Household Time and Risk Preferences and Adaptation to Climate Change

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Abstract

Climate change adaptation is fundamentally a decision to incur certain costs now in return for uncertain benefits and costs in the future. Thus time and risk preferences will shape how individuals and groups adapt on their own and in response to public policies and programs. Drawing on recent advances in behavioral economics, we clarify how these adaptation decisions are shaped by different parameters and forms of time and risk preferences. The magnitude of these parameters and the prevalence of these forms thus become important empirical questions for policymakers. Past studies, however, shed little light on these questions because their empirical designs and estimation strategies are often unable to discriminate among rival explanations for the patterns observed. Applying recent developments in experimental designs and estimators, we conduct field experiments to characterize time and risk preferences in a rural population in the western, arid region of Costa Rica, targeted by policymakers for climate change adaptation investments. Decisions about these investments are often made at the household-level, rather than at the individual-level. Thus, we expand on previous experimental studies by characterizing time and risk preferences at both the levels of individuals and married couples. We conclude by exploring whether the hypotheses about how adaptation investments vary with time and risk preferences are validated by the data, and by describing how climate change adaptation policies should be designed if the patterns observed in study site are prevalent in other low and middle-income nations.

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1 Introduction

Earth's climate is expected to change considerably in the future. Although scientists do not yet know with great certainty the full effects of climate change on human populations, most agree that weather variability and the probability of extreme climate events will increase (Fischer & Knutti, 2015). These changes increase the risk of water scarcity and damage to infrastructure and crops, among other stresses. The costs of adapting to changes in risks will vary across regions and populations, but every society will have to adapt to climate change in some way.

According to the Intergovernmental Panel on Climate Change (Field, 2012), "adaptation is the process of adjustment to actual or expected climate and its effects, in order to either lessen or avoid harm or exploit beneficial opportunities." These adjustments can take many forms. For example, individuals or households can acquire insurance, they can save money for the future, or they can invest in technologies (water storage, floating houses, water-conserving technologies, efficient irrigations systems, change in crops, etc.). Moreover, communities and governments can invest in collective infrastructure (e.g., sea walls) that also help people adapt to climate change.

Citizens in poor countries that depend heavily on natural resources are particularly vulnerable to climate change. Their income, food, and water security are already precarious and they have limited adaptive capacity. To help them adapt, policymakers need to not only develop large-scale interventions, but also develop programs that encourage the citizens in poor nations to make private adaptation investments. To develop policies and programs that encourage such investments, we must understand the factors that shape household adaptation decisions.

Two factors that may play important roles in shaping adaptation decisions are time and risk preferences. An investment in climate change adaptation requires a fixed payment today in exchange for uncertain payoffs at a later time. Adaptation is therefore fundamentally an intertemporal decision under risk. As a result, the parameters and forms of risk and time preferences are likely to shape adaptation decisions. Drawing on recent advances in behavioral economics, we clarify how adaptation decisions are shaped by time and risk preferences.

To empirically assess the role of these preferences in an adaptation context, we apply recent developments in experimental designs and estimators in an artefactual field experiment with a rural population in the western, arid part of Costa Rica that has been targeted by policymakers for climate change adaptation investments. Because most adaptation decisions are intra-household decisions, we elicit risk and time preferences for both individuals and married couples. We then connect the variation in individual and couples' preferences to the variation in an adaptation measure: investment in private water-storage tanks that reduce intra-annual variability in water supply.

Our study makes three contributions. First, it assesses the relationship between preferences and investment in climate change adaptation. The way in which adaptation decisions are affected by risk aversion is ambiguous: more risk aversion can increase or decrease investment in adaptation depending on the level of uncertainty surrounding the benefits of the investment (Koundouri, Nauges, & Tzouvelekas, 2006). Although risk aversion is high in the study population, we find no significant correlation between individual or couples' degrees of risk aversion and our measure of adaptation investment. However, probability weighting is common in this population: people tend to overweigh the likelihood of the most favorable outcomes. Consistent with theory, more "optimistic" households are significantly less likely to invest in adaptation.

The way in which adaptation decisions are theoretically affected by time preferences is unambiguous: higher discount rates and greater time inconsistency (hyperbolic discounting) lead to lower levels of investment. In the study population, we detect no evidence of time inconsistency. Yet, even after adjusting for the curvature of the utility function, individual and couple discount rates are high ($> 30\%$). Consistent with theory, higher discount rates are associated with lower adaptation investment.

The second contribution of the study is an examination of whose preferences – individuals' or married couples' – best explain household adaptation decisions. The measure of adaptation investment is better described by the joint preferences of the couple than by the individual preferences of the head of household. This result is consistent with household survey response about decision-making. Couples have similar risk aversion and probability weighting to individuals, but they are substantially less patient than individuals: their discount rates are an estimated 14 percentage points higher than the rates of individuals. Were these findings to generalize to poor populations in other areas targeted for climate change adaptation programs, they strongly imply a need for policies that focus on incentivizing couple decision-making for climate change adaptation. We discuss the full implications for policy design in the conclusions.

The third contribution of our study is to replicate, improve and extend prior empirical research on risk and time preferences and on the difference in preferences between individuals and couples. Some studies have estimated time preferences in developing nations (Duflo, Kremer, & Robinson, 2008; Pender, 1996; Tanaka, Camerer, & Nguyen, 2010). However, their elicitation designs assume that subjects make decisions over nominal payouts rather than utilities, which implies subjects are risk neutral. If subjects are risk averse, the estimator is biased. To eliminate this bias, we elicit and estimate subjects' risk and time preferences jointly (Andersen, Harrison, Lau, & Rutström, 2008, 2014). Accounting for risk aversion reduces the annualized discount rate substantially: from 500%, under a risk neutral specification, to 45%.

This joint estimator will be biased, however, if risk preferences are not well approximated by Expected Utility Theory (EUT), introduced by Neumann and Morgenstern (1947), but rather by Rank-Dependent Utility (RDU) framework, introduced by Quiggin (1982). Under RDU, risk preferences are shaped not only by a coefficient of risk aversion but also by a (non-linear) transformation of objective probabilities. For our study population, we strongly reject the EUT framework in favor of an RDU model with a Prelec probability weighting function (pwf) that reflects optimistic probability weighting: subjects, on average, overweigh the probability of the best outcome. Adjusting for this weighting reduces estimate annualized discount rates by ten percentage points to 35%.

We also seek to detect another important feature of time preferences: "present-bias" or "hyperbolic discounting", which implies a discounting function where discount rates "decline as the discounted event is moved further away in time" (Laibson, 1997). Such discounting leads an individual to overweigh present consumption so that investments, like adaptation investments, are postponed or never occur. Were present-bias to be widespread in vulnerable populations, adaptation policy design may require certain "commitment device" to effectively encourage private adaptation investments. In contrast to previous studies in developing countries (Bauer, Chytilová, & Morduch, 2012; Duflo, Kremer, & Robinson, 2011; Tanaka et al., 2010), we cannot detect evidence of present bias.

Finally, we add to the inchoate literature that contrasts individual preferences to the preferences of couples (mates). The study includes two innovations: (a) to differentiate a married effect from a group effect (two people, rather than one person, making decision), the design uses both real and "fake" couples (non-mates); and (b) to better characterize the couples' decisions in a structural model, we apply a household bargaining model under uncertainty, which estimates the spouses' respective weights in the household decision process. For the risk preference tasks, a bargaining process appears to take place, with the wife leading the decision. For the time preference tasks, couples express significantly less patience than both husband and wife show individually, in line with predictions that a preference shift occurs when decisions are made as a group (Eliaz, Ray, & Razin, 2006). The results imply that one should not assume that the risk and time preferences of the head of household is representative of the preferences of the married couple or reflect household decision-making.

The remainder of the paper is structured in the following way. We commence with a review of the literature on risk and time preferences and climate change adaptation decision in Section 2. Sections 3 to 6 describe the methodology, experimental design, econometric model, and experimental procedure, respectively. Section 7 provides a descriptive analysis of the experimental data. In Section 8, we present the results for individuals' and couples' time and risk preferences. In Section 9, we assess the relationship between the estimated preferences and the households' investments in water tanks. Section 10 relates the findings to the existing literature, and Section 11 discusses policy implications. Finally, Section 12 concludes.

2 Literature Review

There is an extensive literature that discusses the appropriate framework to model decisions under risk. The main contestants are EUT, which is the most commonly known framework, and RDU when no losses are considered. Under EUT, the expected utility of any risky choice is the sum of the utility of the possible outcomes, weighted by the known probabilities of each outcome. In this framework, risk attitudes are formally characterized as individuals' aversion to variability of final outcomes and are characterized by the concavity of the utility function. Nevertheless, Quiggin (1982) argues that subjects' risk attitudes do not only come from the variability of payoffs. Under RDU, risk aversion is formally characterized as aversion to variability of final outcomes, as well as "pessimism" or "optimism" over probabilities, which is captured by the pwf. The pwf transforms the cumulative distribution of the objective probabilities so that outcomes are weighted differently than they are under EUT. RDU assumes that peoples' decisions are affected not simply by the objective probabilities of an event, but rather by peoples' attitudes towards those probabilities. Thus under RDU, risk aversion is explained by the properties of both the utility function and the pwf (Harrison & Rutstrom, 2008).

The empirical relevance of RDU has been shown in several papers for developed and developing countries (Harrison, Humphrey, & Verschoor, 2010; Tanaka et al., 2010; Wu & Gonzalez, 1996). A priori, we do not know which framework applies to our data. Thus we consider both and test which one is more appropriate for the data.

Regarding time preferences, the discounting utility (DU) model of Samuelson is the traditional framework applied by economists to explain intertemporal decisions and is represented by the exponential discounting function. One of the key features of the DU model is a constant discount rate for different time horizons. Nevertheless, there is some empirical evidence that shows that discount rates are not constant and that they in fact decline over time. A declining discount rate implies that intertemporal preferences are time-inconsistent and people exhibit preference reversals. People who discount hyperbolically do not fulfill the plans they make today because when the time to commit arrives present consumption seems more valuable than the future profits of the new endeavor. This form of discounting is known as hyperbolic discounting and has been modeled in different ways: quasi-hyperbolic model (Phelps & Pollak, 1968), fixed cost model (Benhabib, Bisin, & Schotter, 2010), the Mazur discounting function (Mazur, 1984), the Weibull discounting function (Read, 2001), etc.

The evidence of hyperbolic behavior in rigorous studies that elicit discounting functions is scarce. Moreover, one of the main criticisms to the current studies that test for the presence of hyperbolic discounting is that they do not consider discounted utilities. In an intertemporal decision, individuals compare a utility level today versus a utility level in the future. Thus, a key feature of any good experimental design that seeks to elucidate discounting behavior is to consider the curvature of the utility function. Many experimental studies that test for the presence of hyperbolic discounting, particularly earlier studies, fail to consider this curvature, which could bias their results. Andersen et al. (2008, 2014); Andreoni and Sprenger (2012); Coller, Harrison, and Rutström (2012) introduce the shape of the utility function in their estimation. In Coller et al. (2012), the authors estimate exponential and quasi-hyperbolic models as well as a mixture model of both discounting functions[1]. They find that the sample follows both discounting functions in similar proportions. In contrast, neither Andersen et al. (2014) nor Andreoni and Sprenger (2012) find hyperbolic discounting in their samples. Andersen et al. (2014) posit that one explanation for the difference between their results and Coller et al.'s results is that they use a sample of Danish individuals, whereas Coller et al. (2012) use students in the U.S. The authors suggest that more studies should be done with a variety of populations. In our analysis, we include risk choices to model the curvature of the utility function as in Andersen et al. (2014) and both exponential and hyperbolic discounting functions are tested to see if people have constant or declining discount rates.

Adaptation decisions are taken by individuals but also by collective entities, such as communities or households. Since adaptation decisions at the household level are sometimes taken by the married couple and we do not know if couple decisions are similar to the spouses' decisions, we elicit couples' preferences. Elicitation of risk preferences at the couple level has been done by Abdellaoui, L'Haridon, and Paraschiv (2013); Bateman and Munro (2005); Carlsson, Martinsson, Qin, and Sutter (2013); De Palma, Picard, and Ziegelmeyer (2011). These studies use subjects from developed countries, except for Carlsson et al. (2013) which elicits risk preferences for households in rural China. Bateman and Munro (2005) find that couples show more risk aversion when making choices jointly rather than individually. Abdellaoui, L'Haridon, and Paraschiv (2013) find that women show more risk aversion than couples and men. They also find that spouses have equal weight in the household decision. The authors also test for joint and individual differences using the RDU framework and find little differences: both individuals and couples overweigh small probabilities and underweigh high probabilities but men seem to overweigh small probabilities more and underweigh high probabilities less than women and couples. Carlsson et al. (2013) conclude that the individual and joint decisions are not statistically different from each other, but that the

[1]Two well-cited studies that do not consider the shape of the utility function in their analysis find evidence of hyperbolic discounting (Benhabib et al., 2010; Tanaka et al., 2010)

joint decisions are typically closer to the husbands' decisions. So, the evidence regarding differences between individuals' and couples' decision making under risk is inconclusive.

Regarding time preferences, there are two studies that elicit time preferences at the couple level: Abdellaoui, L'Haridon, Paraschiv, et al. (2013); Carlsson, He, Martinsson, Qin, and Sutter (2012). Carlsson et al. (2012) elicit time preferences using a sample of married couples in rural China, while Abdellaoui, L'Haridon, Paraschiv, et al. (2013) use French couples. Carlsson et al. (2012) find that none of the individual or joint decisions exhibit quasi-hyperbolic discounting, joint decisions are in between the individual choices, and husbands have a stronger influence on joint decisions than wives. Using longer time horizons than Carlsson et al. (2012) (1 month up to 2 years, rather than 4 up to 8 days), Abdellaoui, L'Haridon, Paraschiv, et al. (2013) find that couples are more patient than individuals and that couples discount rates cannot be expressed as a convex combination of spouses' rates. The authors also find increasing and then decreasing annual discount rates over time for individual and joint decisions, contrary to hyperbolic behavior (and thus contrary to time inconsistency). Only Abdellaoui, L'Haridon, Paraschiv, et al. (2013) takes into account the curvature of the utility function. In our study, we take into account the shape of the utility function, use a structural model to estimate the spouses' weight in the household decision, control for the order in which individuals' and couples' decisions are taken, and differentiate a married couple effect from a group effect using random pairs of individuals.

Few studies have analyzed the relationship between risk and time preferences and adaptation to climate change. According to Mendelsohn (2012), adaptation to climate change is any change in behavior that an agent does to reduce the costs or increase the gains from climate change. Adaptation can take many forms: people can buy insurance, keep savings or invest in a new technology. In our study we focus on the last form of adaptation: technology adoption.

Although studies that seek to clarify the factors that determine technology adoption have a long history, few empirical studies assess the role of risk aversion. Some studies elicit risk aversion from survey data and correlate these measures with technology adoptions (Bozzola et al., 2014; Koundouri et al., 2006), but experimental measures of risk aversion using salient incentives are scarce. Moreover, not much attention has been put on the relationship between attitudes towards probabilities captured by the pwf of RDU and adaptation decisions. The only study that we know is Liu (2013). The author studies the case of Chinese cotton farmers who were offered the option to adopt genetically modified cotton to deal with bollworms, the primary cotton pest. The author uses survey questions and experiments to elicit risk preferences, and the econometric methodology of Tanaka et al. (2010) to estimate aversion to variability in gains and losses and probability attitudes. Liu finds that more risk-averse farmers and more loss-averse farmers adopt the new cotton variety later, and that farmers with an inverted S shape pwf adopt the new cotton variety earlier. Liu argues that farmers with an inverted S shape pwf overweigh the small probability of severe bollworm infestation and thus adopt the technology earlier than other farmers.

We know of only one study that examines the relationship between time preferences and the adoption of technologies relevant for climate change adaptation. Duflo et al. (2011) develop a theoretical model that includes present-bias to predict fertilizer take-up by farmers in West Kenya. In the model, naïve hyperbolic farmers who plan to buy fertilizer in the future may procrastinate and end up not buying it. The model predicts that a small, time-limited discount on the cost of acquiring fertilizer increases the quantity of fertilizer that farmers buy, which increases crop yields. In a randomized field experiment, this prediction is verified. Thus, the paper suggests that present-biased behavior reduces fertilizer take-up.

3 Study Site and Sampling

The study takes place in the driest area of Costa Rica that covers the provinces of Guanacaste and part of Puntarenas, close to the border with Nicaragua. The experiment is part of a larger Canadian government-funded research project on climate change adaptation and water scarcity in Central America. Climate modelers in the project have predicted that this area (like most of Central America) will see more frequent and more extreme droughts in the next fifty years. Moreover, since 2014 the area has been experiencing higher temperatures and drought associated with a very strong El Niño-Southern Oscillation.

Around 85% of the communities in these provinces use underground water, which is pumped to homes by a community system of pipes. In about half of the communities, water is managed by the Costa Rican Water Agency "Instituto Costarricense de Acueductos y Alcantarillados" (AyA). The other communities manage their own water systems through community associations called ASADAS. As part of the larger climate adaptation project, surveys were conducted in 2013 in 82 randomly chosen communities that met three conditions: 1) belong to the first decile of driest communities in Costa Rica, 2) their water supply comes from one or more community wells and 3) water supply is managed by the ASADA. The survey teams interviewed a random sample of households and the ASADA management committees. During the households' survey, heads of household were informed that as part of the water project our team would conduct workshops – the experimental sessions – the following year. The survey team explained them that for their participation people would obtain 5 000 Colones (around US$ 10) and have the opportunity to win more. The team asked them if they were interested in participating in the workshops, and to provide their contact numbers if that was the case.

