find evidence of risk aversion, with expected utility decision makers showing a much lower level ($\widehat{r}^{\text{EU}} = 0.20$) than prospect theory decision makers ($\widehat{r}^{\text{PT}} = 1.21$). The estimated weighting function parameter, $\widehat{\gamma} = 0.33$, implies a substantial curvature in the weighting function, especially in the convex region, as shown by the solid inverse-S shaped curve depicted in Figure 2 above. We also see that the estimated standard deviations of the Fechner errors are still large, but only the one related with the EUT model, $\widehat{\sigma}_{\mu}^{\text{PT}} = 0.5$, is statistically significant.

Table 6: Mixture Model Estimates with Homogeneous Mixing Proportions
Assuming Homogeneous Subjects and Normal Fechner Errors

Variable		Expected Utility	Prospect Theory
r	Coefficient	0.20***	1.21*
	Standard Error	0.07	0.65
	95% C. Interval	[0.07, 0.34]	[-0.08, 2.49]
γ	Coefficient	n.a.	0.33*
	Standard Error		0.19
	95% C. Interval		[-0.04, 0.71]
θ	Coefficient	0.24**	0.76***
	Standard Error	0.10	0.10
	95% C. Interval	[0.06, 0.43]	[0.57, 0.94]
σ_{μ}	Coefficient	0.51*	1.40‡
	Standard Error	0.26	0.88
	95% C. Interval	[-0.01, 1.03]	[-0.33, 3.13]
N		3,780	

n.a.: not applicable. ‡ *P-value* is 0.112. S.E. clustered at the individual level.
*** (**) [*] denotes significance at 1% (5%) [10%] level.

While the estimation of the mixture model including covariates for the risk and weighting function parameters (heterogeneous subjects case) would provide a clearer picture of the heterogeneity *within* each type of decision makers, such estimation could not converge. This lack of convergence should not be surprising, since mixture models are data hungry methods, and we have relatively few observations.

Fortunately, we still can examine the distinctive characteristics that define the regime (EUT-type or CPT-type) subjects belong. We proceed in this direction in the next subsection.

4.2.1 Heterogeneous Mixing Weights: Explaining the Regime Switching Behavior

We will test for the existence of a source of heterogeneity *within* the subset of EUT-type or CPT-type subjects that could come from the characteristics associated with their "membership" to one regime or another by estimating the mixing proportion parameter as a linear function of gender (*female*) and farming experience (expressed in years):[31]

$$\widehat{\theta}_i^{\text{EUT}} = \widehat{\theta}_0 + \widehat{\theta}_{fe} Female_i + \widehat{\theta}_{fa} Farming\ experience_i, \tag{19}$$

and then including it in the likelihood function shown in eqn.[17]. Recall that $\widehat{\theta}_0$ is the parameter we have been estimating thus far. Given that the coefficients in the prior equation do not have a direct interpretation, we will use the estimates reported in Table 7 to predict the individual-specific mixing proportions. These predicted values, together with descriptive statistics, will help us find examine whether being female and having a greater farming experience are associated with a higher tendency to behave as expected utility decision maker (EUT type).

Table 7: Mixture Model Estimates with Heterogeneous Mixing Proportions
Assuming Homogeneous Subjects & Normal Fechner Errors

Variable		Estimate	S.E.	95% Conf.	Interval
r^{EUT}	Intercept	0.20**	0.10	0.01	0.40
r^{CPT}	Intercept	0.71***	0.25	0.21	1.22
γ	Intercept	0.54***	0.17	0.21	0.88
θ_i^{EUT}	Intercept	0.72***	0.14	0.456	0.994
	Female	0.24*	0.15	-0.045	0.530
	Farming Experience-Yrs.	0.47***	0.01	0.441	0.498
Predicted θ^{EUT} *at average values*		0.18			
σ_μ^{EUT}	Intercept	0.62**	0.25	0.13	1.13
σ_μ^{CPT}	Intercept	2.19***	0.64	0.94	3.43
N		3,680			

S.E. clustered at the individual level.
*** (**) [*] denotes significance at 1% (5%) [10%] level.

