Competing theories of risk preferences and the demand for crop insurance: Experimental evidence from Peru

Jean Paul Pétraud
jppetraud@impaqint.com

Stephen R. Boucher
srboucher@ucdavis.edu

Michael R. Carter
mrcarter@primal.ucdavis.edu

June 10, 2015

Abstract

Low demand for index insurance in several recent pilot programs has created a puzzle for development economists and policy makers concerned with enhancing farmers risk management capacity in low-income economies. This paper contributes to the resolution of this puzzle by providing empirical evidence on the relative effectiveness of two primary frameworks for modeling decision-making under uncertainty. Specifically, we test whether features of Cumulative Prospect Theory (CPT), or Expected Utility Theory (EUT), better predict farmers' demand for crop insurance. Whereas in EUT, risk preferences can be represented by a single risk aversion parameter, in CPT they are determined by at least four components: probability weighting, the curvature of a utility function, a reference income and loss aversion. The data come from a series of unframed and framed lotteries played with 480 small-holder cotton farmers in southern Peru. The unframed risk games allow us to measure individual-specific preference parameters, for both theories. We use these parameters to generate predictions of farmers' choices in two framed insurance games in which farmers choose to purchase one of two available insurance contracts or to purchase no insurance. In the first game, farmers' earnings are framed as gross revenues and are always positive, i.e., this game is played over gains. In the second game, earnings are framed as net revenues and may be either positive or negative so that this is a game played over mixed prospects. We test the relative performance of the two theories by comparing the predictions of farmers' choices versus their actual choices in the insurance games. An important finding with respect to marketing of insurance contracts is that framing incomes as net revenues instead of gross revenues increases the CPT predicted demand by 24%. In the actual insurance games however, only 8% more farmers chose insurance in the net revenues frame. We find that neither theory is a particularly strong predictor of insurance choices, although EUT fares better than CPT for better educated farmers.

Competing theories of risk preferences and the demand for crop insurance: Experimental evidence from Peru

1 Introduction

The inability to insure against a wide range of risks that they face greatly limits the ability of asset-poor, rural households in developing countries to make the type of investments required to escape poverty (Boucher et al. (2008), Mahul and Stutley (2010)). In addition, uninsured households may deplete human capital and liquidate productive assets in order to smooth consumption when hit by unanticipated negative shocks, with potentially adverse consequences for long run income generation (Barnett et al. (2008), Carter and Lybbert (2012), Carter et al. (2007a), Dercon (2006), Hoddinott (2006)). The provision of affordable, market-based risk management instruments to rural households thus occupies a high priority for international development institutions and national governments alike. Because of its relatively low cost and immunity to asymmetric information problems, index insurance has received growing attention as a means of enhancing rural households' risk management capabilities. Since the late 1990's an expanding pool of insurance programs have been piloted in India, African and Latin America (Boucher and Mullally (2010), Cole et al. (2013), Gine and Yang (2009)).

While some of these programs, most notably the rainfall-based products in India (Clarke et al., 2012) were successfully scaled up, frustration with index insurance has grown as many of the pilot programs experienced low uptake and, often in spite of subsidies, were discontinued (de Bock and Gelade (2012) or Miranda and Farrin (2012)) A range of explanations have been suggested and investigated: poor contract design, pricing and high basis risk (Hill et al. (2013b), Chantarat et al. (2012)), the implicit provision of insurance through limited liability clauses in interlinked credit-insurance contracts (Gine and Yang, 2009), and farmers' lack of understanding of or trust in insurance providers ((Cole et al., 2013), Hazell et al. (2010), Cai et al. (2009), Dercon et al. (2011).) While many behaviors and psychological mechanisms might be at play, this paper takes a step back and investigates a somewhat more basic question, namely: Are we using the right theoretical framework to generate predictions about farmers' demand for crop insurance?

Most models that investigate demand for index insurance assume farmers' behavior is consistent with EUT. A classic starting point is Miranda (1991), who uses an EUT framework to theoretically explore demand for area yield insurance. Carter et al. (2007b) expand on Miranda' analysis to compare the performance of an area yield and a weather index in the context rice farmers in the Lambayeque valley in Peru. Others (Clarke (2011), Mobarak and Rosenzweig (2012)) have extended an hedging instrument model to index insurance. The goal of these models is to generate predictions of farmers' demand for index insurance contracts as a function of the level of basis risk and farmer-specific characteristics such as wealth and risk aversion (Carter et al. (2007b), Clarke (2011)). On advantage of the EUT framework is its relative simplicity and tractability, which allows one to explore insurance demand in more complex risk environments such as potential complementarities between formal index insurance and existing risk sharing arrangements (Mobarak and Rosenzweig (2012), Dercon et al. (2014), Boucher and Delpierre (2013)).