Out of the 82 communities, we chose 30 that satisfy the following criteria: 1) had the lowest number of hours per day with water availability; 2) community leaders were willing to provide a place for the experimental session; 3) community had at least 25 individuals that showed interest in participating in the experimental sessions in the 2013 household survey.

The communities are very small: on average they have 183 inhabitants. Most of the sessions took place after 4 pm in the local school which is located in a very centric area and walking distance from any house. This implies an advantage over having the session at home where the participants are commonly distracted without the disadvantage of costly access to the session. The schedule of the session was suggested by the community leaders to guarantee that most of the people interested in participating were available. Sessions took place from Sunday to Thursday because banks do not open during the weekend and the design established payments one and four days after the session.

A month before the experimental sessions, the team invited the heads of household by phone. Since we want to distinguish between the married effect and group effect, our original objective was to take half of the married couples and pair them up randomly with other married or single individuals, and be able to compare married couples with other different types of couples. Nevertheless, in the pilots we realized that many couples would not be able to come together to the experimental session because of work or children. In order to have enough married couples working as a couple, we decided to form the "fake" couples only with married individuals that came alone to the session and with singles, and acknowledge that this could bias the difference between real and fake couples.

4 Experimental Design

We conduct a risk aversion experiment and a discounting experiment. At the beginning of the session, each person in the sample is assigned a partner and a group that indicates the order in which decisions are taken. Real couples, who are composed by married couples or couples that cohabit, are partnered with their spouses. Fake couples are composed by married people that came alone to the session or singles that were paired up at random. All individuals have to solve discounting tasks and risk aversion tasks individually and in pairs. So, in total each person participates in four events: individual discounting (Di), individual risk aversion (Ri), couple discounting (Dc), couple risk aversion (Rc). To control for order effects regarding the choices made individually and in pairs, we introduce a within session treatment where half of the sample first make the choices in pairs and then individually, while the other half start with the individual tasks.

In the risk aversion experiment, we use a design with 30 binary lottery choices in the gain frame with three prizes from Wakker, Erev, and Weber (1994). We choose to use these lotteries because they are designed to distinguish between EUT and RDU. For each choice, individuals have

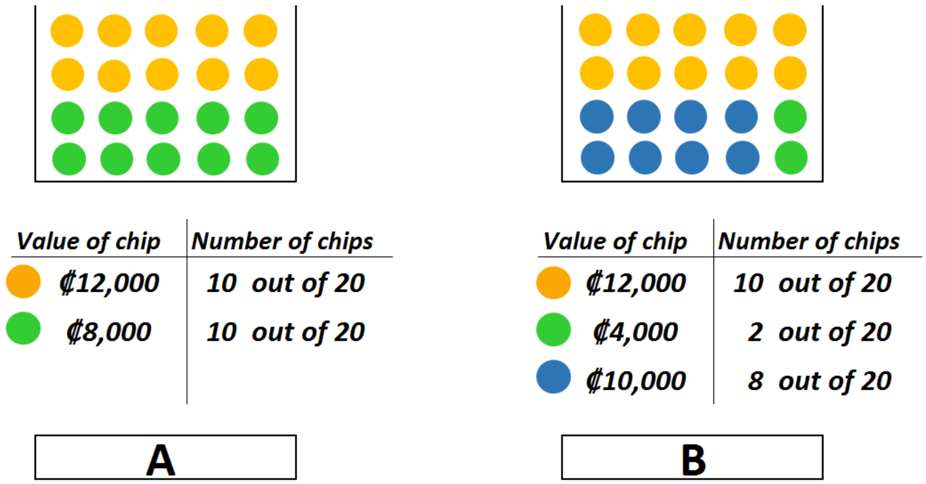

Figure 1: Example of Risk Aversion Decision (in Colones)

to decide between two lotteries A and B. Figure 1 shows the display for one of the decisions.

Each lottery is represented as a bag with twenty colored balls. We use three colors that represent the three different prizes and the number of balls per color reflects the probability of that prize being selected. For example, the lottery A in Figure 1 has two different balls: orange and green. The orange ball stands for 12 000 Colones and has a probability of 50%. We use the exchange rate of 500 Colones per dollar.

In the discounting experiment, individuals are asked to choose between a sooner payment A and a larger, later payment B in a Multiple Price List design (MPL). Payment A is the principal and it is 8 000 Colones (US$16) which is approximately the official daily minimum wage of a worker out of high school in 2013 in Costa Rica[2]. Payment B changes depending on the annual interest rate and the time horizon. There are 6 tasks that correspond to different time horizons. The time horizons used are: 3 days, 1 week, 2 weeks, 1 month, 3 months and 6 months. Each task contains 8 choices between a sooner and a later payment. The annual interest rates of each choice is 50%, 75%, 100%, 150%, 200%, 300%, 450% and 800%. In total, every subject has to solve 48 choices. We use different periods in order to be able to specify the discount rate function. Four out of six horizons are in the very short run because we want to test for the presence of quasi-hyperbolic behavior.

We introduce a between session treatment in which we display the horizons in an ascending

[2]In Costa Rica, the government establishes minimum wages for many occupations. Daily wages go from 7 500 to 16 500 Colones for a computer analyst or an audio technician (de Trabajo y Seguridad Social de Costa Rica, n.d.)

order in half of the community sessions while horizons are presented in a descending order in the other half of the sessions.

One concern when estimating discount rates are the transaction costs associated with the future payment. The literature has tried to deal with this problem by introducing front end delays and/or by using the same payment procedure for both payments. The front end delay (FED) refers to the fact that the sooner payment is not paid now but with a delay of some days, weeks or months. The idea behind this procedure is to make the individual equally confident about the realization of both payments by pushing the sooner payment into the future. The problem with the FED is that the delay can also cover up quasi-hyperbolic behavior.

The transaction costs associated with the later payment are also reduced by using the same payment procedure for sooner and later payments. The idea behind this is that the transaction costs of a payment in cash at the end of the session are smaller than the transaction costs of a bank deposit where the individual requires going to the bank. Having both payments done in the same way eliminates the effect of the payment procedure.

The experimental design deals with this problem by using the same method of payment for all sooner and later payments, and introducing a FED for the earliest payment as a between community treatment. The method of payment is a personal bank transfer where the individual withdraws the money by presenting their Costa Rican id. Half of the communities faced a FED of one month while the other half did not. Since all sessions took place in the afternoon or during the weekends when banks were closed, No FED people were able to withdraw the money the next business day in the morning.

Considering the order of horizons and the FED treatments, there are 4 types of community sessions: 1A, 1D, 2A and 2D where the sessions 1A and 1D are NO FED sessions and horizons are presented in an ascending and a descending order, respectively. In sessions 2A and 2D, we use the 30 day FED and horizons are displayed in an ascending and descending order, respectively.

The choices are presented to the individuals in a table like the one in Figure 2, where only the time period in days, weeks or months and the payoffs in options A and B are shown.

All the participants receive a participation fee of 5 000 Colones (US$ 10) and the additional money they earn in the experiments. The participation fee is paid in cash after completion of the survey and the money from the experiments is paid using a personal bank transfer. Besides an individual survey, married couples also have to answer a brief couple survey.

To determine the amount of payment from the experiments for each individual, we use a "pay one randomly" or POR payment design (Cox et al. 2015). One choice is selected randomly to be played out for each of the experiments in which the subjects participated (Di, Ri, Dc, Rc). We divide the group randomly into four subgroups and each individual in each subgroup receives payment for one of the selected choices. If the individual receives her payment for a decision made in a couple, only she receives the money. For instance, if the husband is selected to get paid for a Dc choice, only he gets paid for the couple's decision in the selected question.

Under the independence axiom of EUT, the method of payment POR is suggested in the literature to avoid inconsistencies in the choices produced by the portfolio effect and the wealth effect. Nevertheless, Cox, Sadiraj, and Schmidt (2015) argues that POR is not incentive compatible to test other theories that do not assume the independence axiom, like RDU or CPT. In these cases, the authors suggest other payment methods that are incentive compatible, like "pay all correlated", "pay all sequentially" or "one task". We acknowledge that this implies a problem in our design since the answers obtained with the POR method of payment are used to test both EUT and RDU. The alternative would be to use the "one task" method that is always incentive compatible. This means that we obtain only one decision from each subject. But this is a very costly procedure and only allows between subjects-data. Since we need to use a within subject design for the main part of the study (time preference elicitation, individual vs. couple decision), we decided to use POR and accept that the RDU estimations may be biased.

5 Econometric Model

We apply maximum likelihood estimation to the structural model of the latent choice to characterize risk and time preferences parameters, as in Andersen et al. (2008, 2014).

We estimate the risk preferences using only the answers of the risk tasks, and through the joint estimation of time and risk preferences. Both procedures should provide similar results.

Using only the risk tasks, we pool all the individuals' and couples' answers and compare different RDU models to determine the model that best fit the data. We focus on the RDU framework because EUT model is embedded in it. The properties of the RDU framework are determined by the utility function and the pwf. If the data fits best an EUT model, then the parameter estimates of the pwf make it the identity function. We apply the CRRA and the Expo-power utility functions and three different types of pwfs: the power pwf $\omega(p) = p^{\gamma}$, the Tversky - Kahneman or inverse-S shaped pwf $\omega(p) = \frac{p^{\gamma}}{(p^{\gamma}+(1-p)^{\gamma})^{\frac{1}{\gamma}}}$ (Tversky & Kahneman, 1992), and the Prelec pwf $\omega(p) = \exp(-\delta[-\ln(p)]^{\phi})$ by Prelec (1998) where $\delta > 0$, $\phi > 0$. In order to compare among the different RDU models, we use the Vuong and Clarke statistics (Clarke, 2003; Vuong, 1989).

In the risk tasks, the individual chooses between lottery A and lottery B. Under RDU, the decision weights replace the probabilities provided by the experimenter. In the model, the decision weights are represented in the following way. For each lottery, the outcomes are ranked and the cumulative probability for each outcome is calculated starting with the highest outcome. The pwf

	A You get the money TOMORROW	B You get the money in 15 DAYS
Decision 1	₡8,000	₡8,154
Decision 2	₡8,000	₡8,230
Decision 3	₡8,000	₡8,304
Decision 4	₡8,000	₡8,452
Decision 5	₡8,000	₡8,597
Decision 6	₡8,000	₡8,878
Decision 7	₡8,000	₡9,282
Decision 8	₡8,000	₡10,154

Figure 2: Example of Discounting Choices for 2 Week Horizon and No FED (in Colones)

is applied to the cumulative probabilities, so that the decision weight for the best outcome is the value of the pwf, and the decision weights for the rest of the outcomes are calculated by subtracting the decision weights of the higher outcomes.

Under RDU, the expected utility of lottery i is the sum of the utilities for each outcome weighted by the decision weights, as in equation (1).

$$RDU_i = \omega_{i1} \cdot U(M_{i1}) + \omega_{i2} \cdot U(M_{i2}) + \omega_{i3} \cdot U(M_{i3}) \tag{1}$$

M_1, M_2 and M_3 are the outcomes; $U(M_1)$, $U(M_2)$ and $U(M_3)$ are the utilities of the outcomes; and ω_1, ω_2 and ω_3 are the decision weights.

As in Andersen et al. (2014), in order to calculate the log likelihood we use the logistic distribution g(.) of the difference of the expected utility of both lotteries divided by the contextual error and the behavioral error μ. The contextual error is the difference of the highest and lowest utility in the choice and normalizes the difference of the expected utility of both lotteries to lie between 0 and 1 for every choice. The behavioral error μ is the Fechner type error which assumes that individuals might make mistakes when comparing the expected utilities of the lotteries. The log likelihood per choice is:

$$\begin{aligned} \ln g(\Delta RDU) &= \ln \tfrac{\exp(\Delta RDU)}{1+\exp(\Delta RDU)} \\ \Delta RDU &= \tfrac{RDU_B - RDU_A}{(High-Low)\cdot\mu} \end{aligned} \tag{2}$$

The final log-likelihood is formed linking all observed risk choices and their likelihood.

$$\ln L(r|x,w)^{RA} = \sum \ln g(\Delta RDU_i) \cdot I(x_i = 1) + \ln g(-\Delta RDU_i) \cdot I(x_i = -1) \tag{3}$$

where I is an indicator function for choices $B(x_i = 1)$ and $A(x_i = -1)$ in the risk aversion tasks.

Once we determine the model that best fits the data, we estimate the individuals' risk preferences, the couples' risk preferences and the differences between both, for all the couples and for real and fake couples. In the individual estimation, decisions are clustered at the individual level. In the couples' estimation, decisions are clustered at the couple level. The methodology allows me to explain all the individuals' parameter estimates as a function of demographic variables like age, gender, income, education and marital status.

In the case of the time preferences, we pool individuals' and couples' answer to determine the best model that fits the data. We compare different discounting functions and also consider the RDU models from the previous analysis. We assume exponential discounting and different forms of hyperbolic discounting: the Mazur discounting function, the Weibull discounting function and the quasi-hyperbolic discounting function presented in equations (4), (5) and (6), respectively.

$$D_M(t) = \frac{1}{(1 + r \cdot t)} \tag{4}$$

$$D_W(t) = \exp(-r \cdot t^{(1/s)}) \tag{5}$$

$$\begin{aligned} D_{QH}(t) &= 1 \quad \text{if} \quad t = 0 \\ D_{QH}(t) &= \tfrac{\beta}{(1+\delta)^t} \quad \text{if} \quad t > 0 \end{aligned} \tag{6}$$

The data shows quasi-hyperbolic behavior when $\beta < 1$ so that the discount rate is very high in the first periods and then declines drastically and converges to δ. The quasi-hyperbolic discounting function reduces to the exponential discounting when $\beta = 1$. The Weibull discounting function shows decreasing discount rates over time for estimates of $s > 1$ and becomes the exponential discounting when $s = 1$. The Mazur discount rate decreases over time for $r > 0$.

In the discounting decisions, individuals have to choose between receiving money in two different periods. In the model, the present value of the utility of money in the earliest period t is PVA in equation (7), while the present value of the utility of money in the later period $t + \tau$ is PVB in equation (8). D_t is the discount factor in period t. If we assume an exponential discounting function, then $D_t = 1/(1 + \delta)^t$ and δ is the constant discount rate.

$$PV_A(t) = D_t \cdot U(M_t) \tag{7}$$

$$PV_B(t) = D_{t+\tau} \cdot U(M_{t+\tau}) \tag{8}$$

The final log likelihood per choice is built using the logistic distribution of the difference PV_B-PV_A divided by the behavioral error of the discounting choices μ_d, as in equation (9).

$$\begin{aligned} \ln g(\Delta PV) &= \ln \tfrac{\exp(\Delta PV)}{1+\exp(\Delta PV)} \\ \Delta PV &= \tfrac{PV_B - PV_A}{\mu_d} \end{aligned} \tag{9}$$

The log likelihood is formed linking all observed discounting choices and their likelihood.

$$\ln L(\delta|x,w)^D = \sum \ln g(\Delta PV_i) \cdot I(x_i = 1) + \ln g(-\Delta PV_i) \cdot I(x_i = -1) \tag{10}$$

Finally, we create a vector that stacks both $\ln L(r|x,w)^{RA}$ and $\ln L(\delta|x,w)^D$ and then we find the risk and time preferences parameters that maximize the joint log-likelihood.

Once we determine the best model, we estimate the individuals' and couples' preferences. To measure the difference between individuals and couples, we pool all their choices and add a dummy variable couple that explain the difference in each parameter.

To estimate the spouses' weight in the household risky decision, we extend on Andersen et al.

(2008) joint estimation. In a risky decision under EUT, the households expected utility of lottery x=A, B is:

$$\begin{aligned} EU^{H,x} &= \textstyle\sum_i^2 \rho_i \cdot EU_i^x \\ EU^{H,x} &= \textstyle\sum_i^2 \rho_i \cdot \left[p(M_1^x) \cdot U_i(M_1^x) + p(M_2^x) \cdot U_i(M_2^x)\right] \\ EU^{H,x} &= p(M_1^x) \cdot U^{H,M_1^x} + p(M_2^x) \cdot U^{H,M_2^x} \end{aligned} \tag{11}$$

where ρ_i is the weight that each spouse i has in the decision and $U_i()$ is the utility of each spouse determined by the individual parameters. We measure the ratio ΔEU^H that represents the couple's latent choice for outcome B.

The conditional log likelihood is built as before, where I is an indicator function for the couples' choices $A(x_j = -1)$ and $B(x_j = 1)$ in the risk aversion tasks and J is the number of choices that couples make.

$$\ln L(r|x,w)^{RA,H} = \sum \ln g(\Delta EU_j^H) \cdot I(x_j = 1) + \ln g(-\Delta EU_j^H) \cdot I(x_j = -1) \tag{12}$$

We build a vector that stacks $\ln L(r|x,w)^{RA,women}$, $\ln L(r|x,w)^{RA,men}$ and $\ln L(r|x,w)^{RA,H}$ and find the utility parameter estimates for men and women, and the weights that maximize the joint log-likelihood.