Our results indicate that female are significantly less likely to behave as expected utility maximizers than male (10 *versus* 19 percent). Likewise, subjects with between 31 and 60 years of farming experience are much less likely to belong to the EUT-type than those with between 10 and years of experience or between 1 to 17 years of experience.[32] Further exploration indicates that higher educated subjects show a higher likelihood of using linear probabilities in their expected utility calculations (unreported results).Together, these results suggest that formal education and "field" experience have opposite effects on the likelihood of behaving as expected utility decision makers.

Furthermore, in this specification, the predicted value of $\widehat{\theta}^{\text{EUT}}$ is 0.18, thus implying that most of the observations (82 percent) are explained by CPT ($\widehat{\theta}^{\text{CPT}}$ is 0.82). Also, we continue to find evidence of risk aversion within both types of subjects, as well as support for nonlinear probability

[31]Including education in the equation results in jointly insignificant regression coefficients.
[32]These age categories correspond to the three quantiles of farming experience.

weighting ($\widehat{\gamma} = 0.54$). Convergence issues prevent us from pursuing further analysis of the data (such as the estimation of individual-specific risk and probability weighting parameters).

4.3 Switching Behavior and Probability Weighting with Large Mistakes

We observed that a large proportion (to be precise, 196 or 52 percent) of subjects switched back and forth from one lottery to the other in our experiment.[33] Two explanations for this multiple switching behavior (MSB) posed by the current literature are the lack of salience in the monetary incentives (Bruner 2007) and a revealed preference for indifference between the two lotteries (Harrison and Rutström 2008).

In this section, we examine a third alternative (potential) explanation for the MSB: a combination of large random calculation errors made by our subjects *and* the use of subjective probability distortions. To analyze this matter, we will consider the risk estimate of an average subject in the heterogeneous subjects case under CPT; that is, we will use $\widehat{r} = 0.74$ (see Table 3). We will then picture the decision rules (or *expected gains*) functions under EUT and CPT in the absence of random mistakes for the heterogeneous subjects cases. These decision rules are given by the difference in expected utilities (or prospective utilities, depending on the model considered) between lottery *Sol* (S) and lottery *Luna* (L), and are a function of the estimated risk parameter, $\widehat{r}$, conditional on the probabilities or decision weights used:[34]

$$\Delta EU_m(\widehat{r}|\ p) = EU_m^S(\widehat{r}) - EU_m^L(\widehat{r}) \tag{20}$$

$$\Delta CPU_m(\widehat{r}, \widehat{\gamma}|\ \widehat{\mathbf{dw}}[p]) = CPU_m^S(\widehat{r}, \widehat{\gamma}) - CPU_m^L(\widehat{r}, \widehat{\gamma}). \tag{21}$$

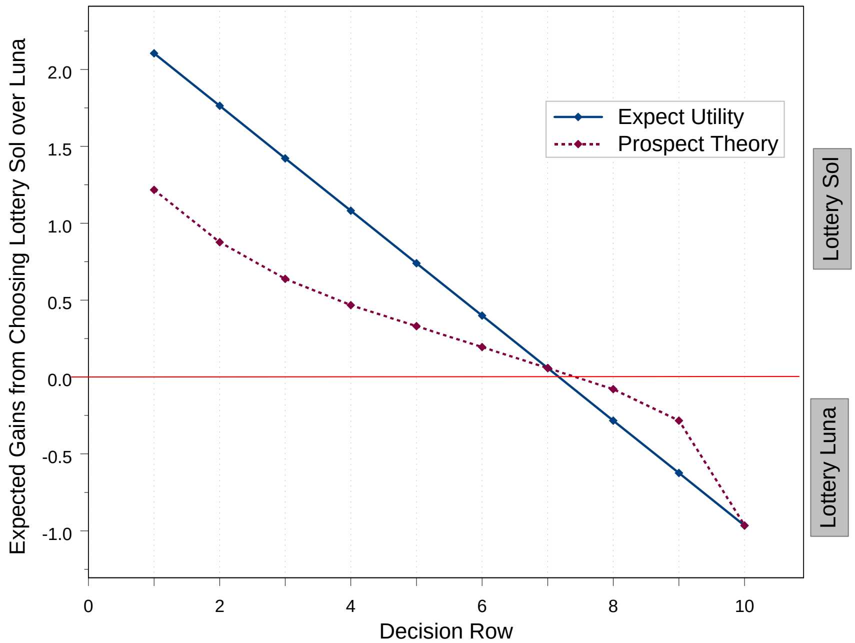
Pictured in Figure 3, we see that those functions are monotonically decreasing over the decision rows, m, displayed in the horizontal axis. A positive value of $\Delta EU_m(\cdot)$ or $\Delta CPU_m(\cdot)$ would obviously mean that lottery S should be selected; while a negative value would imply that lottery L should be chosen. The solid line depicts the *true* expected gains from choosing lottery S over lottery L under EUT, while the dashed line pictures the analogous function for CPT. In both cases, those functions attain a positive value until decision row 7, and thereafter their values become negative, meaning that lottery L should be chosen, in the absence of calculation mistakes. We can see that for a given risk parameter (equal to 0.74), while linear probability weighting results in a straight line with negative slope (the solid line, EUT), non-linear probability weighting implied by the weighting function parameter $\widehat{\gamma}$ of 0.54 (the dotted curve: CPT) flattens the expected gains function for the first nine decision rows.