Another direction of research departs from the conventional EUT framework. For example, Elabed and Carter (2013) model and test how compound lottery aversion decreases the predicted demand for index insurance. The authors posit that farmers' perceptions of basis risk, and thus their insurance demand, may be distorted by a particular non-EUT behavior. This paper also takes the lens of behavioral economics but looks instead at indemnity insurance, that is index insurance without basis risk. This is the first best, a crop insurance instrument in which the indemnity is triggered by the farmer's own yield. We pursue a similar approach and ask, relative to EUT, how might indemnity insurance demand differ if farmers' decision-making is better described by Cumulative Prospect Theory (CPT)?

As behavioral economics has long investigated, (Starmer (2000), Camerer and Loewenstein (2004)), EUT sometimes fails descriptively because it does not take into account some important behavioral drivers of preferences, which Tversky and Kahneman (1992) incorporated in their CPT model. First, people may transform objective probabilities via some heuristic process of probability weighting when assessing the expected utility of a prospect (Quiggin (1991), Quiggin (1993), Barseghyan et al. (2013)). Second, risk attitudes may shift around a reference point (Kahneman and Tversky, 1979): specifically, a significant proportion of people reverse their risk preferences from risk averse to risk seeking when a prospect is framed as losses instead of gains (Thaler (1999), Tversky and Kahneman (1981).) Lastly, the difference between two options looms larger when that difference is framed as a disadvantage rather than an advantage (Tversky and Kahneman (1981), Gaechter et al. (2007), Kremer et al. (2013)); this is described as loss aversion. In sum, whereas, in EUT, an agent's risk attitudes can be expressed with a single parameter, such as the Arrow Pratt coefficient of absolute or relative risk aversion, risk attitudes in CPT are determined by four components. These can be parameterized, in the simplest version of CPT, with a reference point and three parameters representing probability weighing, utility curvature and loss aversion.

A first contribution of this paper is to show theoretically how each of the four components of CPT can affect crop insurance demand and, for an empirically plausible range of preference parameters, that CPT and EUT can generate conflicting predictions about the ranking of alternative crop insurance options. This conceptual exercise is grounded in the context that will constitute our empirical analysis. Specifically, based on the probability distribution of area yields for cotton farmers on Peru's south coast, we design two expected-income equivalent insurance contracts. The first is a linear contract in which the indemnity increases one-to-one with the farmer's loss. The second is a lumpsum contract which pays a constant indemnity independent of the magnitude of loss. Since the linear contract provides greater income smoothing, it will always be preferred under EUT but, as we will see, not necessarily under CPT. In order to demonstrate the role of the reference point and loss aversion, the contracts are introduced under two alternative framings. We first frame outcomes as gross revenues, which are always positive, so that a farmer's comparison across contracts in this frame is always over gains. We then frame outcomes as net revenues, which may be negative if gross revenues do not cover the working capital investment. We show that, while a farmer's ranking of contracts is independent of framing under EUT, under CPT the rankings may be reversed when outcomes are framed as mixed prospects instead of gains.

The second contribution of the paper is to provide empirical evidence of the relative predictive performance of EUT versus CPT in the context of insurance demand for a sample of small-holder cotton farmers from Peru. The empirical analysis consists of two steps. First, we use conventional experimental lotteries to elicit individual-specific preference parameters for the two frameworks: a single utility function curvature parameter for EUT and curvature, probability weighting and loss aversion parameters for CPT. With these parameters in hand, we generate for each individual in the sample predictions of preference rankings across three activities – the two insurance contracts and a no-insurance option – under the two different frames. The empirical distribution of preference parameters and the subsequent mapping to activity choices demonstrates the differences in insurance demand predictions across the two frameworks. Critically, this analysis identifies the fraction of the sample who lie in the portion of parameter space such that the two frameworks generate conflicting predictions of insurance demand.

The second part of the empirical methodology directly elicits farmers' insurance demand in two framed games that present the same three stylized revenue options discussed above. Each farmer played two framed games, once over gains (the gross revenue framing) and once over a mix of gains and losses (the net revenue framing). We then evaluate the relative performance of the two frameworks by comparing the observed choices in the framed games to the predicted choices based on farmers' elicited preference parameters using a test of statistical independence and a Seemingly Unrelated Regression analysis.