In order to estimate the relationship between the behavioral estimates and the adaptation measure, we only keep the observations of the married couples and add the variable water tank to look at the correlation of this variable with each of the parameter estimates of the risk and time preferences. Since we do not know who takes the decision to buy a water tank, in the survey we ask married couples whether the decision was taken by one of the spouses or together. If the decision is taken as a couple, we would expect to see the theoretical relationships when we correlate the variable *water tank* with the couples' preferences.

6 Experimental Procedures

All sessions were conducted by Dr. Bernedo and four assistants. The day of the experiments, we welcomed participants and verified that they had been invited. First, we identified the group of real couples and the group of fake couples. During registration, we paired up the fake couples based on similarity of age and gender so that couples were formed by a man and a woman if possible. Every individual received an id and every couple received an id-couple. We divided the real and fake couples in two groups (A, B) that made the individual and pair decisions in different order. In one side of the room, side A, we placed the real couples and fake couples that make the couple decisions first. In the other side of the room, side B, we placed the subjects that start with the individual decisions. Couples in side B were not seated next to each other: a person from a different couple was seated in between them. Once all individuals were seated, we read the informed consent. After the first round of risk and time preferences games, participants took a short recess where we provided cookies and beverages.

In the second round, individuals in side A completed the tasks individually and couples were seated apart from each other; individuals in side B completed the tasks with their respective couples. Once the experimental session was over, individuals completed a short survey. Real couples completed a couple survey and an individual survey. Both spouses of the real couples fill out the individual survey individually and separated from each other, and the couple survey together. Fake couples just completed an individual survey. In the couple survey, real couples were asked, for instance, how long they have been together, the number of members in the home, whether they have a water tank and who took the decision to buy the water tank.

7 Descriptive Analysis

7.1 Data

The final sample is comprised of 482 individuals. 24 individuals participated only in the individual tasks mainly because we had sessions with an odd number of participants. There are 229 couples: 124 are real couples and 105 are fake couples. Among the fake couples, 40 couples have different gender, 64 couples are woman-woman couples and 1 couple is a man-man couple.

7.2 Risk Task Choices

In this section, we will describe the choices in the risk task of individuals and couples. Then, we follow Wakker et al. (1994) to do a first analysis of the type of model that fits best the data, EUT or RDU.

The 30 choices used in the experiment are composed of 6 sets of 4 choices (the RDU choices) and 6 additional choices or "fillers". The RDU choices were designed by Wakker et al. (1994) to distinguish between EUT and RDU choices. The fillers have lotteries with clearly different expected values and thus, their goal is to motivate subjects to analyze the choices carefully. In all the choices, lottery B is the risky one.

The individuals choose the risky lottery on average 16.62 times out of 30. The average does not vary much by gender, age and marital status but varies by education level and income (rows

7 and 10 in column A of Table 1). "$Age > p50$" corresponds to individuals older than 44 years old, which is the percentile 50 in the sample. "$Income > p75$" represents individuals with income greater than the income range $150,000-250,000$ colones, which is the percentile 75 in the sample. Individuals that have at least completed primary school choose less frequently the risky choices than individuals that have not. Similarly, high income individuals select the risky choices less often than individuals with lower income. Looking at the couples' choices (row 2 in column A of Table 1), the difference between individuals' and couples' choices is not statistically significant. The same occurs with the difference between real and fake couples (row 3). When we analyze separately the sample with only the RDU choices and the sample with only the fillers, we find very similar results between the complete sample and the RDU choices. In the case of the fillers, the sign of the difference between the subsamples is the same in most of the variables, as shown in Table 1, columns B and C.

Following the analysis of Wakker et al. (1994), we focus on the RDU choices arranged in 6 sets of 4 choices and analyze the independence condition and the comonotonic independence condition for a first examination of the EUT and RDU framework. In each set, there are four choices and in each choice the probabilities of both lotteries are the same and do not change within a set. Each lottery has two different prizes and one common prize. Within a set, this common prize is the only one that changes. Take, for instance, the choices in the set in Table 2. In the first choice the common prize is 1000 colones, then it becomes 7000, 13000 and 19000 colones. The independence condition of EUT implies that the preference should not change if a common prize changes. Thus, within a set a violation of EUT occurs when the individual changes her preference. In each set, there are two mutually comonotonic choices. Here, two choices are called mutually comonotonic if the change in the common prize does not alter the ranking of the prizes within a lottery. Comonotonic independence holds when preferences are the same in the mutually comonotonic choices. A violation of RDU occurs when there is a violation of comonotonic independence.

Violations to independence or comonotonic independence signal individuals' behavior but people can also make "errors". Moreover, the lotteries in the RDU choices have similar expected values and in some cases, individuals might be indifferent about the lotteries. The analysis acknowledges the presence of these behavioral errors and assumes that they occur randomly across the decisions.

First, we study whether there is evidence in favor of EUT or RDU. The null hypothesis is that the data follows EUT. In each set like the one in Table 2, there is one test of comonotonic independence and two tests of non-comonotonic independence. If we do not consider the possibility of errors, under the null hypothesis there should be no violations of any type of independence.

Table 1: Average Number of Risky Choices by Subsample.

Group	A. All choices				B. RDU choices				C. Fillers			
	Obs.	Mean	S.E.	p-val.	Obs.	Mean	S.E.	p-val.	Obs.	Mean	S.E.	p-val.
Individuals vs. Couples												
Total individuals	482	16.62			482	13.39			482	3.22		
individuals in couples†	458	16.73	0.29	0.86	458	13.49	0.25	0.96	458	3.24	0.07	0.56
couples	229	16.65	0.37		229	13.47	0.33		229	3.18	0.07	
fake couples	105	16.49	0.5	0.69	105	13.35	0.45	0.75	105	3.13	0.11	0.57
real couples	124	16.78	0.54		124	13.56	0.49		124	3.22	0.1	
Individuals by treatment and demographic variables												
individual decisions first	253	16.5	0.42	0.66	253	13.17	0.36	0.35	253	3.32	0.09	0.09
couples' decisions first	229	16.75	0.39		229	13.64	0.34		229	3.11	0.09	
men	175	16.67	0.48	0.88	175	13.32	0.42	0.82	175	3.35	0.1	0.12
women	307	16.58	0.36		307	13.44	0.31		307	3.15	0.08	
age <p50	242	16.33	0.38	0.31	242	13.16	0.34	0.35	242	3.17	0.08	0.37
age >p50	240	16.91	0.43		240	13.63	0.36		240	3.28	0.1	
no primary school	120	18.23	0.67	0	120	14.83	0.55	0	120	3.4	0.15	0.11
at least primary school	361	16.09	0.31		361	12.92	0.27		361	3.17	0.07	
no high school	399	16.79	0.33	0.21	399	13.54	0.28	0.22	399	3.25	0.07	0.37
at least high school	82	15.83	0.56		82	12.73	0.53		82	3.1	0.11	
not married	241	16.58	0.4	0.9	241	13.31	0.35	0.73	241	3.27	0.09	0.42
married	241	16.65	0.41		241	13.48	0.36		241	3.17	0.09	
income <p75	334	16.84	0.35	0.09	334	13.57	0.3	0.11	334	3.27	0.08	0.17
income >p75	137	15.76	0.5		137	12.68	0.44		137	3.08	0.11	

† Individuals that also participated in couples' tasks.

Table 2: One set of lotteries.

Choice	Safe choice			Risky choice		
	L1	L2	L3	R1	R2	R3
1	0.55 1,000	0.25 12,000	0.2 14,000	0.55 1,000	0.25 9,000	0.2 18,000
2	0.55 7,000	0.25 12,000	0.2 14,000	0.55 7,000	0.25 9,000	0.2 18,000
3	0.25 12,000	0.55 13,000	0.2 14,000	0.25 9,000	0.55 13,000	0.2 18,000
4	0.25 12,000	0.2 14,000	0.55 19,000	0.25 9,000	0.2 18,000	0.55 19,000

However, if we do, the proportion of violations of comonotonic independence should the same as the proportion of violations of non-comonotonic independence. Under the alternative hypothesis that the data follows the RDU model, however, the latter is higher.

In our sample, there are 482 individuals that generate 8666 tests of independence: 2888 comonotonic tests and 5778 non-comonotonic tests[3]. There were 2905 violations of independence[4]. Under the null hypothesis, one third of the violations (969.3) should be violations of comonotonic tests and two thirds (1936.7), of non-comonotonic tests. We find that 894 (30.8%) were violations of comonotonic tests and 2011 (69.2%) were violations of non-comonotonic tests. These results seem to favor RDU over EUT.

Using a similar analysis, we study the special cases of RDU: RDU with pessimism, RDU with

[3]With 482 individuals, there should be $482 \cdot 3 \cdot 6 = 8676$ tests but we had 5 missing answers resulting in 10 fewer tests.

[4]In Wakker et al. (1994), the authors ask the same 24 choices twice to test for consistency of answers. This generates two types of violations of independence: weak and strong violations. A weak violation in an independence test occurs when in a certain choice the individual selects a lottery consistently (selects the same lottery the two times she is asked the same question) but in the adjacent question within a set changes her preference in one of the opportunities. If 1 is a risky choice, 0 is a safe choice, 2 stands for consistently choosing the risky choice and 0, for consistently choosing the safe choice, examples of weak violations are the pairs (0,1), (1,0), (1,2), (2,1). A strong violation in an independence test occurs when the individual chooses consistently in two contiguous questions but changes her preference. Examples of strong violations are the pairs (0,2) and (2,0). The authors find 6% of strong violations and 41% of weak violations. In our study, we find 34% (2905/8666) of violations. Because there are two types of violations and none of them correspond to the type of violation in the analysis, it is not possible to directly compare the number of violations of Wakker et al. (1994) and the number of violations in the study. However, we can compare the types that have a similar probability of violation if it were at random. When considering two choices, the chance of weak violation in Wakker et al. (1994) is 44% (4 out of 9 possibilities) and the chance of violation in the study (2 out of 4) is 50%. Thus, it seems that the 34% of violations in the study is lower than the 41% of weak violations of in the Wakker et al. (1994)'s sample.

optimism, RDU with inverse-S shaped pwf and S shaped pwf. These cases prohibit violations of comonotonic independence but also impose additional restrictions on the non-comonotonic tests depending on the type of RDU. For instance, pessimistic individuals put more weight on the probability of the lowest prize. When the common prize changes from the lowest to the middle rank, pessimistic individuals are more inclined to prefer the lottery whose lowest prize is now higher. A change like that happens in the second and third choices of the set shown in Table 2. In the second choice the common prize is the lowest prize in both lotteries and increases from 7000 to 13000 colones in the third choice. With such an increase, the common prize becomes the new middle prize in both lotteries. In the third choice, the new lowest prize of the safe lottery is 12000 colones which is higher than the new lowest prize (9000 colones) of the risky lottery. Because the new lowest prize is higher in the safe lottery, a change of preference from the safe to the risky lottery is not expected in the case of a pessimistic individual. The converse applies for the optimistic RDU individuals.

When the common prize changes from the middle to the highest rank, pessimistic individuals prefer the lottery with the highest new middle prize. Such a change occurs in decisions three and four in Table 2. In decision three the common prize is the middle prize 13000 colones and it increases to 19000 colones. The new middle prize in the safe lottery is 14000 colones and in the risky lottery is 18000 colones. Because the new middle prize is higher in the risky lottery, pessimistic individuals are not expected to change their preference from the risky to the safe lottery. The converse is true for the optimistic RDU individuals.

In the case of the inverse-S shaped probability weighters, they overweigh the probability of the extreme lottery outcomes. Thus, the restrictions for an inverse-S shaped pwf match those of an RDU-pessimist when the common prize changes from the lowest to the middle rank, and match those of an RDU-optimist when the common prize changes from the middle to the highest rank. The opposite holds true for an S-shaped pwf.

Within each set of four lotteries like the one in Table 2, there are six types of possible violations of independence: from the safe to the risky lottery and from the risky to the safe one in each of the three independence tests. From these six violations of independence, four correspond to violations of RDU with pessimism (RDU with optimism, RDU with inverse-S shaped pwf or RDU with S shaped pwf). Under the null hypothesis, two thirds of the violations are expected to be violations of RDU with pessimism. The same logic applies to the other types of RDU.

We find 1939 violations of RDU with pessimism, which correspond to two thirds of the violations. There are 1860 violations of RDU with optimism that correspond to 64% of the total violations. Regarding RDU with inverse S shape pwf, while we find 1750 (60%) violations, there are 2049 (71%) violations of RDU with S shaped pwf. So, the data seem to fit RDU with optimism and inverse-S pwf rather than EUT. As expected, results are very similar when we only consider the individuals that participated in the couples' experiments.

We do the same type of analysis using the data of couples. There are 229 couples that generate 4120 tests[5]. We find 1405 violations of independence[6]. Under the null hypothesis, one third should be violations of comonotonic tests and two thirds of non-comonotonic tests. There were 400 violations of comonotonic tests which represent 28.5% of the total violations, a lower proportion than the case of the individuals. So, the data seems to fit the RDU model. For the special cases of RDU, there are less than two thirds of the violations for RDU with optimism (64%) and we find similar results for RDU with pessimism (65%) and RDU with inverse-S shaped pwf (57%). The only special case that exceeds the two thirds condition is the RDU with S shaped pwf (72%). So, all the RDU types except RDU with S shaped seem to be preferable than the EUT model.

The data allows another type of analysis where we compare the proportion of risky choices in each decision across individuals. If the difference in the proportion of risky choices is statistical significant, it provides evidence against independence. In the six sets of four choices, the common prize increases eighteen times $(6 * 3)$. In the sample of individuals, we find eight statistically significant differences. Of these, two (25%) correspond to comonotonic tests and this proportion is less than the one third dictated by the null hypothesis which indicates RDU behavior. Of the other six statistically significant changes, four were evidence against RDU with pessimism (in favor of RDU with optimism) and the other two show evidence against RDU with optimism (in favor of RDU with pessimism). All the six significant changes were in line with RDU with inverse S shaped pwf (against S-shaped pwf). So, the results of this analysis support once again RDU with inverse S shaped pwf and RDU with optimism to a small degree. We find very similar results when we consider only the choices of individuals that take decisions in pairs.

In the case of the couples' answers, we find five statistically significant differences and one of them is a comonotonic test. Under the null hypothesis of EUT, this proportion (20%) provides some evidence for the RDU model. Two of the differences are against RDU with optimism and the other two are against RDU with pessimism. All the changes are in line of RDU with inverse-S shaped pwf and against the S shaped pwf. RDU with inverse-S shaped pwf seems to be the model supported by the data.

In summary, in the descriptive analysis we do not find statistically significant differences between the number of risky choices selected by individuals and couples and between the real and fake couples' choices. More educated and higher income people choose less often the risky

[5] We should have 4122 tests $(229 \cdot 6 \cdot 3)$ but we ended up with less tests due to missing values.

[6] This is almost the same percentage as in the individuals. Thus, the sample of couples violates the independence axiom even less frequently than the Wakker et al. (1994) sample.

Table 3: Number of Observed Violations and Number of Violations Predicted by the H_0.

	RDU		RDU pessimism		RDU optimism		RDU inverse S-shaped		RDU S-shaped		EUT
Individuals†											
Observed	894	31%	1,939	67%	1,860	64%	1,750	60%	2,049	71%	2,905
Predicted by H_0	968	33%	1,937	67%	1,937	67%	1,937	67%	1,937	67%	
Couples											
Observed	400	28%	909	65%	896	64%	795	57%	1,010	72%	1,405
Predicted by H_0	468	33%	937	67%	937	67%	937	67%	937	67%	

† Individuals that also participated in couples' tasks show the same percentages.

Table 4: Number of Statistically Significant Differences in the Proportion of Risky Choices.

Number of Differences	Individuals	Indiv. in couples†	Couples
Total	8	7	5
In mutually comonotonic choices	2	1	1
Against RDU with optimism	2	2	2
Against RDU with pessimism	4	4	2
Against RDU with S shaped pwf	6	6	4
Against RDU with inverse-S shaped pwf	0	0	0

† Individuals that also participated in couples' tasks.

choices. The analysis of the RDU choices shows that individuals are better described by the RDU model rather than by EUT model, specifically the RDU model with inverse-S shaped pwf and RDU with optimism to a small degree. Couples' choices show similar results.

7.3 Discounting Task Choices

We use local polynomial regressions (LPR) and probit estimations for a descriptive exploration of the discounting behavior and the effect of the treatments: the FED, the order in which horizons are displayed and the order in which couples and individual decisions are presented to the participants.

The LPR estimates the conditional distribution of the later payment choices given the implied annual interest rate (AIR). The relationship of both variables is expected to be positive. Figure 3 shows the LPR with the individual choices. The interception between the curve and the dashed line at 50% of the later payment choices gives the median discount rate 163% for the individual sample, as shown in Table 5. This is the level at which subjects jump to the choice B on average and it does not take into account any correction for the curvature of the utility function.

Looking at the effect of the demographic variables, we do not find any difference in the fitted lines by gender, income, age or marital status. However, education seems to be an important source of heterogeneity in the sample. Individuals that have not completed primary school show lower discount rates (99%) than the ones that did (168%). Looking at the different horizons, we find that the discount rate seem to decrease the longer the horizon, as shown in Figure 4 and Table 5.

Figure 5 shows the graphs for the FED and no FED groups. Individuals that face no FED are more willing to choose later payments than the individuals with a 30 day FED, which indicates lower discount rate levels for the no FED group.