Now, the question is whether nonlinear probability weighting is sufficient to explain MSB in this context. Figure 3 can be misleading in answering this question, given that it shows the expected gains under different utility functions (for EUT and CPT), which are ordinal measures that have

[33] 121 subjects, or 32 percent, switched only once.

[34] Note that these equations are similar to the ones used above (eqns.[15] and [3], respectively), with the value of the risk estimate of 0.74 already plugged in, but excluding the noise parameter.

Figure 3: Expected Gains under EUT and CPT



different underlying distributions of calculation mistakes. One route to follow in examining the plausibility of MSB in this context is to calculate the probability of making mistakes under the error distributions estimated above (i.e., $\widehat{\mu} \mid \text{EUT} \sim N[0, 2.79]$ and $\widehat{\mu} \mid \text{CPT} \sim N[0, 1.38]$) and see if the magnitude of those errors can mislead subjects in their choices across decision rows.

Thus, the probability of *not* making mistakes (i.e., of choosing lottery S when this lottery has higher expected gains; and selecting lottery L, otherwise) under EUT is given by eqn.[5]:

$$\Pr(\text{no mistakes}) = \Pr(EU_m^S - EU_m^L + \mu > 0) = \Phi\left(\frac{EU_m^S - EU_m^L}{\widehat{\sigma}_\mu}\right),$$

where $\Phi(\cdot)$ denotes the c.d.f. of the standard normal distribution of the expression in parenthesis. The probability of making mistakes [Pr (mistakes)] is then [$1 - \Pr(\text{no mistakes})$]. An analogous expression holds for CPT. We then plugged the estimated values of the true expected gains from choosing lottery S into the prior expression and computed such probabilities for each decision row m.

Table 8 reports the results of these calculations together with the decision weights ($\mathbf{dw}[p]$) (expressed by eqn.[12]) used to produce Figure 3. These decision weights are implied by the weighting functions reported in eqn.[13] imposing the value of $\widehat{\gamma} = 0.54$. We see that in the CPT case, subjects overweight (i.e., $\mathbf{dw}[p] > p$)[35] small and medium probabilities (up to row 6); and

[35]Note that we said earlier that overweighting [underweighting] meant that $\mathbf{w}(p) > p$ [$\mathbf{w}(p) < p$]. We are here

thereafter, they underweight (large) probabilities, a result that is reflected in the shape of the CPT expected gains function pictured above.

Armed with these results, we are now in position to answer the question posed earlier. Contrarily to our expectations, the answer is no. To see why, note that as long as the probability of making mistakes is *greater* under CPT than EUT, the former model would explain *better* the switching behavior. And, the larger the gap between the probabilities of making mistakes under those models, the greater the "explanatory power" of the model with the higher probability of mistakes. As shown in Table 8, CPT explains the switching behavior slightly better than EUT in rows 3, 4, 5, 8, and 9, while EUT does better in rows 1, 7, and 10. In rows 2 and 6, both models explain such behavior similarly well. Note that the probability of making mistakes under both models gets large from decision rows 5 through 9 (40 to almost 50 percent), probably as a result of the greater difficulty that subjects had in choosing the lottery with the higher mean in those rows.