We don't find strong results in favor of one theory or the other. However, from a policy standpoint, we have three interesting findings: First, framing indeed matters. In the framed games, 41% of farmers make different choices when insurance outcomes are framed as net revenues, that include negative prospects, instead of gross revenues, where prospects were all positive. Also, more farmers choose to insure in games where prospects are framed as net revenues. Second, EUT better explains decisions but the relationship with risk aversion is the inverse of what theory predicts. There is a significant negative relationship between risk aversion and insurance demand. However counter-intuitive, this is consistent with other empirical findings about crop insurance demand in developing countries (Gine et al. (2008), Cole et al. (2013), Hill et al. (2013a)). When the sample is split between farmers who graduated from high school and those who did not, we find that high school graduates do behave according to theory: on average, risk averse high school graduates are more likely to choose to insure. The last policy relevant finding is a new unsolved puzzle: one third of the sample chooses the lumpsum option in the gains frame, although none is predicted to do so by either model. This suggests that some features of this option are appealing to farmers in a way that is not captured by either expected utility model.

The paper proceeds as follows: Section 2 describes the stylized cotton farmer's revenue distribution and the two insurance options in order to show how prediction of insurance demand differ over a range of plausible preference parameters under EUT and CPT. Section 3 describes how we elicited individual CPT parameters from 480 farmers in the valley. Section 4 uses the individual parameters to show how demand predictions for our sample change depending, not only on whether EUT or CPT is used, but also depending on which contract is offered and how they are framed. Section 5 describes the results of the contextualized part of the empirical test, where farmers were asked to make decisions in the insurance games. Section 6 uses independence tests and SUR regressions to assess the statistical power of both EUT and CPT predictions for our sample with regards to decisions in the framed games. The last section summarizes the paper and concludes.

2 CPT predictions for a crop insurance example

Empirical evidence for CPT does not only come from subject pools from university labs in rich countries, but also from field work in developing countries. For example, Harrison et al. (2010), Galarza (2009), and Tanaka et al. (2010) find supportive evidence of CPT preferences in Africa, Latin America and Asia. As reviewed by Camerer (2004), empirical tests of CPT have been performed in various contexts, in order to explain a variety of real life choices in risky environments, and in domains ranging from stock markets, to consumer choices, gambling, and, more to the point here, insurance. With regards to insurance, CPT can explain behaviors such as aversion to deductibles or overpaying for insurance against the unlikely breakdown of a consumer good (Johnson et al., 1993). For crop insurance demand, however, the implications of the CPT model are not as straight forward. Overweighing small probabilities might affect the weight given to some outcomes that may or may not matter with respect to given insurance options. Whether the reflection effect will cause insurance choice predictions that are different from those predicted by EUT depends on where the reference point is positioned in relation to the crop insurance indemnity threshold (Gelade, 2011).

In this section, we describe in detail each component of CPT in the context of a yield distribution of a typical cotton farmer in the Pisco Valley of Peru. Pisco is a relevant setting because many farmers are vulnerable to weather events, such as El Niño. In particular, cotton farmers in the valley are small-holders exposed to crop risk. We start by describing the farmer's stylized yield distribution and how the perceived distribution of revenues associated with each yield level will depend on whether they are viewed as gross revenues or net revenues. We describe how two insurance options reduce the riskiness of revenues associated with the yield distribution. The next step is to use this example to see how each of the CPT components affects choice predictions. To this effect, we numerically simulate expected utilities derived from the CPT model and graph the distribution of predicted insurance preferences.

2.1 Insurance options with stylized yields and revenues

Table 1 presents a stylized picture of the yield risk faced by a cotton farmer in the Pisco Valley. The example is based on historical yield data from 1980-2010 available from the Ministry of Agriculture. The first three panels show five states of the world, or events $s = 1...5$ with their associated probabilities p_s and yields y_s. Some features of this distribution are important with respect to investigating CPT in a realistic experimental setting. First, the expected yield of this farmer is 42.6 quintals per hectare (qq/ha), which our data confirms is realistic for our sample. Second, all states of the world where yields are average or higher have been lumped into one event (state of the world number 5) with a probability of 55% and a yield of 60 quintals per hectare. As this same distribution is used in the framed game, the number of outcomes had to be kept as small as possible. Yet we needed enough details in the distribution of low revenues so that the difference between the three revenue distributions (no insurance, lumpsum and linear insurance) was salient. Lastly, the probabilities assigned to the states 1 through 4 are small so that probability weighting could affect how each distribution is perceived.