Regarding the order in which horizons are presented, Figure 6 shows that the fraction of later payment choices is higher when horizons are presented in an ascending order. This result holds

Table 5: Median Discount Rate for Different Subsamples.

Results are stated in percentages.

Variables	Median	95% Conf. Interval	
All individuals	163	134	166
Individual characteristics			
women	160	138	165
men	144	134	164
married	158	143	167
not married	139	131	163
age >p50	150	136	161
age <p50	162	136	167
at least primary school	168	165	171
no primary school	99	68	112
at least high school	157	147	171
no high school	139	134	165
income >p75	158	145	169
income <p75	161	137	166
Time horizon			
3,4,5 day horizon	185	168	196
7 day horizon	156	145	177
14 day horizon	159	152	171
30 day horizon	141	124	163
90 day horizon	139	128	151
180 day horizon	123	115	138
Treatment variables			
couples' decisions first	164	139	169
individual decisions first	143	130	156
30 day FED	175	171	179
no FED	122	116	132
ascendant order	129	121	140
descendant order	172	168	176
ascendant order if no FED	111	103	121
descendant order if no FED	147	128	153
ascendant order if 30 day FED	151	142	165
descendant order if 30 day FED	181	177	184

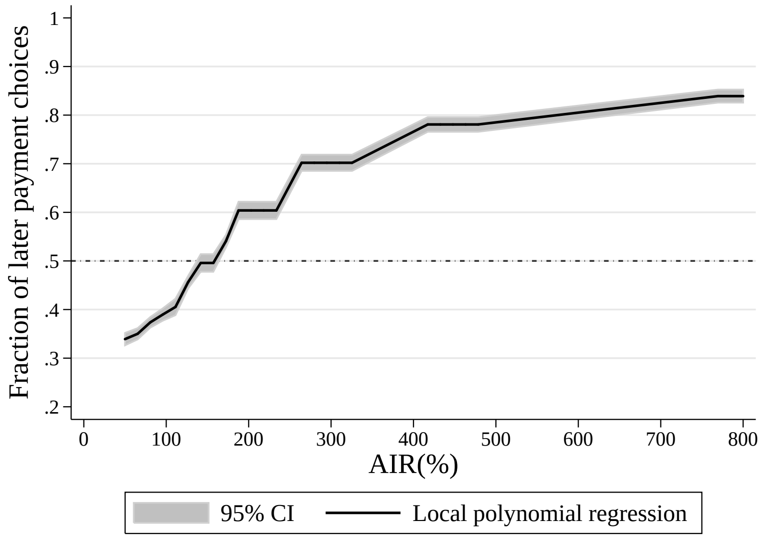

Figure 3: Local Polynomial Regression with Individuals' Decisions

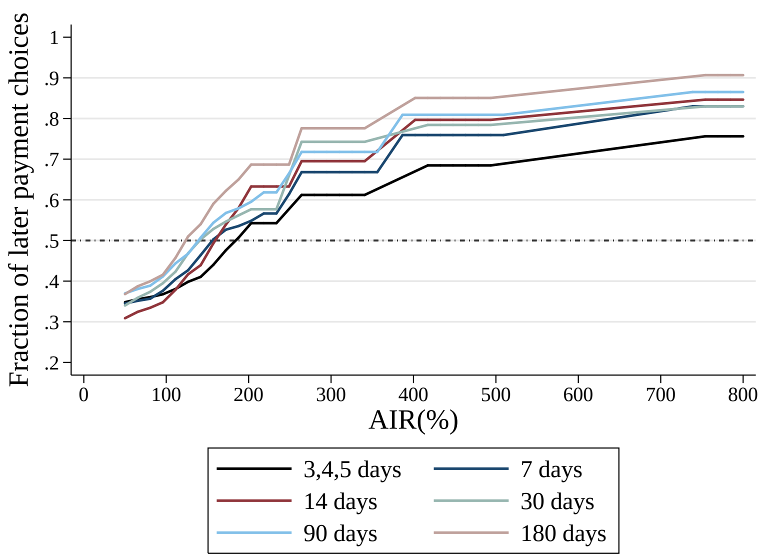

Figure 4: LPR by Horizon using Individuals' Decisions

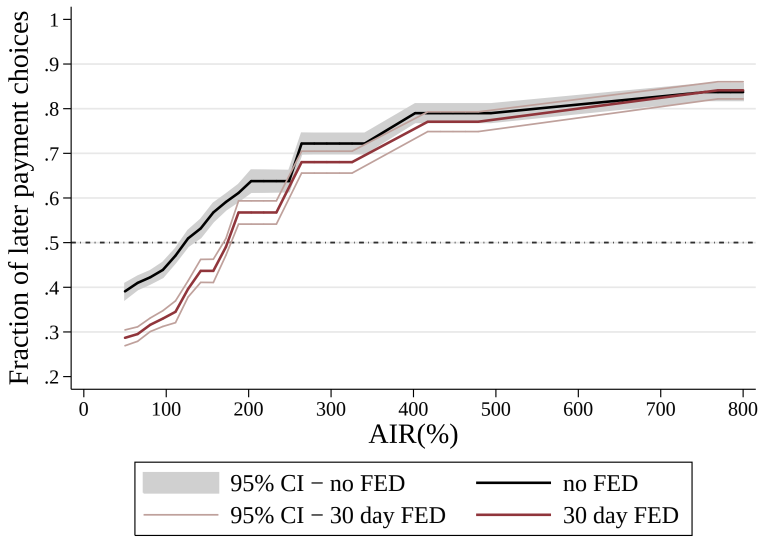

Figure 5: LPR by FED using Individuals' Decisions

when we analyze the data by FED, as shown in Figure 7. With respect to the order in which couple and individual decisions are taken, the order does not seem to affect the willingness to wait for a later payment.

Next, we use probit estimations to explore the discounting behavior in the individual decisions (Table 6). The dependent variable is the variable choice and the independent variables are sociodemographic and treatment variables. Results are in line with the previous graphical analysis. Calculating the marginal effects at the means, we find that a 30 day FED decreases the probability of choosing a later payment by 7 percentage points. Having the horizons displayed in an ascending order increases the odds of choosing the later payment by 8 percentage points. Presenting the couples' decisions first decreases the probability of choosing a later payment by 1 percentage point. The effect of gender, age and income are not statistically significant but the effects of being married and primary school are. Both, being married and having at least finished primary school decrease the percentage of later payments by 3 and 6 percentage points, respectively.

The LPR with couples' decisions shows no clear difference between real and fake couples' decisions. The same happens when we compare individuals' and couples' decisions, as shown in Figure 8. However, the median discount rate for couples is slightly higher than the one for individuals. As in the case of the individual decisions, the average discount rate seems to be lower the longer the horizon. The difference between no FED and 30 day FED almost disappear in the couples' decisions, as shown in Figure 9.

As in the case of individuals, the order in which the horizons are presented to the couples

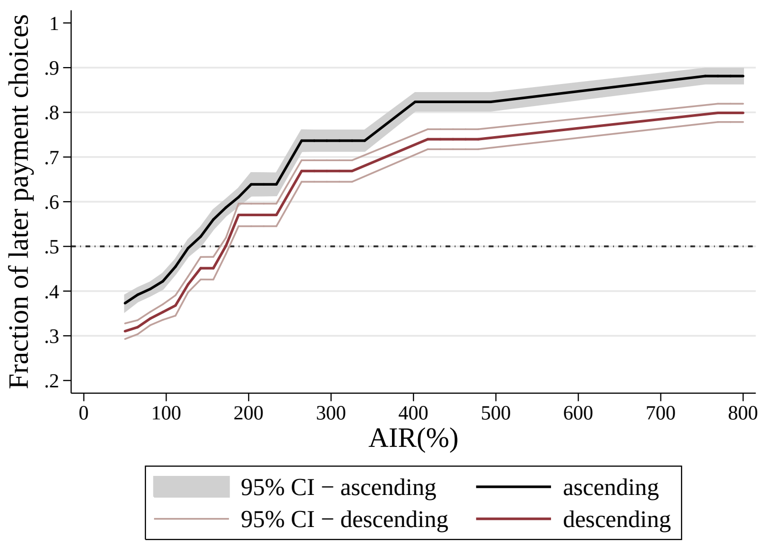

Figure 6: LPR by Order of Horizons using Individuals' Decisions

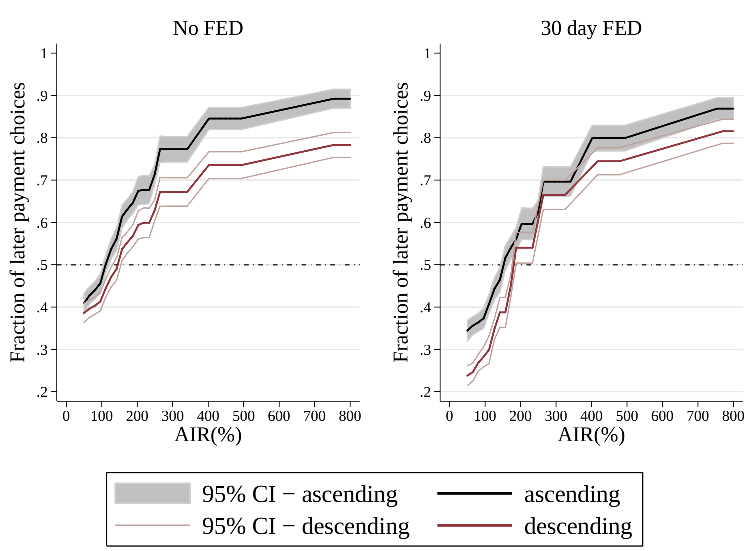

Figure 7: LPR by Order of Horizons and FED using Individuals' Decisions

Table 6: Marginal Effects at Means Using Individual Decisions.

Variables	dy/dx	Std.Err.	P>z	95% Conf. Interval	
30 day FED	-0.07	0.01	0.00	-0.08	-0.06
couples' decisions first	-0.01	0.01	0.08	-0.02	0.00
ascendant order	0.08	0.01	0.00	0.06	0.09
gender	0.01	0.01	0.31	-0.01	0.02
age >p50	0.00	0.01	0.74	-0.02	0.01
married	-0.03	0.01	0.00	-0.05	-0.02
primary school	-0.06	0.01	0.00	-0.07	-0.04
income >p75	0.00	0.01	0.51	-0.02	0.01

does affect couples' willingness to wait for a later payment. When horizons are presented in an ascending order, couples show a higher fraction of later payment choices, which implies lower discount rates. This difference persists for each type of FED.

Looking at the probit estimation, we find a statistically significant difference between individuals' and couples' choices. Couples seem to be less patient than individuals. There is no statistically significant difference between real and fake couples' choices. Facing a 30 day FED reduces the probability of choosing a later payment by 2 percentage points, a smaller effect than in the case of the individuals. Presenting the couples' decisions first increases the probability of later payments by 5 percentage points. Finally, displaying the horizons in an ascending order increases the chances of choosing a later payment by 8 percentage points, a similar result than the one of individuals.

Figure 10 shows that couples' decisions show more patience when they are completed before the individual decisions but only for lower levels of the AIR. The difference in the median discount rate in Table 7 supports this finding.

8 Structural Estimation

8.1 Risk Preferences

In this section we analyze the risk preferences of individuals and couples using only the risk tasks. First, we determine the model that fits best the data. Then we analyze the risk preferences of the different subsamples: individuals, couples, real and fake couples.

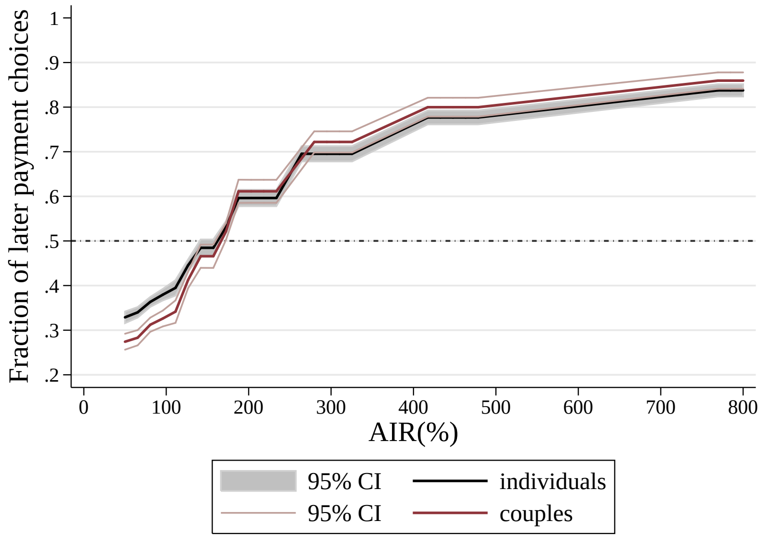

Figure 8: LPR using Individuals' and Couples' Decisions

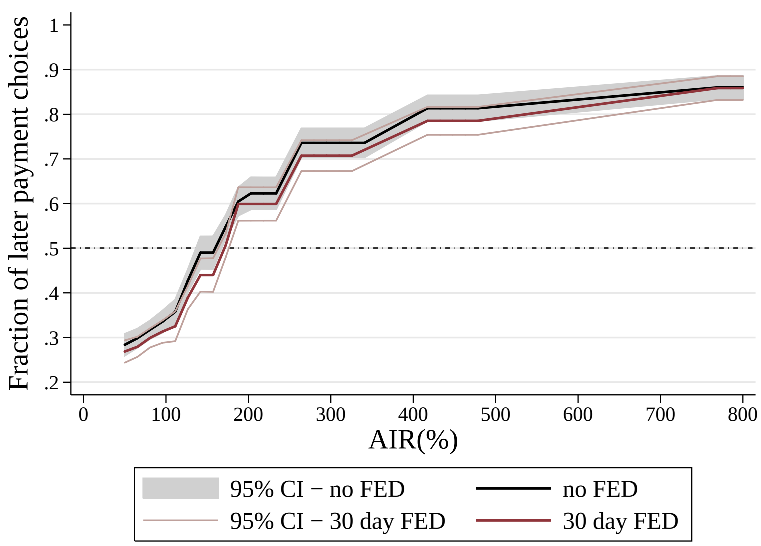

Figure 9: LPR by FED using Couples' Decisions

Table 7: Couples' Median Discount Rate by Subsamples.

Results are stated in percentages.

Variables	Median	95% Conf. Interval	
Individuals vs. couples			
Individuals in couples	165	137	168
couples	170	168	172
real couple	163	137	169
fake couple	171	166	177
Time horizon			
3,4,5 day horizon	191	159	243
7 day horizon	201	153	247
14 day horizon	157	150	177
30 day horizon	144	133	175
90 day horizon	156	130	171
180 day horizon	161	135	168
Treatment variables			
couples' decisions first	139	130	158
individual decisions first	177	173	181
30 day FED	171	167	176
no FED	161	137	168
ascendant order	142	129	153
descendant order	173	160	187
ascendant order if no FED	146	122	159
descendant order if no FED	181	175	186
ascendant order if 30 day FED	138	128	159
descendant order if 30 day FED	177	173	181

Table 8: Marginal Effects at Means using Couples' Decisions.

Variables	dy/dx	Std. Err.	P>z	95% Conf. Interval	
couple	-0.01	0.00	0.07	-0.02	0.00
real	0.01	0.01	0.29	-0.01	0.03
30 day FED	-0.02	0.01	0.01	-0.04	-0.01
couples' decisions first	0.05	0.01	0.00	0.04	0.07
ascendant order	0.08	0.01	0.00	0.06	0.10

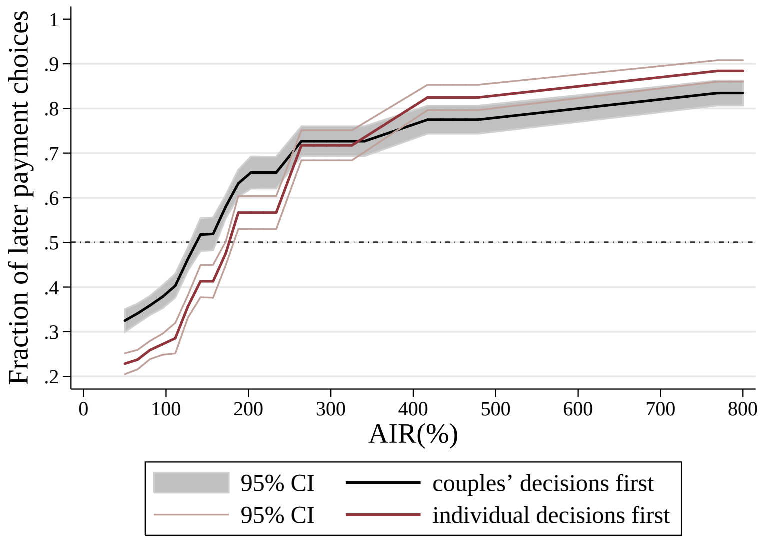

Figure 10: LPR by Order of Decisions using Couples' Decisions

8.1.1 Selection of the Model

The most common model applied to estimate risk preferences is the EUT framework and the CRRA utility function. We test the appropriateness of different models of EUT and RDU using all observations in the data, the choices from all individuals and couples. We consider two different utility functions, the CRRA and the expo-power utility functions, and three different probability weighting functions: the power pwf, the inverse-S shaped pwf and the Prelec pwf. In all the RDU models, the t-test rejects the null hypothesis that the pwf parameters are equal to one. This means that the hypothesis that individuals behave as in a EUT framework is rejected in all the models. The results are presented in Table A1.