Table 8: Expected Gains from Lottery Sol and Decision Weigths under EUT and CPT

Variables	Decision Row									
	1	2	3	4	5	6	7	8	9	10
EUT Heterogeneous subjects case, with $\widehat{\sigma}_\mu = 2.79^a$										
Probability, p^b	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	1.00
Expected gain from choosing lottery S over L^c	2.10	1.76	1.42	1.08	0.74	0.40	0.06	-0.28	-0.62	-0.97
Probability of mistake^d	0.23	0.26	0.31	0.35	0.40	0.44	0.49	0.46	0.41	0.36
CPT Heterogeneous subjects case, with $\widehat{\gamma} = 0.54$ & $\widehat{\sigma}_\mu = 1.38^e$										
Decision weight, $\mathbf{dw}(p)^b$	0.36	0.46	0.53	0.58	0.62	0.66	0.70	0.74	0.80	1.00
Expected gain from choosing lottery S over L^c	1.22	.88	0.64	0.47	0.33	0.19	0.06	-0.08	-0.28	-0.97
Probability of mistake^d	0.19	0.26	0.32	0.37	0.41	0.44	0.48	0.48	0.42	0.24

[a] Estimates from Table 2. [b] The probabilities (p) and decision weights ($\mathbf{dw}(.)$) correspond to the higher prize under each lottery. E.g., p_1(higher prize) = 0.1, p_2(lower prize) = 0.9, $w(p_2) = 0.64$, $dw(p_1) = 1 - w(p_2) = 0.36$. [c] Calculated assuming a risk estimate of 0.54. [d] This is the probability of choosing the lottery with the lower expected gains. [e] Estimates from Table 3.

A more complete estimation of subject-specific calculation mistakes, together with subject-specific risk parameters, would have likely helped to better examine the switching behavior. This analysis is deferred to future research.

using analogously that definition for the case of $\mathbf{dw}(p)$ instead of $\mathbf{w}(p)$.

5 Estimation Results Excluding 'Irrational' Subjects

In our experiment, a large number of subjects (105 to be precise) mistakenly chose the lottery *Sol* in the 10th decision row, thus preferring to get 1,800 Soles for sure, instead of the 3,500 Soles for sure that they could have gotten by choosing lottery *Luna*. As one may expect, those subjects—which we call *irrational*— attained lower levels of schooling (two years less of education), and are significantly older (in more than 4 years),[36] than subjects who did not make such mistake. Excluding those 105 individuals from our original sample of 378 subjects (3,780 observations), results in a restricted sample of 273 subjects (2,730 observations). From that subsample, we have individual-level information for 265 individuals (2,650 observations).

The regression results for this restricted sample show evidence of risk aversion, both when we consider separately that the EUT or CPT models fully explain the data and when we allow the data to be explained by both models via the estimation of mixture models. Indeed, we observe that subjects are *less* risk averse than in our full sample (see column 3 of Tables D.1 and D.2). Moreover, the standard deviation of the calculation mistakes is relatively smaller. In the EUT case (Table D.1), the magnitude of the mistakes now ($\widehat{\sigma}_\mu = 2.00$) is 26 percent lower than the expected utility obtained by those choosing lottery *Sol* (across all decision rows) and 35 percent lower than that corresponding to subjects who chose lottery *Luna*. In the CPT case (Table D.2), the standard deviation of the mistakes ($\widehat{\sigma}_\mu = 0.66$) represent only about 20 percent of the expected utilities obtained from those choosing either lottery *Sol* or lottery *Luna* (across decision rows). The exclusion of the irrational subjects from the sample has removed a large proportion of the errors.

Three other major results remain similar to findings for the entire sample: (i) higher education indicators continue to predict risk aversion, though only for the CPT model; (ii) there is strong evidence of subjective probability weighting, though the value of the weighting function parameter, $\widehat{\gamma} = 0.27$, implies a non-monotonically increasing curve (the curve is decreasing for low probabilities, but not for medium or large ones). And (iii) most of the subjects (70 percent) appear to behave as prospect theory decision makers (Table D.3).