Table 1: A farmer's yields and revenues under six scenarios

States	s	1	2	3	4	5
Probabilities	p_s	0.1	0.1	0.1	0.15	0.55
Yields (qq/ha)	y_s	8	16	24	32	60
Gross revenues (1000 Nuevo Soles)						
No insurance	x_s^N	4	8	12	16	30
With linear insurance						
	Indemnity	12	8	4	0	0
	Premium	3.1	3.1	3.1	3.1	3.1
	x_s^L	12.9	12.9	12.9	12.9	26.9
With lumpsum insurance						
	Indemnity	5.3	5.3	5.3	5.3	0
	Premium	3.1	3.1	3.1	3.1	3.1
	x_s^S	6.2	10.2	14.2	18.2	26.9
Net revenues (1000 Nuevo Soles)						
No insurance	$x_s^N - 16$	-12	-8	-4	zero	14
With lumpsum insurance	$x_s^S - 16$	-9.8	-5.8	-1.8	2.2	10.9
With linear insurance	$x_s^L - 16$	-3.1	-3.1	-3.1	-3.1	10.9

The next panel shows revenues framed as gross revenues[1], first without insurance, then with the lumpsum and the linear insurance options. Gross revenues, (x_s^N), are calculated for a parcel of 5 hectares, with a unit price of cotton output set at 100 NS per quintal. There are two types of motivations for including both contracts. The first one is to contrast with usual index insurance products which are often designed as one-fit-all contracts, and thus might overlook farmers' preference heterogeneity. Second, in the

[1]Revenues are noted in thousands of Nuevo Soles (NS), the Peruvian currency (1USD= 2.7 NS in 2011)

context of this test of CPT, it was crucial to offer an option, the lumpsum, which should never be preferred if farmers' decisions fit the EUT model, but which should be preferred by some farmers under the CPT.

The linear contract guarantees a minimum level of gross revenues (x_s^L) of 12,900 NS for any $s \leq 4$. In other words, the indemnity threshold is at 32 quintals per hectare, which is 75% of the expected value of y_s. Since the actuarially fair price or the expected indemnity is 2,400 NS, the premium of 3,100 NS includes a loading factor of about 30%, which represents a conservative estimate of administrative and operating costs. A farmer might not be risk averse enough as to choose the linear contract shown here. To see this, note that gross revenues in the linear contract have a smaller variance than without insurance, but, because of the 30% loading factor, they also have a smaller expected value. Yet, in EUT, sufficiently risk averse agents should prefer to insure.

EUT also predicts that the linear contract is always preferred to the lumpsum contract, which is the second insurance option, x_s^S, shown in table 1. Both contracts have the same indemnity threshold, the same price and the same expected value.[2] However, since the variance of the linear contract is smaller, the distribution of revenues under the lumpsum contract is a mean preserving spread of that of the linear contract, so, indeed the linear contract should always be preferred by risk averse farmers under EUT.

If instead of thinking in terms of gross revenues, farmers think in terms of net revenues or if it is how an insurance provider chooses to frame contracts, we now see negative revenues for some states of the world (the last panel of table 1.) The net revenues, $x_s^N - 16$, assume that farmers invest $16,000$ NS in land preparation, labor, fertilizer and other costs to produce cotton on their five-hectare parcel, so that the farmer breaks even

[2]Because of rounding necessary for the games, the expected value of the lumpsum distribution of revenues is slightly lower, 20,585 NS than for the linear, at 20,600 NS.

on their cultivated parcel when they have a yield of at least 32 quintals per hectare ($s = 4$ and $s = 5$.) This sunk investment determines when net revenues are positive or negative. It is also what CPT and the behavioral literature in general call a reference point (henceforth noted x_r).

The psychological foundation for the reference point is that people isolate portions of their income in what is coined budgeting by Thaler (1999). Practically and intuitively, it makes sense for a farmer to think of their crop revenue distribution in terms of when they cover their operating costs, or for a household to think in terms of when they have enough to pay for food and schooling. Under EUT, a change in framing such as this one, which only shifts the reference point, should not affect one's ranking of prospects. Hence a farmer should prefer the same option regardless of whether revenues are framed as gross revenues or net revenues. However, this is not always the case under CPT. To see how, in CPT, these and other features of these distributions may affect preferences for crop insurance, the next section applies the theory to the context of our crop insurance example. Note that, in this applied example, gross revenues relate to the theoretical situation where the decision domain includes only gains (positive outcomes), while net revenues relate to the frame where the domain also includes some negative outcomes (mixed prospects).