To compare the different RDU models we use the Vuong and Clarke statistics for non-nested models. The results of the Vuong and Clarke statistics appear in Table 9. We compare models by pairs where the number on top is the value of the Vuong (part A) or Clarke statistic (part B) and the number at the bottom is the p-value of the test. For instance, we compare model 1 (the RDU model with CRRA utility and power pwf) with model 2 (RDU model with CRRA utility function and inverse-S pwf). If the value of the Vuong test is positive and statistically significant, model 1 is better than model 2. If the value of the Clarke statistic is greater than a fixed value[7] and statistically significant, model 1 is better than model 2. According to both statistics, the model that best describes the data is the RDU framework with expo-power utility function and Prelec pwf.

[7]This value is half the total number of questions in the risk task for all the sample (10 662).

The parameter estimates of Prelec pwf show that the sample in general overweighs the extreme values but overweighs more the best outcomes, which show optimism behavior.

8.1.2 Individuals' Decisions

First, we analyze the individual decisions. For comparison, we will present the results of the constant relative risk aversion (CRRA) model in the EUT framework which is the model assumed in most studies of individual risk preferences. The CRRA coefficient for the individual decisions is 0.38. In order to study the heterogeneity of the sample, we include one treatment variable and the socioeconomic variables. The treatment variable *order* is 1 when the individual completed the couples' tasks first and 0, otherwise. The socioeconomic variables are: *gender, age, primary school, married*, and *income*. Age is a binary variable that is 1 if individual is older than 44 years old, which is the percentile 50 in the sample. *Primary school* is 1 if the individual has at least completed primary school. *Married* is 1 if the individual is currently married. *Income* takes the value of 1 if the household income is greater than the income range $150,000-250,000$ colones (percentile 75). None of the variables are statistically significant. Looking at the total effects of these variables, *order, age, primary school* and *income* are statistically significant. While older individuals show lower relative risk aversion, individuals that have at least finished primary school and high household income show higher levels of CRRA coefficient. Individuals that completed the couple tasks first show higher levels of CRRA coefficient.

However, the EUT framework with CRRA utility function is not the suitable model for this sample. The best model is the RDU model with expo-power utility function and Prelec pwf (A2). Because the sign of the parameter is negative, individuals show decreasing relative risk aversion (DRRA). In Figure 11, we present the Prelec pwf function for the individual sample, using the coefficients of the homogenous model. The graph on the left shows the pwf. It looks like an inverse-S shaped pwf that is mostly concave. The graph on the right shows with an example the effect of the pwf on the weights. In a lottery of four prizes (red) where each objective probability is 25%, the Prelec pwf transforms the weights so that individuals overweigh the extreme outcomes but overweigh more the best outcomes. Thus, individuals can be described as optimistic.

We add covariates to analyze the heterogeneity of the sample. We find that the individuals that completed the couple tasks first show more risk aversion. Women show less risk aversion than men and older individuals show less risk aversion than younger individuals. People that have finished primary school are more risk averse than people that have not and married people are more risk averse than singles. Some variables also affect the parameter estimates of the pwf. Individuals that completed the couple tasks first and that have at least finished primary school show more optimism. On the contrary, older individuals show more pessimism than younger individuals. These results

Table 9: Clarke and Vuong Statistics for RDU Models.

Values below are p-values.

	CRRA		EP		
	Inverse-S	Prelec2	Power	Inverse-S	Prelec2
A. Vuong Statistic					
CRRA Power	6.378	-6.37	-8.023	-2.617	-8.185
	0.000	*1.000*	*1.000*	*0.996*	*1.000*
CRRA Inverse-S		-11.446	-6.988	-15.274	-14.268
		1.000	*1.000*	*1.000*	*1.000*
CRRA Prelec2			5.258	1.402	-8.326
			0.000	*0.081*	*1.000*
EP Power				-2.099	-7.468
				0.982	*1.000*
EP Inverse-S					-5.415
					1.000
B. Clarke Statistic					
CRRA Power	11,797	9,557	10,222	10,126	10,132
	0.000	*1.000*	*1.000*	*0.996*	*1.000*
CRRA Inverse-S		9,645	9,527	8,572	9,472
		1.000	*1.000*	*1.000*	*1.000*
CRRA Prelec2			11,204	10,523	10,502
			0.000	*0.972*	*0.986*
EP Power				10,126	9,557
				1.000	*1.000*
EP Inverse-S					10,005
					1.000

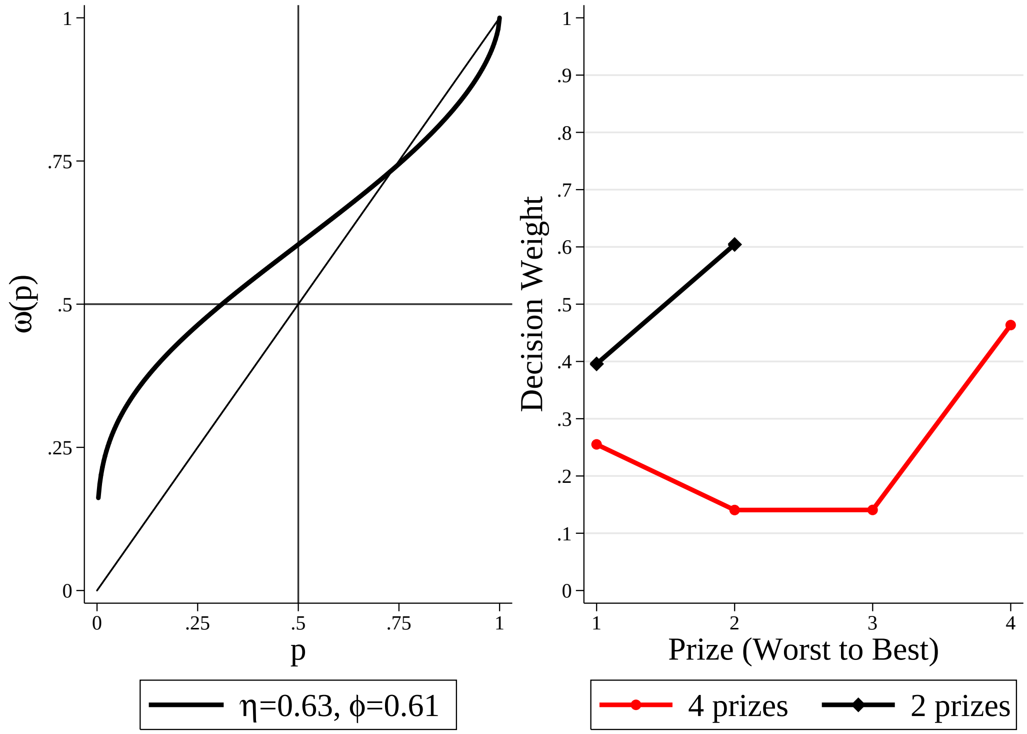

Figure 11: Prelec PWF and Decision Weights

are similar to the total effects found in the EUT-CRRA model. Results are shown in Table A4.

8.1.3 Individuals' and Couples' Decisions

Next, we analyze whether individual preferences are similar to couple preferences. To analyze the hypothesis, we pool the decisions of all individuals and all couples and add the variable *couple* as a covariate that takes the value of 1 if the decision was done by a couple. The coefficient represents the effect of being in a couple. We also estimate this effect for real and fake couples, separately.

When comparing all individuals' decisions with the couples' decisions using the EUT model with CRRA utility function, we find that the variable *couple* increases the relative risk aversion by 0.17 (from 0.34 to 0.51). However, in the best model the variable *couple* only has a statistically significant effect in one of the pwf parameters (ϕ) but the effect is very small as shown in Figure 12 and Table A5 in Appendix A.

In order to look for differences between real and fake couples, we analyze the sample of real and fake couples separately. As explained before, a real couple is a married couple or a couple that cohabits. A fake couple is a group of two people paired up at random that take decisions together

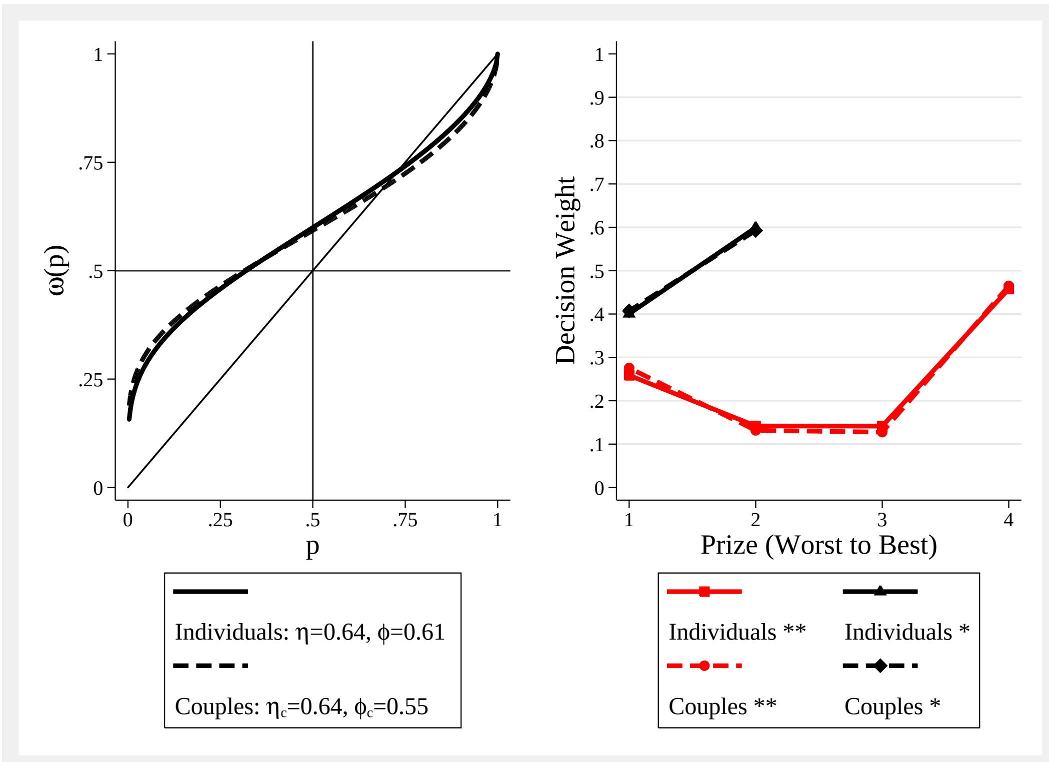

Figure 12: Prelec PWF and Decision Weights for Individuals and Couples

Table 10: Summary of Estimates by Model and Subsample.

Model	Individuals			Couples		
	All	Real	Fake	All	Real	Fake
EUT						
r	0.35	0.38	0.31	0.49	0.44	0.55
RDU						
r	0.74	0.74	0.73	0.78	0.76	0.80
α	-0.16	-0.16	-0.15	-0.24	-0.20	-0.29
η	0.61	0.64	0.59	0.60	0.61	0.60
ϕ	0.61	0.63	0.57	0.57	0.57	0.57

in the session. The sample of real (fake) couples is composed of individual and couple decisions of real (fake) couples.

In the EUT-CRRA model, real and fake couples show different results. While individuals' and couples' preferences of real couples are similar, they differ substantially in the case of fake couples. However, in the best model the variable couple only affects one of the pwf parameters in the sample of real couples and the effect is very small. The results are shown in Table A6 in Appendix A.

Then we analyze the sample of individuals and couples separately. For the individual decisions, the CRRA coefficient under the EUT framework is 0.35. In the best model, individuals show DRRA and the Prelec pwf indicates that individuals are optimistic. We analyze the rest of the subsamples in the same manner. The results are shown in Table 10.

In summary, we do not find significant differences between individuals and couples in either the fake couples or the real couples.

8.1.4 Bargaining Model

The fact that there is no statistically significant difference between individuals' and real couples' preferences in any of the models suggests that real couples' preferences are a combination of the spouses' preferences. We analyze this possibility by eliciting the decision power within the household under a EUT framework. Interestingly, we find that women are the ones that guide the decision in situations under uncertainty with a decision weight of 0.92 (Table 11).

This result is in line with Carlsson et al. (2013) who also find that individuals and married couples' preferences are similar but they find that couples' preferences are more similar to the

Table 11: Bargaining Power within the Real Couples.

Parameter	Point Estimate	St. Error	p-value	95% Conf. Interval	
EUT with CRRA utility function					
	Log-Likelihoood: -7,230.41		Observations: 11,158		
r_women	0.50	0.12	0.00	0.26	0.75
r_men	0.24	0.25	0.34	-0.25	0.74
weight_women	0.92	0.13	0.00	0.66	1.19
μ	0.19	0.01	0.00	0.16	0.21

husbands', rather than the wifes' as in our case. This result also explains previous findings in developing countries that show women in charge of the money related decisions (Collins, Morduch, Rutherford, & Ruthven, 2009).

8.2 Joint Estimation: Time and Risk Preferences

In this section, we estimate the discount rate for individuals and couples. Risk preferences are also estimated and serve as a robustness check of the previous results. First, we will establish the model that describes best the data. Then we will analyze the parameters of the different subsamples.

8.2.1 Determination of the Model

In order to determine the best model for the data, we consider four different discounting functions: the exponential, the Prelec, the Weibull and the Mazur. As in the previous analysis, we also apply the EUT and the RDU framework. We use the CRRA utility function and two pwfs: the power and the Prelec[8]. In any of the models, neither the quasi-hyperbolic nor the Weibull discounting function show hyperbolic behavior. Moreover, both models show some evidence of the opposite behavior. Since there is no theoretical framework that supports increasing discount rates over time, we discard these models. The Mazur discounting function shows slightly decreasing discount rates. We compare the Mazur discounting function with the exponential discounting function using the statistics for non-nested models. The results are shown in Table 12.

In contrast to the analysis of risk preferences, in this case the Vuong and Clarke statistics show slightly different results. Using the Vuong statistic, the best model is the exponential discounting

[8]We discarded the inverse-s shaped pwf because in the analysis considering only the risk choices, the inverse-s shaped pwf was always exceeded by the power or the Prelec-2 pwf. We also consider the expo-power utility function but the models did not converge.

function with a CRRA utility function and the Prelec pwf. With the Clarke statistic, the best model uses the power pwf instead. Both models show very similar results. However, the hit rate for the Prelec model is higher than the one for the power model. We will present the results of both models in Appendix and focus on the results of the Prelec in the explanations. It is important to remark that the best model is under the RDU framework which supports the results of the analysis of risk of the previous section.

8.2.2 Individuals' Decisions

We start with the analysis of the individual decisions. The simplest model is the exponential discounting function. When we assume a linear utility function, the discount rate is 382%. If we consider the curvature of the utility function and assume a EUT- CRRA utility function, the discount rate is 39%, far smaller than the discount rate with a linear utility function. The results of the estimation of the different models with the sample of individuals are presented in Table A7, Table A8 and Table A9 in Appendix A. Looking at the heterogeneity of the sample, only education has an effect on the CRRA coefficient. More educated people are less risk averse. None of the treatment variables have an effect on the CRRA coefficient or the discount rate.

The best model is the exponential discounting function using the RDU framework with CRRA utility function and Prelec pwf. The value of δ is 29%, and the CRRA estimate is 0.8. The parameter estimates of the pwf function are $\eta = 0.42$ and $\phi = 0.73$ so that individuals are optimistic which also confirms the results of the risk analysis. It is interesting to notice that the value of the CRRA coefficient is higher than the value found in the analysis with only risk choices. A possible explanation for this result is that the time preferences choices only contain information on the curvature of the utility function or the aversion to variability. Thus, this characteristic of the intertemporal choices affects the EUT-CRRA estimate in the joint estimation and pushes them upwards. Figure 13 shows the pwf for the best model that is very similar in shape to the power pwf.

Looking at the effect of socioeconomic and treatment variables in the best model, people that have finished primary school show lower relative risk aversion and less optimism. Tanaka et al. (2010) also finds that more educated individuals are less risk averse. The authors do not find study the relationship with the pwf parameter estimates. These effects are opposite than the ones found in the analysis with the risk tasks. We prefer the results with the joint estimation because risk preferences have been estimated with more data. Age has a statistically significant effect on one of the pwf parameter estimates: older people overweigh extreme values more than younger people. Neither the treatment nor the socioeconomic variables have a statistically significant effect on the discount rate. The results are shown in Table A10 in Appendix A.

Table 12: Clarke and Vuong Statistics for Discounting Models.