6 Conclusion

This paper studies how decision making under risk is made in a developing country context. In particular, the results verify the existence of psychological factors in the choices made. More specifically, subjects appear to make probability distortions (they overweight small probabilities and underweight medium and large probabilities), result that is consistent with rank-dependent utility models, such as prospect theory. Moreover, we show evidence of heterogeneity in the data generating process, in the sense that distinct sets of subjects are found to behave differently than others; in particular, about 30 percent of the subjects behave as expected utility decision makers and about 70 percent of them behave as prospect theory decision makers. Clear implications of

[36] All the mean T-tests performed in those cases have a *p-value* < 0.001.

these results are that these departures from expected utility theory should be taken into account when designing policies that will affect subjects' decisions under risk (such as the introduction of a new agricultural technology, broadly understood); and that assuming that only one decision model explains the entire data may lead to potentially biased outcomes.

The paper also shows that field subjects exhibit risk averse preferences. This finding is robust to different specifications, including the one that allows to account for heterogeneity in the data generating process. In general, higher education appears correlated with a greater propensity to take risks. This result not only suggests a linkage between (a proxy for) cognitive abilities and risk preferences, but also points to interesting possible implications for the diffusion of new technologies that inherently involve risks. We may, for instance, hypothesize that if the elicited preferences indeed reflect preferences held when making actual economic decisions, the innovative producers would likely come from the higher end of the education sample distribution. As we continue to provide further evidence about the main correlates of risk (and other relevant measures of preferences), it is likely that we will unveil important connections between experimental measures and economic outcomes.

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Appendix A. Basic Statistics

Variable	Mean	Std. Dev.	N
Demographics and Education			
Age (years)	54.9	13.3	367
Aged less than 40	0.14	0.35	367
Aged between than 40 and 50	0.19	0.39	367
Aged between than 50 and 60	0.33	0.47	367
Aged over 60	0.33	0.47	367
Female (Yes=1)	0.27	0.44	367
Education (years)	6.33	4.11	365
Illiterate	0.05	0.23	365
Some year of primary school	0.51	0.50	365
Some year of secondary school	0.34	0.47	365
Completed more than secondary school	0.09	0.29	365
Agriculture and Assets			
Farming experience (years)	23.9	12.7	368
Size of owned agricultural plot (hectares)	6.03	5.57	367
Size of cultivated land (hectares)[1]	5.01	4.13	365
Planted cotton (Yes=1)[1]	0.83	0.39	368
Cotton yields (quintals per hectare)[1]	46.8	14.8	293
Self-reported value of owned ag plot (000 Soles)[2]	7.43	8.78	307
Self-reported value of house (000 Soles)[3]	15.92	21.0	321
Self-reported value of wealth (000 Soles)[4]	20.42	21.8	362
Credit and Insurance			
Got credit for farming activities (Yes=1)[1]	0.61	0.49	378
Got formal credit	0.38	0.49	232
Got informal credit	0.34	0.47	232
Got credit from cotton mills	0.28	0.45	232
Has any other type of insurance (Yes=1)[5]	0.44	0.50	378
Health insurance (mostly public)	0.36	0.48	368
Life insurance	0.14	0.37	367
Accident insurance	0.10	0.30	367

[1] It refers to the 2007-2008 farming season. [2] The question was "how much do you think you would have to pay to rent a hectare of land with similar characteristics to your main parcel.
[3] The question was "how much do you think you'd have to pay to buy a house with similar characteristics to your own".[4] *Wealth* includes the values of land and house.
[5] This figure is mostly affected by the access to publicly provide health insurance. The access rate to privately provided insurance (life & accident insurance), is between 10 and 14 percent.

Appendix B. Experiment Instructions

What follows are the instructions given to subjects. The monitor used slides that were projected on a wall. The parts in [square brackets] are directions the monitor should follow and the parts in {curly brackets} are notes to clarify the information provided to subjects or the procedures followed.