2.2 Alternative hypothesis: Cumulative Prospect Theory

CPT differs from EUT in four different ways. First, probabilities are transformed by a function $\pi(p)$. Second, agents have an endogenous reference income, x_r, which defines gains and losses. Third, the shape of the utility function is different over positive outcomes ($u^+(x)$) and over negative outcomes ($u^-(x)$), and, fourth, loss aversion (λ) means a steeper slope of the utility function for negative outcomes. This section reviews these elements in detail in the context of the Pisco farmer's income prospects and insurance options.

2.2.1 CPT over gains only

Looking first at prospects where outcomes are all positive, the difference between CPT and EUT lies in probability weighting. Note that events are ranked by yield and, since we assumed that farmers costs are the same under each state, a higher yield is always preferred, $y_s \succeq y_u \quad \forall \ s \geq u$. Probabilities are transformed in a non-linear fashion with decision weights $\pi^+(p_s)$. This is a two-step process where probabilities are first modified by a weighting function $w(p_s)$ and then transformed in a rank dependent process. As in EUT, a Bernoulli utility $u^+(x_s)$ is applied to each monetary outcome of a prospect, and, because of diminishing sensitivity (also risk aversion in EUT,) it is usually assumed to be concave. Hence, the CPT expected utility over positive outcomes is:

$$EU(p_s, x_s) = \sum_{s=1}^{5} \pi^+(p_s) \ u^+(x_s) \tag{1}$$

More specifically, the transformed discreet probabilities $\pi(p_s)$ are rank dependent and decumulative decision weights, so that, without insurance, the expected utility of gross revenues is:

$$\begin{aligned} EU(p_s, x_s) =& (1 - w(.9)) \ u^+(4) \ + (w(.9) - w(.8)) \ u^+(8) + \ (w(.8) - w(.7)) \ u^+(12) \\ &+ \ (w(.7) - w(.55)) \ u^+(16) + \ w(.55) \ u^+(30) \end{aligned} \tag{2}$$

Note that this collapses to EUT if $w(p_s) = p_s$. The probability weights $w(p_s)$ typically underweight large probabilities and overweight small ones. CPT does not specify a particular functional form for $w(p_s)$, but the one defined by Prelec (1998) is commonly used:

$$w(p) = exp(-(-ln(p))^{\alpha}) \tag{3}$$

Figure 1: The Prelec probability weighting function.

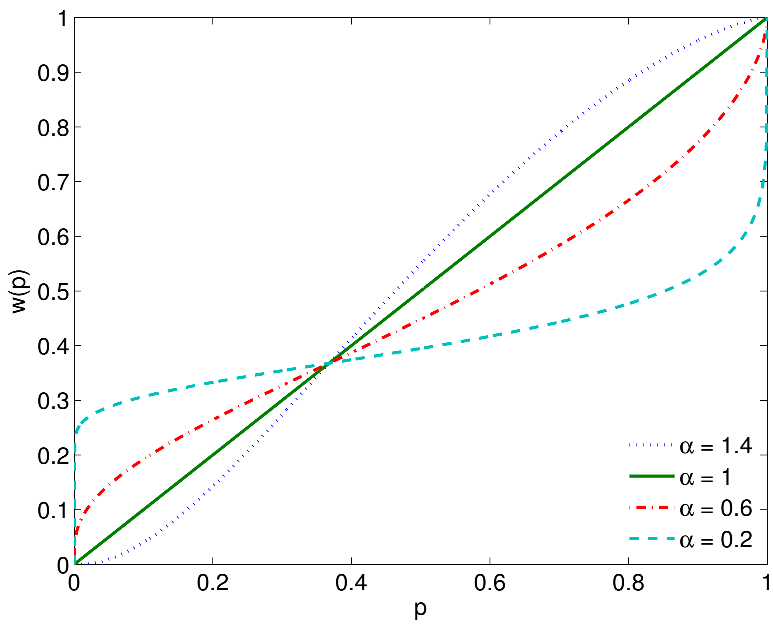
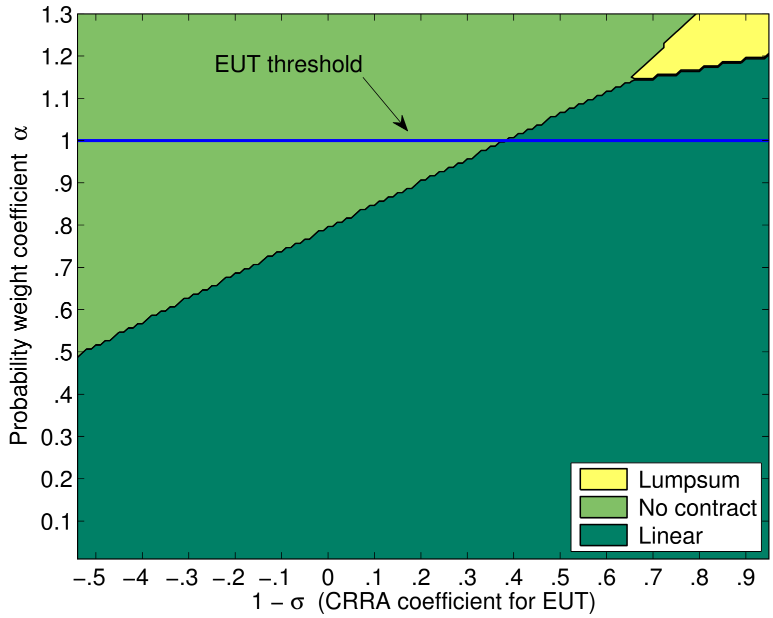