	A	B	C	D	E
	Mazur EUT	Expon. RDU Prelec2	Mazur RDU Prelec2	Expon. RDU Power	Mazur RDU Power
A. Vuong Statistic					
Exp. EUT	7.316	-14.947	-14.351	-14.630	-14.111
	0.000	*1.000*	*1.000*	*1.000*	*1.000*
Mazur EUT		-15.404	-14.892	-15.145	-14.701
		1.000	*1.000*	*1.000*	*1.000*
Exp. RDU Prelec2			10.142	3.715	5.155
			0.000	*0.000*	*0.000*
Mazur RDU Prelec2				1.770	3.422
				0.038	*0.000*
Exp. RDU Power					10.299
					0.000
B. Clarke Statistic					
Exp. EUT	28,828	21,104	24,807	21,455	23,187
	0.000	*1.000*	*1.000*	*1.000*	*1.000*
Mazur EUT		24,641	22,219	23,583	22,551
		1.000	*1.000*	*1.000*	*1.000*
Exp. RDU Prelec2			30,864	22,891	26,120
			0.000	*1.000*	*1.000*
Mazur RDU Prelec2				25,660	24,006
				1.000	*1.000*
Exp. RDU Power					30,033
					0.000

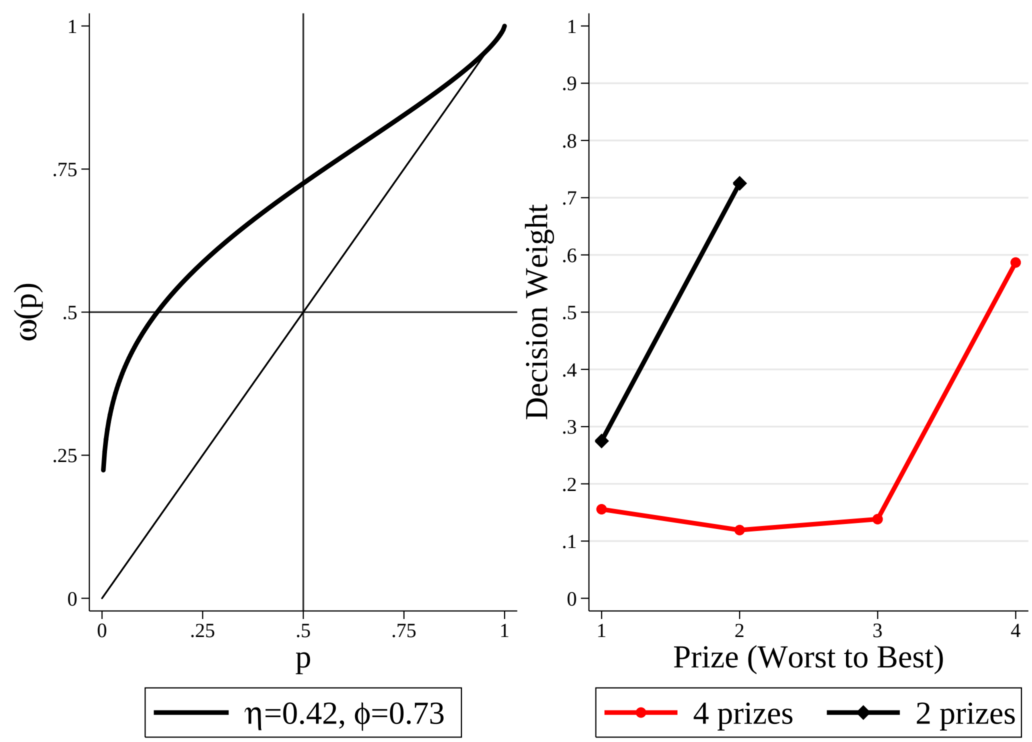

Figure 13: Prelec PWF and Decision Weights in the Discounting Model

8.2.3 Individuals' and Couples' Decisions

Following the risk analysis, we estimate the difference between all individuals and all couples using the variable couple. We distinguish between real and fake couples by estimating the difference between individuals and couples in each group. Finally, we estimate the parameters for each subsample.

Considering all individuals and couples choices, the variable couple in the exponential model using the EUT framework and CRRA utility function increases the discount rate by 18% (from 43% to 62%). The variable couple also reduces the CRRA coefficient by 0.04. This effect is statistically significant but small. In the best model, couples have a higher discount rate than individuals by 14% (from 30% to 44%). The variable couple also reduces the CRRA coefficient and reduces one of the pwf coefficients but the effects are very small. Results are shown in Table A11 in Appendix A.

Results for real and fake couples are presented in Table A12 and Table A13 in Appendix A. We will focus only on the results of the best model. Real couples have a discount rate of 46% that is 14% higher than the one of individuals. Real couples have a lower CRRA coefficient than individuals but the effect is small, as is the effect on the pwf. We find similar results in the sample of fake couples but in this case there is a more significant effect on the pwf. Fake couples seem to be less optimistic that their respective individuals. This result is confirmed in the RDU model with power pwf.

In Table 13, we present the estimates for every subsample. In general, we can see that there is not much difference between the risk preferences of individuals and couples in the best model. Couples show higher discount rates than individuals both in real and fake couples. These results confirmed the findings in the descriptive analysis.

9 Analysis of Correlations

We analyze the correlations between each of the parameter estimates of risk and time preferences and the investment in water tank in the structural model. We measure the correlations using the best model of the joint estimation. As a robustness check, we measure the same correlations with the second best model.

Only 20% of the real couples in the sample have a water tank. In the couple survey, we asked the real couples that that have a water tank whether the decision was taken by the couple or by any of the spouses. In 84% of the cases, the decision was taken by the couple and in 16% the decision was taken by the head of household. Thus, we expect to find a stronger correlation between real

Table 13: Summary of Estimates by Discounting Model and Subsample.

Model	Individuals			Couples		
	All	Real	Fake	All	Real	Fake
Exponential-EUT						
r	0.72	0.68	0.81	0.72	0.68	0.77
δ	0.46	0.53	0.31	0.56	0.66	0.44
Exponential-RDU						
r	0.80	0.78	0.81	0.78	0.77	0.79
η	0.41	0.44	0.37	0.45	0.44	0.46
ϕ	0.73	0.74	0.71	0.64	0.65	0.63
δ	0.32	0.32	0.31	0.41	0.43	0.38

couples' preferences and the water tank investment.

The results using all the real couples' choices are presented in Table 14. Real couples' relative risk aversion is the same for couples that have water tanks and couples that do not have water tanks. However, real couples that have water tanks show less optimism (higher η) than real couples that do not have water tanks as shown in Figure 14. Also, we find that real couples that are less patient (higher δ) are less prone to invest in water tanks. However, when we look at the correlation between head of households preferences and water tank, we do not find any statistically significant relationship as shown in Table 14. We also do not find a statistically significant correlation with the other spouse's preferences. As a robustness check, we use the exponential model with RDU power pwf. We find the same results as shown in Table A14 in Appendix A.

10 Discussion of results

In this section, we will compare the results of the structural estimation with the findings of the literature. Regarding the estimation of the risk preferences, the results with just the risk tasks and the joint estimation show very similar results which demonstrate the robustness of the estimation procedure. The best model for individuals and couples in the study site is an RDU model with Prelec pwf. Applying the joint estimation, we find that the sample shows a CRRA coefficient of 0.8 (0.64 in the estimation with the risk tasks only). This means that people not only are averse to the variability of final outcomes but also have an attitude towards probabilities. Specifically, the parameters estimates show that both individuals and couples overweigh the objective probability

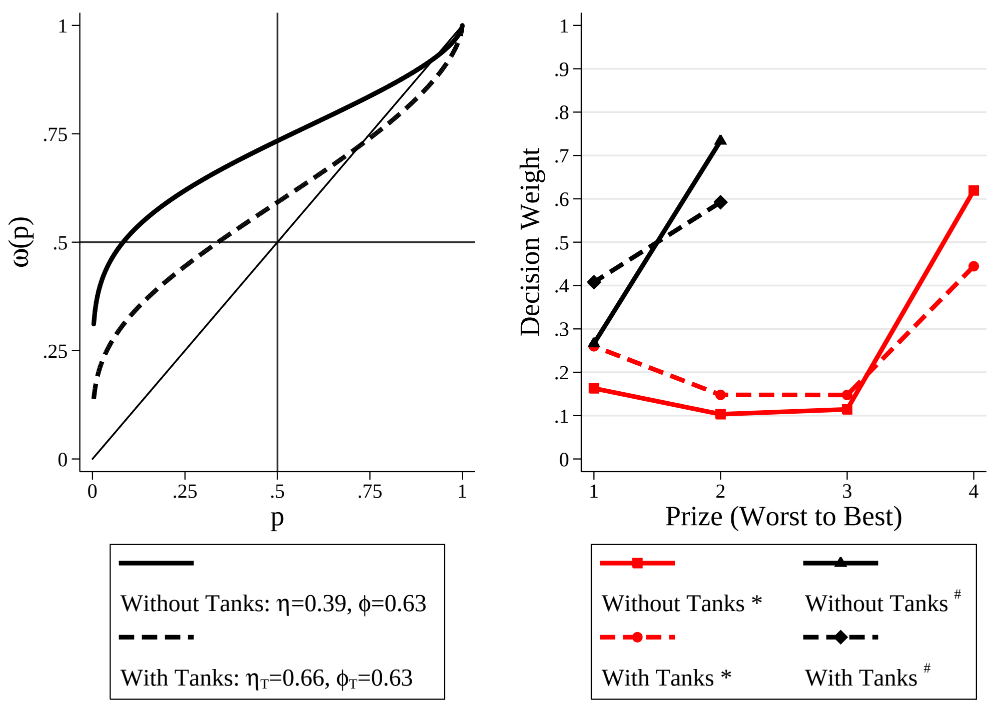

Figure 14: Prelec PWF and Decision Weights With and Without Tanks

Table 14: Correlation of Variable *Water Tank* with Parameter Estimates.

Parameter	Variable	Point Est.	Std. Error	p-value	95% Conf. Interval	
A. Couples						
	Log-Likelihoood: -5,996.99			Observations: 9,593		
r	tank	0.013	0.054	0.805	-0.092	0.118
	const	0.778	0.028	0.000	0.723	0.834
η	tank	0.264	0.120	0.027	0.030	0.499
	const	0.392	0.051	0.000	0.292	0.493
ϕ	tank	0.184	0.177	0.297	-0.162	0.531
	const	0.626	0.073	0.000	0.484	0.769
δ	tank	-0.306	0.151	0.043	-0.602	-0.009
	const	0.479	0.106	0.000	0.271	0.687
μ_r	const	0.121	0.008	0.000	0.105	0.138
μ_d	const	2.961	0.886	0.001	1.225	4.697
B. Heads of household						
	Log-Likelihoood: -6117.90			Observations: 9,515		
r	tank	-0.020	0.055	0.715	-0.128	0.087
	const	0.749	0.037	0.000	0.677	0.821
η	tank	0.228	0.156	0.145	-0.079	0.534
	const	0.390	0.060	0.000	0.272	0.508
ϕ	tank	-0.015	0.198	0.939	-0.403	0.373
	const	0.716	0.101	0.000	0.518	0.914
δ	tank	-0.194	0.197	0.325	-0.581	0.192
	const	0.480	0.148	0.001	0.190	0.770
μ_r	const	0.160	0.014	0.000	0.133	0.187
μ_d	const	5.435	1.850	0.003	1.809	9.061

of the best outcome. Using the risk tasks, we find that individuals overweigh the extreme values with a clear tendency to overweigh more the best outcome. In the joint estimation, the pwf is more concave and the optimistic behavior is even stronger. This result is confirmed when we applied the RDU model with power pwf. Moreover, more education reduces the risk aversion and the optimism. The results differ from the ones found by Harrison et al. (2010) for Uganda, India and Ethiopia in comparable estimations. The authors find a CRRA coefficient of 0.5 and a convex pwf when assuming the Prelec pwf and a S-shaped pwf when assuming the Tversky-Kahneman pwf. The shape of the Prelec pwf indicates that people underweigh the extreme values with a tendency to overweigh more the worst outcomes. Tanaka et al. (2010) find a CRRA of 0.41 and 0.37 in the north and south of China, respectively. Liu (2013) elicited risk preferences for individuals in Vietnam and finds a CRRA coefficient of 0.52. Both studies use the same elicitation procedure and a one parameter Prelec function. They find individuals overweigh the small probabilities, like an inverse-S shaped pwf, but there is no tendency towards optimism or pessimism. Their pwf does have the flexibility to allow for that.

Using a pool estimation, we do not find a significant difference between individuals and couples risk preferences. When we estimate the balance of power, we find that on average women carry the decision of the household with a weight of 0.92. This result is in line with Carlsson et al. (2013)'s results who finds that couples' decisions are mostly a combination of the spouses decisions. It is also in line with Abdellaoui, L'Haridon, and Paraschiv (2013). They differ from Bateman and Munro (2005) who find that couples are more risk averse than individuals.

We use an exponential discounting model to describe the time preferences of individuals. We have to emphasize the importance of correcting the estimate with the curvature of the utility function. Without it, we find a discount rate of 382%, far higher than the 39% considering a EUT-CRRA framework and the 29% with a RDU-Prelec pwf. We compare the discount rate estimate with the results of studies that also consider the curvature of the utility function and the EUT framework. The discount rate is similar to the $25\% - 35\%$ discount rate found by Andreoni and Sprenger (2012) and to the 28% found by Coller et al. (2012) when they assume an exponential discounting function. The subjects in both studies are American students. Our discount rate is higher than the 9% estimated by Andersen et al. (2014) for the Danish population. This is the first time this methodology has been applied in a developing country and do not show much difference with other results found in developed countries.

Contrary to much of the literature but consistent with studies (Andersen et al., 2014; Andreoni & Sprenger, 2012; Laury, McInnes, & Swarthout, 2012) with better designs and structural models, we find little evidence of hyperbolic discounting in the individuals and couples' sample. This is in line with results of Carlsson et al. (2012) and contrary to Abdellaoui, L'Haridon, Paraschiv, et al.

(2013).

Using a pool estimation, we find significant differences between individuals' and couples' discount rates, in both real and fake couples. Couples show discount rates that are 14% higher than the ones of individuals. This result contradicts the findings of Carlsson et al. (2012) where the joint choices are in between the spouses and the results of Abdellaoui, L'Haridon, Paraschiv, et al. (2013) who find that couples are more patient.

Finally, we estimate the correlation between risk and time preferences and water tanks. Only Liu (2013) analyzes the relationship between investment in adaptation and risk preferences parameters. According to a survey undertaken in the site, the decision to buy a water tank is mostly made jointly by married couples. The correlation between the married couples' parameter estimates and water tanks show the expected relationships. However, when we estimate the correlations with only the heads of household' preferences, we do not find any statistically significant correlation. We find similar results using the next best model with power pwf. These results seem to suggest that adaptation decisions made by married couples are better shaped by the couples' preferences, as suggested by Mazzocco (2004) for the case of savings.

We find a negative correlation between the married couples' discount rates and the adaptation decision, and no correlation between the married couples relative risk aversion coefficient and water tanks. However, less optimistic married couples invest more in adaptation. Theory is ambiguous about the impact of risk aversion on investment in adaptation. More risk averse subjects are expected to invest in adaptation because they want to protect themselves against future climate variability, but more risk averse individuals will invest less in new technologies because they are not certain about their efficacy (Koundouri et al., 2006). Theory does not take into account the attitudes towards probabilities but we could infer that the same forces affect the relationship between pwf parameter estimates and investment in adaptation. Our results show that these opposite forces countervail each other in the case of risk aversion but the concerns regarding climate change prevail when considering the attitudes towards probabilities.

11 Policy Implications

We have found that individuals in the rural communities in Guanacaste, Costa Rica, are optimistic and impatient. The optimistic behavior affects the investment in adaptation to climate change. For instance, consider the case where there are only two possible future scenarios with the same probability of occurrence, one good where there is no much climate variability and the other where climate shocks increase substantially. Using the parameter estimates, individuals allocate a weight of 73% to the best scenario and a weight of 27% to the worst scenario. Thus, the probability of the best scenario is overweight which dissuades people from investing in adaptation. Moreover, our results reveal annual constant discount rates of individuals and couples that are very high. For instance, a one dollar invested today requires a profit in 10 years of 16 dollars for individuals and 36 dollars for real couples. With such discount rates and optimism, private investment is discouraged as we showed in the results, and policymakers will need to use different strategies to incentivize it. When possible, policymakers could promote the use of technologies that show benefits in the short run, even when no drastic weather changes occur. One example of such technologies are resource-conserving technologies. If other type of products need to be adopted, then policymakers could enhance these products with prizes or raffles, like it has been applied in the case of saving products (Filiz-Ozbay, Guryan, Hyndman, Kearney, & Ozbay, 2015).

Investments in adaptation that involve considerable amounts of money or goods shared by groups are done by collective entities like households. In this study we analyze the case of private water tanks that are mainly a household investment. This type of investment (floating houses, water storages, solar panels) is best explained by the preferences of the married couple, rather the preferences of the head of household. Thus, policies that want to encourage this type of investment in adaptation should consider the characteristics of the couples, and not just the characteristics of the individuals. Moreover, policymakers should target their messages and interventions to the couple and not necessarily assume that the message that one of the spouses receives is shared with the other spouse.

12 Conclusions

Private investment in adaptation to climate change constitutes a decision to spend money today in return for uncertain payoffs in the future. Thus, time and risk preferences are important factors that shape adaptation decisions. This study assesses the characteristics of these preferences for populations in rural and drought-prone areas of Costa Rica, and connects them to household investments in water tanks.

Our findings paint a gloomy picture: the population tends to be optimistic and exhibits large discount rates, and both factors correlate significantly with a reduced likelihood to invest in adaptation measures. On the other hand, the couples' (high) level of risk aversion does not appear to encourage adaptation investments. As a result, without governmental intervention many households are unlikely to make significant personal investments in climate change adaptation. This further highlights the need for policymakers and researchers to design public policies and programs that encourage private adaptation investments, and it demonstrates that these policies need to overcome substantial hurdles in the form of personal preferences in order to be effective.