The objective of this activity is to win money. There are 4 possible prizes: 90, 1400, 3500, and 1800 soles. How are you going to win these prizes?

[Show slide 1: Lottery prizes]

To win these prizes, first you will have to choose between two options, the option Sol and the option Luna. If you choose the option Sol, you can win a maximum prize of 1,800 soles and a minimum prize of 1,400 soles. And if you choose the option Luna, you can win a maximum prize of 3,500 soles and a minimum prize of 90 soles. Note that with the option Sol the difference between the maximum and minimum prize is small, while it is large in the case of the option Luna.

In addition, in the option Sol the maximum prize of 1,800 soles is smaller than the maximum prize of 3,500 soles in the option Luna, and the minimum prize of 1,400 soles in the option Sol is greater than the minimum prize of 90 soles in the option Luna.

Thus, you will pick between Sol and Luna in 10 rows, one after another. Once you have picked between Sol and Luna, the prize you will receive in each row will depend on the number that you obtain by rolling a 10-sided die like the one your assistants are now showing you. This die has 10 sides numbered from 1 to 10; that is, it is equally likely to get any of the 10 numbers.

We will now see an example of the prizes you may earn. Please look at the second row on page 7 in your binders {page 7 displayed the 10 decision rows}.

[Show slide 2: Lottery prizes in row 2]

[Pick a volunteer] Let's see... [Say name], in the second row, which do you prefer: Sol or Luna? {s/he will say Sol/Luna}. Now throw the die. The die is showing the number [1,2,3,...,or 10]. Since [say name] chose [Sol/Luna], we see that in the second row the prize that corresponds to the number [1,2,3,...,10] is [say amount]. Now, if [say name] would have chosen [Luna/Sol], the prize that corresponds to [1,2,3,...,10] is [say amount].

Let's do another example.

[Show slide 3: Lottery prizes in row 8]

[Pick another volunteer]. Let's see... [say name], in the eighth row, which do you prefer: Sol or Luna? [s/he will say Sol/Luna]. Now throw the die. The die is showing the number [1,2,3,...,10]. Since [say name] chose [Sol/Luna], we see that in the eighth row the prize that corresponds to the number [1,2,3,...,10] is [say amount]. Now, if [say name] would have chosen [Luna/Sol], the prize that corresponds to [1,2,3,...,10] is [say amount].

Now we will compare the prizes that could be obtained from the two rows we have used in our examples.

[Show slide 4: Lottery prizes in rows 2 and 8]

If throwing the die results in the number 4, those who chose Sol in row 2 would win 1,400 soles and those that chose Luna in row 2 would win 90 soles. In row 8, if throwing the die results in number 4, those who chose Sol would win 1,800 soles and those who chose Luna would win 3,500 soles.

Note that in row 8 there are more chances of winning the maximum prize than there are in row 2, in both Sol and Luna. This is because in row 8 there are 8 chances to win the maximum prize and only 2 chances to win the minimum prize, while in row 2, there are only 2 chances to win the maximum prize and 8 chances to win the minimum prize.

Now look at page 7 [Show slide 5: Lottery prizes in the 10 rows]... in which you can see that as one goes down the table, the chances to win the larger prize are greater; and the chances of winning the smaller prize are fewer.

Notice that in the last row, row 10, regardless of which number appears on the die, the prize you will receive will be 1,800 soles if you choose Sol and 3,500 soles if you choose Luna.

Hypothetical Payoffs Round

We are now going to do a practice round. Please look at your worksheets on page 7 of your binders. In this sheet you have to choose, for each of the 10 rows, between the option Sol and the option Luna, marking with an “X” on the drawing of the sun or the moon.

Please mark on your practice sheet for each of the 10 rows the option that you prefer in each row.

After that, we will choose one row to determine the prize you would win. Assistants, please begin the practice round in your valleys.

{Assistants advised the monitor when all choices in their valleys were made.}

Now, we will see what you would have won. To determine the row you will play, we will throw the 10-sided die in each valley. Assistants, throw the die one time in each of your valleys...

{Assistants advised the monitor when dice were rolled one time in their valleys.}

Now that we know which row was chosen in each valley, each of you will throw the 10-sided die to determine your prize. Assistants, have each farmer in your valley throw the die.