Figure 1 shows how the shape of the Prelec function changes with α. In the standard CPT model, $\alpha < 1$, and the probability weighing function has an inverse-S shape. In this case, small probabilities are overweighted and large ones underweighted, and the more so the smaller is α. Conversely, when $\alpha > 1$ the probability weighting function has an S shape and large probabilities are overweighted. Finally, CPT collapses to EUT, and $w(p_s) = p_s$, when $\alpha = 1$.

Assuming $u(x_s) = x_s^{\sigma}$, figure 2 shows the effect of probability weighting on predictions of insurance choices for the Pisco farmer when the revenue distributions associated with insurance options in table 1 are gross revenues. The Prelec coefficient α increases along the vertical axis and $1-\sigma$, the coefficient of constant relative risk aversion increases

Figure 2: Insurance demand predictions over gross revenues.



along the horizontal axis. If $\alpha = 1$, choices are as in EUT, where only sufficiently risk averse farmers (with $1 - \sigma > 0.39$) are predicted to choose insurance (the linear contract) because the price is actuarially unfavorable. The effect of decreasing α, that is, increasing the curvature of the inverse S-shaped weighing function, decreases the threshold for $1 - \sigma$ above which farmers choose to insure. The intuition is straight forward: The low probability, low value, outcomes for which the insurance provides coverage are overweighted, thus making insurance more appealing and increasing the likelihood that farmers buy insurance.

In contrast, as α increases above 1, farmers with a very low degree of curvature σ in their utility function, and an S-shaped weighting function, choose the lumpsum contract. They prefer the lumpsum to the linear contract because outcomes for yields below 32 are underweighted in the lumpsum distribution of revenues and not in the distribution with a linear contract. Thus the lumpsum appears to have a higher expected value than the linear contract if α is big enough. Furthermore, probability weighting affects the perceived distribution of probabilities of outcomes the same way under the lumpsum contract or no insurance, so that a sufficiently risk averse farmer prefers the lumpsum contract to no contract at all.

In sum, if revenues are framed as gross revenues and if farmers tend to overweight small probabilities, ignoring probability weighting in this example would mean underestimating insurance demand.