The findings in this study give rise to a range of interesting avenues for continued research. For instance, our results call into question the existence of present-bias among populations in developing countries. Prior studies that find evidence for present bias base their conclusion on a set of questions that could suggest the presence of this feature but that do not allow the elicitation of discounting functions. More research (using adequate experimental and econometric designs) is needed to answer this important question conclusively for developing countries.

In addition, the present study focuses on a type of adaptation investment (water tanks) that was not only familiar to the population, but that households had chosen independently. The correlation between preferences and adaptation decisions might differ for technologies that are introduced externally and that have a less foreseeable impact.

Lastly, a common criticism of artefactual field experiments is that, even though they allow us to obtain rich data to estimate parameter estimates, they do not put the subject in the real context for which the preferences are estimated. In spite of that, we find intuitive correlations between (regularly elicited) preferences and household adaptation investments. Nonetheless, in this context a framed field experiment could provide tremendous additional insight into the mindset of individuals and couples in view of climate change adaptation decisions.

Appendices

A Tables

Table A1: Best Model Analysis: Parameter Estimates using all the Choices.

Parameter	Point Est.	Std. Error	p-value	95% Conf. Interval	
A. EUT with CRRA utility function					
	Log-Likelihoood: -13,937.67		Observations: 21,324		
r	0.42	0.08	0.00	0.26	0.57
μ	0.21	0.01	0.00	0.19	0.23
B. EUT with Expo-Power utility function					
	Log-Likelihoood: -13,840.94		Observations: 21,324		
r	0.59	0.05	0.00	0.49	0.69
α	-0.04	0.02	0.03	-0.08	0.00
μ	0.19	0.01	0.00	0.17	0.20
C. RDU with CRRA utility function and Power pwf					
	Log-Likelihoood: -13,669.61		Observations: 21,324		
r	0.78	0.02	0.00	0.73	0.82
γ	0.43	0.03	0.00	0.37	0.50
μ	0.18	0.01	0.00	0.16	0.19
D. RDU with CRRA utility function and Inverse-S pwf					
	Log-Likelihoood: -13,826.26		Observations: 21,324		
r	0.18	0.08	0.02	0.03	0.34
γ	0.74	0.02	0.00	0.71	0.77
μ	0.17	0.01	0.00	0.16	0.18
E. RDU with CRRA utility function and Prelec pwf					
	Log-Likelihoood: -13,586.62		Observations: 21,324		
r	0.65	0.02	0.00	0.61	0.70
η	0.51	0.03	0.00	0.45	0.57
ϕ	0.61	0.03	0.00	0.55	0.68
μ	0.16	0.01	0.00	0.15	0.17
F. RDU with Expo-Power utility function and Power pwf					
	Log-Likelihoood: -13,656.25		Observations: 21,324		
r	0.87	0.02	0.00	0.84	0.90
α	-0.51	0.08	0.00	-0.66	-0.36

γ	0.46	0.03	0.00	0.39	0.53
μ	0.18	0.01	0.00	0.16	0.19
G. RDU with Expo-Power utility function and Inverse-S pwf					
	Log-Likelihoood: -13,609.72		Observations: 21,324		
r	0.51	0.03	0.00	0.45	0.57
α	-0.02	0.01	0.00	-0.04	-0.01
γ	0.68	0.02	0.00	0.65	0.71
μ	0.15	0.01	0.00	0.14	0.16
H. RDU with Expo-Power utility function and Prelec pwf					
	Log-Likelihoood: -13,541.45		Observations: 21,324		
r	0.75	0.02	0.00	0.71	0.79
α	-0.18	0.03	0.00	-0.25	-0.12
η	0.62	0.04	0.00	0.54	0.69
ϕ	0.59	0.03	0.00	0.53	0.65
μ	0.16	0.01	0.00	0.15	0.17

Table A2: Parameter Estimates using Individuals' Choices.

Parameter	Point Est.	Std. Error	p-value	95% Conf. Interval	
A. EUT with CRRA utility function					
	Log-Likelihoood: -9,517.27		Observations: 14,455		
r	0.38	0.08	0.00	0.23	0.53
μ	0.23	0.01	0.00	0.21	0.25
B. EUT with Expo-Power utility function					
	Log-Likelihoood: -9,454.79		Observations: 14,455		
r	0.57	0.05	0.00	0.47	0.66
α	-0.04	0.01	0.01	-0.07	-0.01
μ	0.20	0.01	0.00	0.18	0.22
C. RDU with CRRA utility function and Power pwf					
	Log-Likelihoood: -9,361.66		Observations: 14,455		
r	0.76	0.02	0.00	0.71	0.81
γ	0.43	0.03	0.00	0.37	0.50
μ	0.20	0.01	0.00	0.18	0.21
D. RDU with CRRA utility function and Inverse-S pwf					
	Log-Likelihoood: -9,457.39		Observations: 14,455		
r	0.17	0.08	0.03	0.01	0.32
γ	0.75	0.02	0.00	0.72	0.78
μ	0.19	0.01	0.00	0.17	0.20
E. RDU with CRRA utility function and Prelec pwf					
	Log-Likelihoood: -9,321.10		Observations: 14,455		
r	0.64	0.03	0.00	0.59	0.70
η	0.51	0.03	0.00	0.44	0.58
ϕ	0.63	0.03	0.00	0.57	0.70
μ	0.18	0.01	0.00	0.16	0.19
F. RDU with Expo-Power utility function and Power pwf					
	Log-Likelihoood: -9,352.12		Observations: 14,455		
r	0.85	0.02	0.00	0.82	0.89
α	-0.45	0.08	0.00	-0.60	-0.30
γ	0.46	0.03	0.00	0.40	0.53
μ	0.20	0.01	0.00	0.18	0.22
G. RDU with Expo-Power utility function and Inverse-S pwf					
	Log-Likelihoood: -9,329.05		Observations: 14,455		
r	0.50	0.03	0.00	0.45	0.56
α	-0.02	0.01	0.00	-0.03	-0.01
γ	0.69	0.02	0.00	0.66	0.72

μ	0.16	0.01	0.00	0.15	0.17
H. RDU with Expo-Power utility function and Prelec pwf					
	Log-Likelihoood: -9,291.87		Observations: 14,455		
r	0.74	0.03	0.00	0.69	0.79
α	-0.16	0.04	0.00	-0.23	-0.09
η	0.63	0.04	0.00	0.55	0.71
ϕ	0.61	0.03	0.00	0.55	0.66
μ	0.18	0.01	0.00	0.16	0.19

Table A3: Marginal and Total Effects Using Individuals' Choices and EUT

All estimations are calculated using CRRA utility function.

Parameter		Point Est.	Std. Error	p-value	95% C.I.	
A. Marginal effects						
	Log-Likelihoood: -9,235.60			Observations: 14,096		
r	order	0.10	0.13	0.46	-0.16	0.36
	gender	0.08	0.13	0.54	-0.18	0.34
	age	-0.17	0.16	0.28	-0.47	0.14
	primary school	0.55	0.37	0.14	-0.18	1.28
	married	0.10	0.14	0.50	-0.18	0.37
	income	0.19	0.13	0.14	-0.06	0.44
	const	-0.22	0.36	0.55	-0.93	0.49
μ	const	0.21	0.01	0.00	0.19	0.24
B. Total effects						
r	order	0.26	0.15	0.08	-0.03	0.56
	gender	0.12	0.16	0.45	-0.19	0.44
	age	-0.30	0.17	0.08	-0.64	0.04
	primary school	0.87	0.38	0.02	0.12	1.62
	married	0.09	0.16	0.54	-0.21	0.40
	income	0.30	0.14	0.03	0.03	0.57

Table A4: Marginal Effects using Individuals' Choices and RDU Prelec pwf

All estimations are calculated using Expo-Power utility function.

Parameter		Point Est.	Std. Error	p-value	95% C.I.	
		Log-Likelihoood: -9,230.30		Observations: 14,425		
r	order	0.10	0.05	0.06	0.00	0.20
	gender	-0.11	0.05	0.02	-0.20	-0.02
	age	-0.28	0.06	0.00	-0.39	-0.17
	primary school	0.13	0.05	0.01	0.04	0.22
	married	0.12	0.05	0.02	0.02	0.21
	income	0.01	0.04	0.73	-0.06	0.09
	const	0.55	0.08	0.00	0.40	0.71
α	order	0.00	0.00	0.30	-0.01	0.00
	gender	0.01	0.01	0.25	-0.01	0.02
	age	0.02	0.02	0.23	-0.01	0.05
	primary school	0.00	0.00	0.93	0.00	0.00
	married	-0.01	0.01	0.26	-0.02	0.01
	income	0.00	0.00	0.27	0.00	0.01
	const	-0.03	0.02	0.19	-0.07	0.01
η	order	-0.17	0.10	0.08	-0.36	0.02
	gender	0.15	0.11	0.18	-0.07	0.37
	age	0.39	0.12	0.00	0.14	0.63
	primary school	-0.21	0.11	0.07	-0.43	0.02
	married	-0.13	0.10	0.18	-0.32	0.06
	income	0.01	0.11	0.90	-0.20	0.22
	const	0.86	0.14	0.00	0.59	1.14
ϕ	order	-0.02	0.07	0.75	-0.16	0.11
	gender	-0.06	0.07	0.40	-0.20	0.08
	age	-0.21	0.06	0.00	-0.33	-0.09
	primary school	0.08	0.08	0.36	-0.09	0.24
	married	-0.06	0.07	0.41	-0.19	0.08
	income	0.07	0.08	0.37	-0.08	0.23
	const	0.74	0.10	0.00	0.54	0.94
μ	const	0.16	0.01	0.00	0.14	0.17

Table A5: Individuals' vs. Couples' Choices.

Parameter		Point Est.	Std. Error	p-value	95% C.I.	
A. EUT with CRRA utility function						
	Log-Likelihoood: -13,457.36			Observations: 20,605		
r	couple	0.17	0.07	0.01	0.04	0.30
	const	0.34	0.10	0.00	0.15	0.53
μ	const	0.21	0.01	0.00	0.19	0.22
B. RDU with Expo-Power utility function and Prelec pwf						
	Log-Likelihoood: -13,059.60			Observations: 20,605		
r	couple	0.03	0.03	0.30	-0.03	0.10
	const	0.74	0.03	0.00	0.67	0.80
α	couple	-0.04	0.05	0.46	-0.14	0.06
	const	-0.17	0.05	0.00	-0.26	-0.08
η	couple	-0.06	0.06	0.31	-0.17	0.05
	const	0.64	0.06	0.00	0.53	0.75
ϕ	couple	-0.05	0.03	0.09	-0.12	0.01
	const	0.61	0.03	0.00	0.55	0.66
μ	const	0.16	0.01	0.00	0.15	0.17

Table A6: Individuals' vs. Couples' Decisions of Real and Fake Couples.

Parameter		Point Est.	Std. Error	p-value	95% C.I.	
1. Real Couples						
A. EUT with CRRA utility function						
	Log-Likelihoood: -7,232.38			Observations: 11,158		
r	couple	0.07	0.08	0.34	-0.08	0.22
	const	0.37	0.11	0.00	0.15	0.59
μ	const	0.19	0.01	0.00	0.17	0.21
B. RDU with Expo-Power utility function and Prelec pwf						
	Log-Likelihoood: -7,014.35			Observations: 11,158		
r	couple	0.01	0.04	0.79	-0.07	0.10
	const	0.74	0.04	0.00	0.66	0.82
α	couple	0.00	0.07	0.99	-0.13	0.13
	const	-0.17	0.06	0.00	-0.28	-0.06
η	couple	-0.07	0.08	0.36	-0.23	0.08
	const	0.66	0.07	0.00	0.52	0.81
ϕ	couple	-0.08	0.04	0.04	-0.15	0.00
	const	0.63	0.04	0.00	0.55	0.71
μ	const	0.15	0.01	0.00	0.13	0.16
2. Fake Couples						
A. EUT with CRRA utility function						
	Log-Likelihoood: -6,218.42			Observations: 9,447		
r	couple	0.29	0.13	0.02	0.04	0.54
	const	0.29	0.17	0.09	-0.04	0.62
μ	const	0.23	0.01	0.00	0.20	0.26
B. RDU with Expo-Power utility function and Prelec pwf						
	Log-Likelihoood: -6,038.50			Observations: 9,447		
r	couple	0.06	0.06	0.29	-0.05	0.17
	const	0.73	0.06	0.00	0.62	0.84
α	couple	-0.09	0.09	0.31	-0.25	0.08
	const	-0.16	0.08	0.03	-0.31	-0.01
η	couple	-0.04	0.09	0.69	-0.21	0.13
	const	0.61	0.09	0.00	0.44	0.78
ϕ	couple	-0.03	0.05	0.61	-0.13	0.08
	const	0.58	0.04	0.00	0.49	0.66
μ	const	0.17	0.01	0.00	0.15	0.19

Table A7: Joint Estimation using Individuals' Choices and EUT

All estimations are calculated using CRRA utility function.

Parameter	Point Est.	Std. Error	p-value	95% C.I.	
A. Exponential discounting function					
	Log-Likelihoood: -24,640.65		Observations: 37,587		
r	0.75	0.05	0.00	0.65	0.85
δ	0.39	0.11	0.00	0.17	0.60
μ_r	0.28	0.02	0.00	0.24	0.33
μ_d	5.75	2.86	0.05	0.14	11.37
B. Quasi-hyperbolic discounting function					
	Log-Likelihoood: -24,546.42		Observations: 37,587		
r	0.70	0.05	0.00	0.61	0.80
δ	0.60	0.15	0.00	0.30	0.90
β	1.06	0.02	0.00	1.01	1.11
μ_r	0.27	0.02	0.00	0.23	0.31
μ_d	9.40	4.60	0.04	0.39	18.41
C. Mazur discounting function					
	Log-Likelihoood: -24,652.85		Observations: 37,587		
r	0.79	0.06	0.00	0.68	0.90
K	0.28	0.09	0.00	0.11	0.46
μ_r	0.79	0.06	0.00	0.68	0.90
μ_d	0.28	0.09	0.00	0.11	0.46
D. Weibull discounting function					
	Log-Likelihoood: -24,580.84		Observations: 37,587		
r	0.71	0.05	0.00	0.61	0.81
r_{wei}	0.67	0.15	0.00	0.37	0.96
s_{wei}	0.55	0.06	0.00	0.45	0.66
μ_r	0.27	0.02	0.00	0.23	0.31
μ_d	8.51	4.10	0.04	0.47	16.54

Table A8: Joint Estimation using Individuals' Choices and RDU with Prelec Pwf

All estimations are calculated using CRRA utility function.

Parameter	Point Est.	Std. Error	p-value	95% C.I.	
A. Exponential discounting function					
	Log-Likelihoood: -24,387.51		Observations: 37,587		
r	0.80	0.02	0.00	0.77	0.84
η	0.42	0.03	0.00	0.36	0.48
ϕ	0.73	0.05	0.00	0.63	0.83
δ	0.29	0.05	0.00	0.20	0.38
μ_r	0.18	0.01	0.00	0.17	0.20
μ_d	3.43	0.68	0.00	2.11	4.75
B. Quasi-hyperbolic discounting function					
	Log-Likelihoood: -24,296.52		Observations: 37,587		
r	0.79	0.02	0.00	0.75	0.82
η	0.43	0.03	0.00	0.37	0.48
ϕ	0.71	0.05	0.00	0.62	0.81
δ	0.39	0.06	0.00	0.28	0.51
β	1.04	0.01	0.00	1.01	1.06
μ_r	0.18	0.01	0.00	0.17	0.20
μ_d	4.17	0.84	0.00	2.51	5.82
C. Mazur discounting function					
	Log-Likelihoood: -24,398.21		Observations: 37,587		
r	0.82	0.02	0.00	0.78	0.85
η	0.41	0.03	0.00	0.35	0.47
ϕ	0.74	0.06	0.00	0.63	0.85
K	0.25	0.04	0.00	0.17	0.32
μ_r	0.18	0.01	0.00	0.17	0.20
μ_d	3.08	0.61	0.00	1.88	4.29
D. Weibull discounting function					
	Log-Likelihoood: -24,330.45		Observations: 37,587		
r	0.79	0.02	0.00	0.75	0.83
η	0.43	0.03	0.00	0.37	0.48
ϕ	0.72	0.05	0.00	0.62	0.81
r_{wei}	0.46	0.06	0.00	0.34	0.58
s_{wei}	0.57	0.06	0.00	0.46	0.68
μ_r	0.18	0.01	0.00	0.17	0.20
μ_d	3.94	0.79	0.00	2.40	5.48

Table A9: Joint Estimation using Individuals' Choices and RDU with Power Pwf.

All estimations are calculated using CRRA utility function.