{Assistants advised the monitor when all choices in their valleys were made.}

{The monitor then chose two valleys to illustrate the procedure to determine winnings for this game.}

Let’s see... [say name in valley 1], we are going to see what would have been your prize. First, which row was selected in your valley?... And in that row, did you pick Sol or Luna? ... And what number did you get when you threw the die?.....Then [say name] in row [say resulting row], with the option [Sol/Luna] and the number [say number of die roll], would win [say amount]. If [say name] would have chosen the other option [Luna/Sol], he would win [say amount].

Let’s see... [say name in valley 2], we are going to see what would have been your prize. First, which row was selected in your valley?... And in that row, did you pick Sol or Luna?... And what number did you get when you threw the die?.....Then [say name] in row [say resulting row], with the option [Sol/Luna] and the number [say number of die roll], would win [say amount]. If [say name] would have chosen the other option [Luna/Sol], he would win [say amount].

This was a practice round. Now we are going to do it for real money.

High Payout Round

How will we determine how much money you will win for participating in this activity? This will depend on the prizes obtained in the row that is chosen at random, in the same way that your earnings were selected in the earlier activities. To choose the row, you will throw a 10-sided die one time for each valley, just as you did in the practice round. We will pay you one sol in cash for each 600 soles of prize winnings. That is, the minimum amount that you could win is 90/600= 0.15 soles, and the maximum amount is 3,500/600= almost 6 soles.

Please look at your sheet for this activity, on page 8 of your binders.

[show slide 6: lottery prizes in the 10 rows]

In this activity you have to choose, just like in the practice round, between the options Sol and Luna, marking with an “X” on the drawing of the sun or the moon in each row, from 1 to 10. Before we start, are there any questions?

{Pause for questions.}

Now, please, mark on your sheets for this activity in each one of the 10 rows the option that you prefer.

Appendix C. Risk Game Worksheet Sample

	SOL				LUNA			
	Boxes	Amount	Boxes	Amount	Boxes	Amount	Boxes	Amount
1	1	S/. 1800	2 3 4 5 6 7 8 9 10	S/. 1400	1	S/. 3500	2 3 4 5 6 7 8 9 10	S/. 90
2	1 2	S/. 1800	3 4 5 6 7 8 9 10	S/. 1400	1 2	S/. 3500	3 4 5 6 7 8 9 10	S/. 90
3	1 2 3	S/. 1800	4 5 6 7 8 9 10	S/. 1400	1 2 3	S/. 3500	4 5 6 7 8 9 10	S./ 90
4	1 2 3 4	S/. 1800	5 6 7 8 9 10	S/. 1400	1 2 3 4	S/. 3500	5 6 7 8 9 10	S/. 90
5	1 2 3 4 5	S/. 1800	6 7 8 9 10	S/. 1400	1 2 3 4 5	S/. 3500	6 7 8 9 10	S/. 90
6	1 2 3 4 5 6	S/. 1800	7 8 9 10	S/. 1400	1 2 3 4 5 6	S/. 3500	7 8 9 10	S/. 90
7	1 2 3 4 5 6 7	S/. 1800	8 9 10	S/. 1400	1 2 3 4 5 6 7	S/. 3500	8 9 10	S/. 90
8	1 2 3 4 5 6 7 8	S/. 1800	9 10	S/. 1400	1 2 3 4 5 6 7 8	S/. 3500	9 10	S/. 90
9	1 2 3 4 5 6 7 8 9	S/. 1800	10	S/. 1400	1 2 3 4 5 6 7 8 9	S/. 3500	10	S/. 90
10	1 2 3 4 5 6 7 8 9 10	S/. 1800			1 2 3 4 5 6 7 8 9 10	S/. 3500		

Appendix D. Regression Results for the Restricted Sample

Table D.1: EUT Estimates with Heterogeneous Subjects and Normal Fechner Errors
(*Restricted Sample: N = 2,650*)