2.2.2 CPT when a reference point determines gains and losses (mixed prospects)

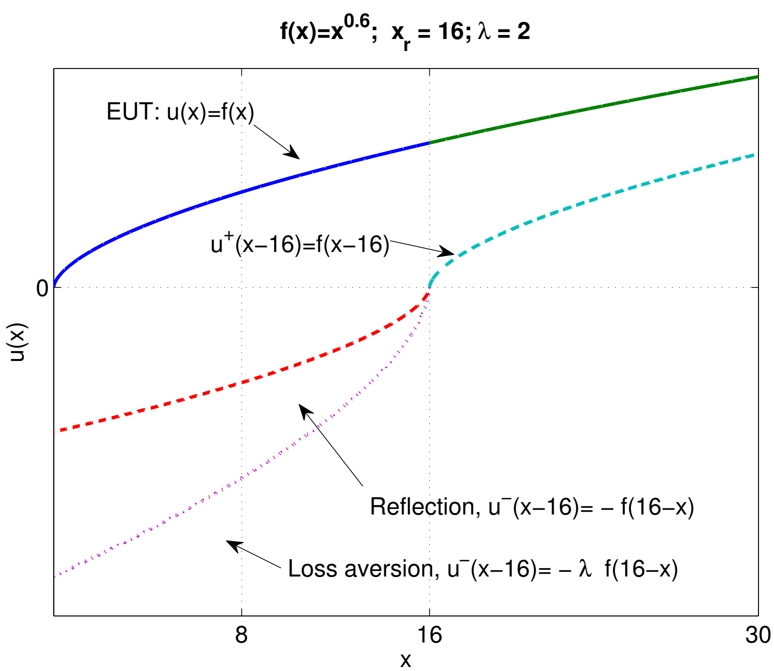
Because the riskiness of distributions is not affected when changing the framing from gross to net revenues, moving the reference point does not affect ranking of prospects in EUT. As described in the previous section however, such a reference point is at the center of the CPT model. This is for two reasons. First the shape of the utility function is convex over negative outcomes and concave over positive ones (risk seeking and risk averse in EUT.) Second, CPT models loss aversion as an increase in the slope of the utility function over negative outcomes. Hence the general model in (1) becomes more complex when the reference point x_r is positive. The expected utility expression is split between the ranked negative and positive outcomes (with superscript $^-$ and $^+$, for negative and positive outcomes, respectively, and $u(0) = 0$):

$$EU(p_s, x_s) = \sum_{s=1}^{r-1} \pi^-(p_s)\ \lambda u^-(x_s - x_r) + \sum_{s=r+1}^{N} \pi^+(p_s)\ u^+(x_s - x_r) \tag{4}$$

Comparing this to (1), we see that in (4) the utility function and the rank dependent decision weights may be different for positive and negative outcomes. In the standard CPT model, u^- is convex and u^+ is concave. Furthermore, $\lambda > 1$ captures loss aversion, and introduces an asymmetry between utilities of positive and negative outcomes. Keeping the same functional form for $u(.)$, we can model the reflection effect as follows:

$$u(x - x_r) = \begin{cases} 0 & \text{if } x = x_r \\ u^+(x - x_r) = (x - x_r)^\sigma & \text{if } x > x_r \\ \lambda u^-(x - x_r) = -\lambda(x_r - x)^\sigma & \text{if } x < x_r \end{cases} \tag{5}$$

Figure 3: The effect of a reference point under CPT.

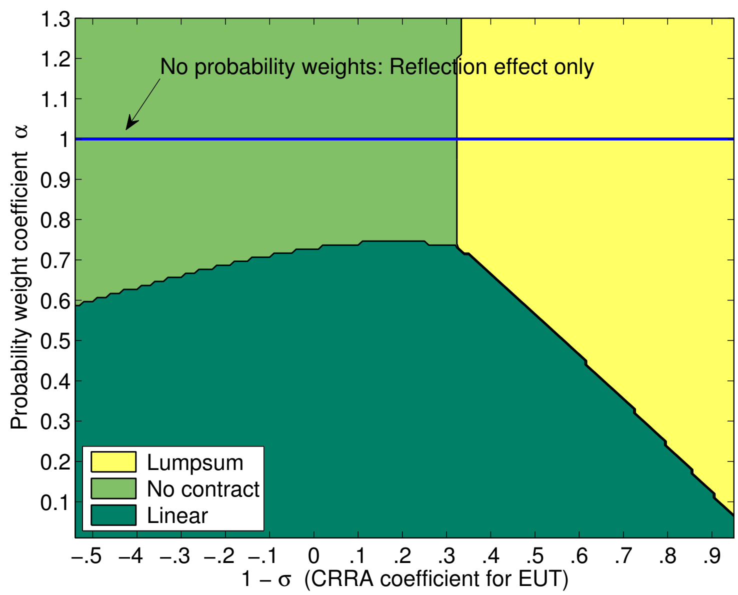


Applying (5) to continuous revenues with a reference point $x_r = 16$, figure 3 illustrates how this reference point can generate a reflection effect and loss aversion. The top solid curve is a conventional EUT concave utility function, implying risk aversion over the entire domain of revenues. The two dotted curves depict the utility function under CPT with a reference point at $x_r = 16$. The reflection effect implies that farmers are risk averse over gains, for outcomes below x_r, but they are risk seeking for outcomes below the reference point. A positive value of the loss aversion parameter λ increases the slope of the utility functions over losses and thus introduces an asymmetry in the function, representing an additional "penalty" for losses.