Parameter	Point Est.	Std. Error	p-value	95% C.I.	
A. Exponential discounting function					
	Log-Likelihoood: -24,400.11		Observations: 37,587		
r	0.86	0.02	0.00	0.83	0.89
γ	0.38	0.03	0.00	0.33	0.44
δ	0.20	0.03	0.00	0.13	0.26
μ_r	0.20	0.01	0.00	0.18	0.21
μ_d	1.98	0.35	0.00	1.29	2.68
B. Quasi-hyperbolic discounting function					
	Log-Likelihoood: -24,311.79		Observations: 37,587		
r	0.85	0.02	0.00	0.82	0.88
γ	0.39	0.03	0.00	0.33	0.44
δ	0.26	0.04	0.00	0.18	0.34
β	1.03	0.01	0.00	1.01	1.04
μ_r	0.20	0.01	0.00	0.18	0.21
μ_d	2.27	0.42	0.00	1.45	3.09
C. Mazur discounting function					
	Log-Likelihoood: -24,408.81		Observations: 37,587		
r	0.87	0.02	0.00	0.84	0.90
γ	0.38	0.03	0.00	0.32	0.43
K	0.17	0.03	0.00	0.12	0.23
μ_r	0.20	0.01	0.00	0.18	0.21
μ_d	1.86	0.33	0.00	1.21	2.50
D. Weibull discounting function					
	Log-Likelihoood: -24,345.36		Observations: 37,587		
r	0.85	0.02	0.00	0.82	0.89
γ	0.39	0.03	0.00	0.33	0.44
r_{wei}	0.31	0.05	0.00	0.22	0.41
s_{wei}	0.58	0.06	0.00	0.47	0.70
μ_r	0.20	0.01	0.00	0.18	0.21
μ_d	2.17	0.39	0.00	1.40	2.95

Table A10: Marginal Effects of Treatment and Socioeconomic Variables in the Joint Estimation.

All estimations are calculated using exponential discounting function and RDU with CRRA utility function and Prelec pwf.

Parameter		Point Est.	Std. Error	p-value	95% C.I.	
	Log-Likelihoood: -23,547.06			Observations: 36,652		
r	order	-0.01	0.02	0.49	-0.05	0.02
	gender	0.00	0.02	0.95	-0.03	0.04
	age	0.02	0.02	0.18	-0.01	0.05
	primary school	-0.06	0.03	0.04	-0.12	0.00
	married	0.01	0.02	0.44	-0.02	0.04
	income	-0.03	0.02	0.23	-0.07	0.02
	const	0.85	0.04	0.00	0.78	0.92
η	order	0.00	0.04	0.98	-0.08	0.08
	gender	0.00	0.04	0.95	-0.09	0.08
	age	-0.06	0.04	0.12	-0.15	0.02
	primary school	0.21	0.09	0.02	0.03	0.39
	married	-0.02	0.04	0.62	-0.10	0.06
	income	0.10	0.06	0.11	-0.02	0.21
	const	0.30	0.07	0.00	0.16	0.44
ϕ	order	-0.10	0.15	0.50	-0.40	0.19
	gender	-0.11	0.16	0.51	-0.43	0.21
	age	-0.34	0.17	0.04	-0.66	-0.01
	primary school	-0.07	0.21	0.74	-0.48	0.34
	married	-0.17	0.15	0.25	-0.47	0.12
	income	0.07	0.17	0.67	-0.27	0.42
	const	1.10	0.25	0.00	0.60	1.59
δ	order	0.01	0.04	0.90	-0.07	0.08
	FED	0.15	0.10	0.13	-0.05	0.35
	ascendant	-0.07	0.05	0.16	-0.18	0.03
	gender	-0.03	0.04	0.35	-0.11	0.04
	age	0.00	0.04	0.91	-0.09	0.08
	primary school	0.18	0.16	0.26	-0.13	0.49
	married	0.00	0.04	0.91	-0.08	0.07
	income	0.05	0.09	0.60	-0.13	0.23
	const	0.17	0.08	0.04	0.01	0.33
μ_r	const	0.18	0.01	20.43	0.00	0.16
μ_d	const	3.07	0.71	4.31	0.00	1.67

Table A11: Joint Estimation using Couples' Choices.

Parameter		Point Est.	Std. Error	p-value	95% C.I.	
A. Exponential discounting function and EUT with CRRA utility function						
	Log-Likelihoood: -34,829.60			Observations: 53,575		
r	couple	-0.04	0.01	0.00	-0.06	-0.02
	const	0.74	0.05	0.00	0.65	0.83
δ	couple	0.18	0.06	0.00	0.07	0.30
	const	0.43	0.12	0.00	0.20	0.66
μ_r	const	0.25	0.02	0.00	0.21	0.29
μ_d	const	6.21	2.86	0.03	0.60	11.82
B. Exponential discounting function and RDU with CRRA utility function and Prelec pwf						
	Log-Likelihoood: -34,829.60			Observations: 53,575		
r	couple	-0.04	0.01	0.00	-0.06	-0.02
	const	0.81	0.02	0.00	0.77	0.84
η	couple	0.04	0.03	0.14	-0.01	0.10
	const	0.41	0.03	0.00	0.35	0.47
ϕ	couple	-0.10	0.05	0.03	-0.19	-0.01
	const	0.72	0.05	0.00	0.62	0.82
δ	couple	0.14	0.03	0.00	0.08	0.21
	const	0.30	0.05	0.00	0.20	0.40
μ_r	const	0.16	0.01	0.00	0.15	0.17
μ_d	const	3.30	0.60	0.00	2.12	4.47
C. Exponential discounting function and RDU with CRRA utility function and Power pwf						
	Log-Likelihoood: -34,422.22			Observations: 53,575		
r	couple	-0.04	0.01	0.00	-0.05	-0.02
	const	0.87	0.02	0.00	0.84	0.90
γ	couple	0.05	0.03	0.15	-0.02	0.11
	const	0.36	0.03	0.00	0.31	0.42
δ	couple	0.11	0.02	0.00	0.06	0.15
	const	0.19	0.03	0.00	0.12	0.26
μ_r	const	0.17	0.01	0.00	0.16	0.19
μ_d	const	1.73	0.30	0.00	1.14	2.32

Table A12: Joint Estimation using Real Couples' Choices.

Parameter		Point Est.	Std. Error	p-value	95% C.I.	
A. Exponential discounting function and EUT with CRRA utility function						
	Log-Likelihoood: -18,791.04			Observations: 29,013		
r	couple	-0.03	0.01	0.01	-0.05	-0.01
	const	0.69	0.06	0.00	0.58	0.80
δ	couple	0.22	0.09	0.02	0.04	0.40
	const	0.50	0.15	0.00	0.21	0.79
μ_r	const	0.22	0.02	0.00	0.18	0.26
μ_d	const	9.39	4.74	0.05	0.10	18.69
B. Exponential discounting function and RDU with CRRA utility function and Prelec pwf						
	Log-Likelihoood: -18,545.94			Observations: 29,013		
r	couple	-0.03	0.01	0.01	-0.05	-0.01
	const	0.79	0.02	0.00	0.74	0.83
η	couple	-0.01	0.04	0.86	-0.08	0.07
	const	0.44	0.05	0.00	0.35	0.53
ϕ	couple	-0.10	0.06	0.07	-0.22	0.01
	const	0.74	0.07	0.00	0.60	0.87
δ	couple	0.14	0.05	0.00	0.05	0.24
	const	0.31	0.07	0.00	0.17	0.46
μ_r	const	0.15	0.01	0.00	0.13	0.17
μ_d	const	3.68	0.88	0.00	1.95	5.41
C. Exponential discounting function and RDU with CRRA utility function and Power pwf						
	Log-Likelihoood: -18,565.51			Observations: 29,013		
r	couple	-0.03	0.01	0.01	-0.05	-0.01
	const	0.85	0.02	0.00	0.81	0.89
γ	couple	-0.01	0.04	0.88	-0.09	0.08
	const	0.40	0.05	0.00	0.31	0.49
δ	couple	0.10	0.03	0.00	0.04	0.16
	const	0.20	0.05	0.00	0.11	0.29
μ_r	const	0.16	0.01	0.00	0.14	0.18
μ_d	const	1.93	0.38	0.00	1.20	2.67

Table A13: Joint Estimation using Fake Couples' Choices.

Parameter		Point Est.	Std. Error	p-value	95% C.I.	
A. Exponential discounting function and EUT with CRRA utility function						
	Log-Likelihoood: -16,024.59			Observations: 24,562		
r	couple	-0.053	0.014	0.000	-0.080	-0.025
	const	0.815	0.093	0.000	0.633	0.997
δ	couple	0.149	0.062	0.017	0.027	0.272
	const	0.307	0.197	0.119	-0.079	0.692
μ_r	const	0.301	0.042	0.000	0.219	0.383
μ_d	const	3.180	2.910	0.274	-2.523	8.884
B. Exponential discounting function and RDU with CRRA utility function and Prelec pwf						
	Log-Likelihoood: -15,826.45			Observations: 24,562		
r	couple	-0.054	0.014	0.000	-0.081	-0.027
	const	0.825	0.023	0.000	0.779	0.871
η	couple	0.099	0.042	0.020	0.016	0.182
	const	0.368	0.041	0.000	0.288	0.449
ϕ	couple	-0.097	0.075	0.196	-0.245	0.050
	const	0.703	0.080	0.000	0.546	0.859
δ	couple	0.148	0.041	0.000	0.068	0.228
	const	0.286	0.074	0.000	0.140	0.432
μ_r	const	0.173	0.011	0.000	0.151	0.195
μ_d	const	2.898	0.808	0.000	1.315	4.481
C. Exponential discounting function and RDU with CRRA utility function and Power pwf						
	Log-Likelihoood: -15,843.17			Observations: 24,562		
r	couple	-0.051	0.013	0.000	-0.077	-0.025
	const	0.891	0.027	0.000	0.837	0.945
γ	couple	0.112	0.050	0.026	0.013	0.210
	const	0.325	0.039	0.000	0.248	0.402
δ	couple	0.115	0.030	0.000	0.056	0.175
	const	0.167	0.056	0.003	0.058	0.276
μ_r	const	0.189	0.013	0.000	0.163	0.215
μ_d	const	1.530	0.466	0.001	0.617	2.444

Table A14: Correlation of Variable Tank using RDU with Power pwf

All estimations are calculated using CRRA utility function.

Parameter		Point Est.	Std. Error	p-value	95% C.I.	
A. Couples						
	Log-Likelihoood: -6,008.77			Observations: 9,593		
r	tank	0.008	0.051	0.873	-0.091	0.108
	const	0.855	0.025	0.000	0.806	0.904
γ	tank	0.297	0.133	0.025	0.037	0.557
	const	0.340	0.051	0.000	0.240	0.439
δ	tank	-0.173	0.097	0.073	-0.363	0.016
	const	0.287	0.065	0.000	0.159	0.414
μ_r	const	0.133	0.010	0.000	0.113	0.152
μ_d	const	1.451	0.354	0.000	0.757	2.145
A. Heads of Household						
	Log-Likelihoood: -6,123.22			Observations: 9,515		
r	tank	-0.021	0.054	0.701	-0.127	0.085
	const	0.813	0.031	0.000	0.751	0.874
γ	tank	0.267	0.192	0.165	-0.110	0.644
	const	0.342	0.056	0.000	0.232	0.452
δ	tank	-0.123	0.139	0.376	-0.396	0.150
	const	0.334	0.094	0.000	0.150	0.519
μ_r	const	0.173	0.016	0.000	0.141	0.204
μ_d	const	2.974	0.820	0.000	1.368	4.581

References

Abdellaoui, M., L'Haridon, O., & Paraschiv, C. (2013). Individual vs. couple behavior: an experimental investigation of risk preferences. *Theory and decision*, *75*(2), 175–191.

Abdellaoui, M., L'Haridon, O., Paraschiv, C., et al. (2013). Do couples discount future consequences less than individuals. *Université De Rennes*, *1*, 2013–20.

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

Andersen, S., Harrison, G. W., Lau, M. I., & Rutström, E. E. (2014). Discounting behavior: A reconsideration. *European Economic Review*, *71*, 15–33.

Andreoni, J., & Sprenger, C. (2012). Estimating time preferences from convex budgets. *American Economic Review*, *102*(7), 3333–56.

Bateman, I., & Munro, A. (2005). An experiment on risky choice amongst households*. *The Economic Journal*, *115*(502), C176–C189.

Bauer, M., Chytilová, J., & Morduch, J. (2012). Behavioral foundations of microcredit: Experimental and survey evidence from rural india. *The American Economic Review*, *102*(2), 1118–1139.

Benhabib, J., Bisin, A., & Schotter, A. (2010). Present-bias, quasi-hyperbolic discounting, and fixed costs. *Games and Economic Behavior*, *69*(2), 205–223.

Bozzola, M., et al. (2014). Adaptation to climate change: Farmers' risk preferences and the role of irrigation. In *European association of agricultural economists conference on'agri-food and rural innovations for healthier societies.*

Carlsson, F., He, H., Martinsson, P., Qin, P., & Sutter, M. (2012). Household decision making in rural china: Using experiments to estimate the influences of spouses. *Journal of Economic Behavior & Organization*, *84*(2), 525–536.

Carlsson, F., Martinsson, P., Qin, P., & Sutter, M. (2013). The influence of spouses on household decision making under risk: an experiment in rural china. *Experimental Economics*, *16*(3), 383–401.

Clarke, K. A. (2003). Nonparametric model discrimination in international relations. *Journal of Conflict Resolution*, *47*(1), 72–93.

Coller, M., Harrison, G. W., & Rutström, E. E. (2012). Latent process heterogeneity in discounting behavior. *Oxford economic papers*, *64*(2), 375–391.

Collins, D., Morduch, J., Rutherford, S., & Ruthven, O. (2009). *Portfolios of the poor: how the world's poor live on $2 a day*. Princeton University Press.

Cox, J. C., Sadiraj, V., & Schmidt, U. (2015). Paradoxes and mechanisms for choice under risk. *Experimental Economics*, *18*(2), 215–250.

De Palma, A., Picard, N., & Ziegelmeyer, A. (2011). Individual and couple decision behavior under risk: evidence on the dynamics of power balance. *Theory and decision*, *70*(1), 45–64.

de Trabajo y Seguridad Social de Costa Rica, M. (n.d.). *Decreto nÂ 37784-mtss.* http://rerumnovarum.or.cr/documentos/SalariosSectorPrivado/2013/DecretodesalariossectorprivadoIIsemestre2013.pdf. (Online, 2013)

Duflo, E., Kremer, M., & Robinson, J. (2008). How high are rates of return to fertilizer? evidence from field experiments in kenya. *The American economic review*, *98*(2), 482–488.

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

Eliaz, K., Ray, D., & Razin, R. (2006). Choice shifts in groups: A decision-theoretic basis. *The American economic review*, *96*(4), 1321–1332.

Field, C. B. (2012). *Managing the risks of extreme events and disasters to advance climate change adaptation: special report of the intergovernmental panel on climate change*. Cambridge University Press.

Filiz-Ozbay, E., Guryan, J., Hyndman, K., Kearney, M., & Ozbay, E. Y. (2015). Do lottery payments induce savings behavior? evidence from the lab. *Journal of Public Economics*, *126*, 1–24.

Fischer, E. M., & Knutti, R. (2015). Anthropogenic contribution to global occurrence of heavy-precipitation and high-temperature extremes. *Nature Climate Change*, *5*(6), 560–564.

Harrison, G. W., Humphrey, S. J., & Verschoor, A. (2010). Choice under uncertainty: evidence from ethiopia, india and uganda*. *The Economic Journal*, *120*(543), 80–104.

Harrison, G. W., & Rutstrom, E. E. (2008). Risk aversion in the laboratory. *Risk Aversion in Experiments*, *12*, 41.

Koundouri, P., Nauges, C., & Tzouvelekas, V. (2006). Technology adoption under production uncertainty: theory and application to irrigation technology. *American Journal of Agricultural Economics*, *88*(3), 657–670.

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

Laury, S. K., McInnes, M. M., & Swarthout, J. T. (2012). Avoiding the curves: Direct elicitation of time preferences. *Journal of Risk and Uncertainty*, *44*(3), 181–217.

Liu, E. M. (2013). Time to change what to sow: Risk preferences and technology adoption decisions of cotton farmers in china. *Review of Economics and Statistics*, *95*(4), 1386–1403.

Mazur, J. E. (1984). Tests of an equivalence rule for fixed and variable reinforcer delays. *Journal of Experimental Psychology: Animal Behavior Processes*, *10*(4), 426.

Mazzocco, M. (2004). Saving, risk sharing, and preferences for risk. *The American Economic Review*, *94*(4), 1169–1182.

Mendelsohn, R. (2012). The economics of adaptation to climate change in developing countries. *Climate Change Economics*, *3*(02), 1250006.

Neumann, L. J., & Morgenstern, O. (1947). *Theory of games and economic behavior* (Vol. 60). Princeton university press Princeton.

Pender, J. L. (1996). Discount rates and credit markets: Theory and evidence from rural india. *Journal of development Economics*, *50*(2), 257–296.

Phelps, E. S., & Pollak, R. A. (1968). On second-best national saving and game-equilibrium growth. *The Review of Economic Studies*, *35*(2), 185–199.

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

Quiggin, J. (1982). A theory of anticipated utility. *Journal of Economic Behavior & Organization*, *3*(4), 323–343.

Read, D. (2001). Is time-discounting hyperbolic or subadditive? *Journal of risk and uncertainty*, *23*(1), 5–32.

Tanaka, T., Camerer, C. F., & Nguyen, Q. (2010). Risk and time preferences: Linking experimental and household survey data from vietnam. *American Economic Review*, *100*(1), 557–571.

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

Vuong, Q. H. (1989). Likelihood ratio tests for model selection and non-nested hypotheses. *Econometrica: Journal of the Econometric Society*, 307–333.

Wakker, P., Erev, I., & Weber, E. U. (1994). Comonotonic independence: The critical test between classical and rank-dependent utility theories. *Journal of Risk and Uncertainty*, *9*(3), 195–230.

Wu, G., & Gonzalez, R. (1996). Curvature of the probability weighting function. *Management* *science*, *42*(12), 1676–1690.