Coefficient	Variable	Estimate	Std.Error	*p-value*	95% Conf.	Interval
r_i^{EUT}	Intercept	0.18	0.09	0.04	0.00	0.35
	Female	0.04	0.07	0.58	-0.10	0.18
	Young (Age $<$ 40)	-0.18	0.10	0.06	-0.38	0.01
	Middle (Age: [50-60])	-0.15	0.09	0.09	-0.32	0.03
	Old (Age $>$ 60)	-0.02	0.09	0.80	-0.20	0.16
	Illiterate	-0.28	0.14	0.04	-0.56	0.00
	Some secondary	-0.07	0.07	0.36	-0.22	0.08
	Skilled ($>$ sec. educ.)	-0.10	0.12	0.41	-0.32	0.13
	Low Pisco (lower zone)	0.12	0.07	0.09	-0.02	0.27
	High Pisco (upper zone)	0.10	0.11	0.33	-0.10	0.31
Predicted r^{EUT} at average values		*0.11*				
σ_u	Intercept	2.00	0.16	0.00	1.70	2.32

Notes: S.E. clustered at the individual level. The omitted category for *age* is for those aged 40-50. The omitted category for *education* is for those with some primary education.

Table D.2: CPT Estimates Assuming Heterogeneous Subjects and Fechner Normal Errors
(*Restricted Sample: N = 2,650*)

Coefficient	Variable	Estimate	Std.Error	*p-value*	95% Conf.	Interval
r_i^{CPT}	Intercept	0.70	0.11	0.00	0.50	0.92
	Female	0.06	0.06	0.32	-0.06	0.19
	Young (Age $<$ 40)	-0.21	0.09	0.03	-0.39	-0.03
	Middle (Age: [50-60])	-0.09	0.08	0.28	-0.26	0.07
	Old (Age $>$ 60)	-0.03	0.08	0.72	-0.19	0.13
	Illiterate	-0.12	0.12	0.34	-0.36	0.12
	Some secondary educ.	-0.15	0.07	0.03	-0.29	-0.01
	Skilled ($>$ sec. educ.)	-0.23	0.11	0.03	-0.43	-0.02
	Low Pisco (lower zone)	0.07	0.06	0.29	-0.06	0.19
	High Pisco (upper zone)	-0.06	0.09	0.49	-0.23	0.11
Predicted r^{CPT} at average values		*0.59*				
γ_i	Intercept	0.39	0.05	0.00	0.30	0.48
	Female	-0.03	0.03	0.38	-0.09	0.03
	Young (Age $<$ 40)	0.13	0.07	0.05	-0.0001	0.26
	Middle (Age: [50-60])	0.01	0.04	0.76	-0.07	0.10
	Old (Age $>$ 60)	0.01	0.04	0.80	-0.07	0.09
	Illiterate	-0.02	0.05	0.67	-0.12	0.08
	Some secondary educ.	0.08	0.04	0.05	-0.0003	0.15
	Skilled ($>$ sec. educ.)	0.15	0.07	0.04	0.01	0.28
	Low Pisco (lower zone)	0.01	0.03	0.86	-0.06	0.07
	High Pisco (upper zone)	0.10	0.06	0.09	-0.02	0.22
Predicted γ at average values		*0.46*				
σ_μ	Intercept	0.66	0.09	0.00	0.50	0.83

Notes: S.E. clustered at the individual level. The omitted category for *age* is for those aged 40-50. The omitted category for *education* is for those with some primary education.

Table D.3: Mixture Model Estimates: EUT and CPT with Fechner Normal Errors
(*Restricted Sample: N = 2,730*)

Variable		Expected Utility	Prospect Theory
r	Intercept	0.42***	1.14***
	Standard Error	0.08	0.03
	95% C. Interval	[0.26, 0.58]	[0.85, 1.42]
γ	Intercept	n.a.	0.27***
	Standard Error		0.03
	95% C. Interval		[0.22, 0.33]
θ	Intercept	0.29***	0.71***
	Standard Error	0.04	0.04
	95% C. Interval	[0.21, 0.36]	[0.64, 0.79]
σ_μ	Intercept	0.31***	
	Standard Error	0.07	
	95% C. Interval	[0.18, 0.44]	

n.a.: not applicable.

*** denotes significance at 1 % level. S.E. clustered at the individual level.