Before we look at how loss aversion and the reflection effect alter insurance demand, we wrap up the model with decision weights. In rank dependent CPT, π^- is cumulative while π^+ is still decumulative. Continuing with our example from table 1, a farmer's expected utility under CPT without insurance is:

$$EU(p_s, x_s) = \tag{6}$$
$$\lambda\,[w(.1)\ u^-(-12)\ + (w(.2) - w(.1))\ u^-(-8)\ + (w(.3) - w(.2))\ u^-(-4)]$$
$$+w(.55)\ u^+(14)$$

Figure 4: Insurance predictions with the reflection effect but no loss aversion.



In order to disaggregate the implications of the reference point in our example, we first assume no loss aversion. Figure 4, as figure 5, depicts how farmers' insurance choices are affected by probability weighting and the coefficient of constant relative risk aversion. In contrast to figure 5, in which outcomes are restricted to gains, figure 4 depicts choices when outcomes are both gains and losses with a reflection point ($x_r = 16,000$ NS) but no loss aversion ($\lambda = 1$). Starting with no probability weighting ($\alpha = 1$) farmers choose either the lumpsum contract or no contract at all. The lumpsum contract is preferred to the linear contract for more risk averse farmers (higher $1 - \sigma$.) To see why the lumpsum contract is preferred, first note that both contracts yield the same expected value of revenues, but that the share of expected value over negative outcomes (state of the world is 1, 2 or 3) is larger with the linear contract. However, while the revenues from the linear contracts are constant (-3,100 NS) over this range, they vary when the contract is lumpsum, hence the convexity of the utility function over losses tilts the balance towards the lumpsum contract.

At $\alpha = 1$, the lumpsum contract is also preferred to no insurance for those high curvature farmers because it provides less variance over the (concave) gains range and similar variance over the (convex) negative outcomes. Yet when $1 - \sigma$ decreases sufficiently, and because of the loading factor, no insurance is preferred to both contracts.

Decreasing α accentuates the inverse S-shaped probability weighting, making the linear contract increasingly more appealing relative to the two other options. This is because the low probability, negative, outcomes in both the lumpsum and the no insurance revenue distributions are overweighted, and this decreases the perceived expected value of the prospects for these two options. In contrast, the expected value of the linear contract is hardly affected by probability weighting in this example because that prospect encompasses only two outcomes with mid-range probabilities.

Figure 5: Insurance demand predictions with the reflection effect and moderate loss aversion ($\lambda = 2$).

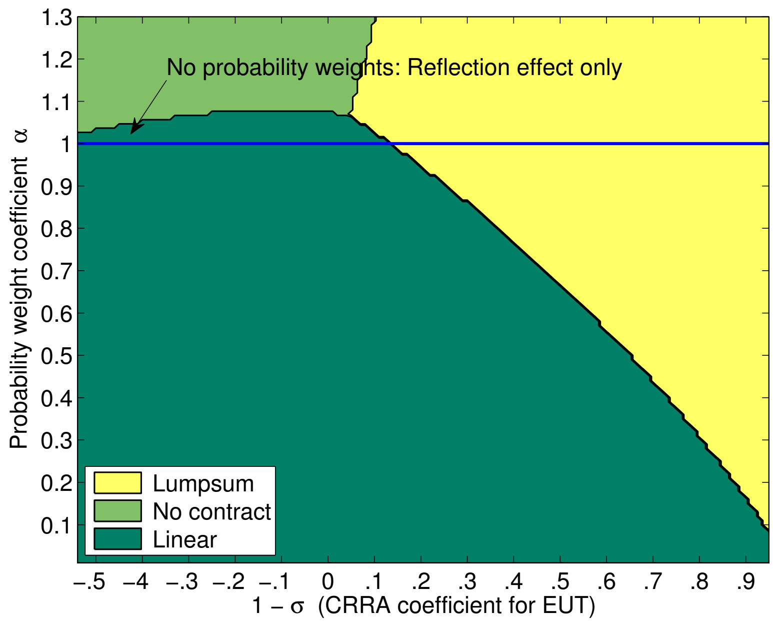
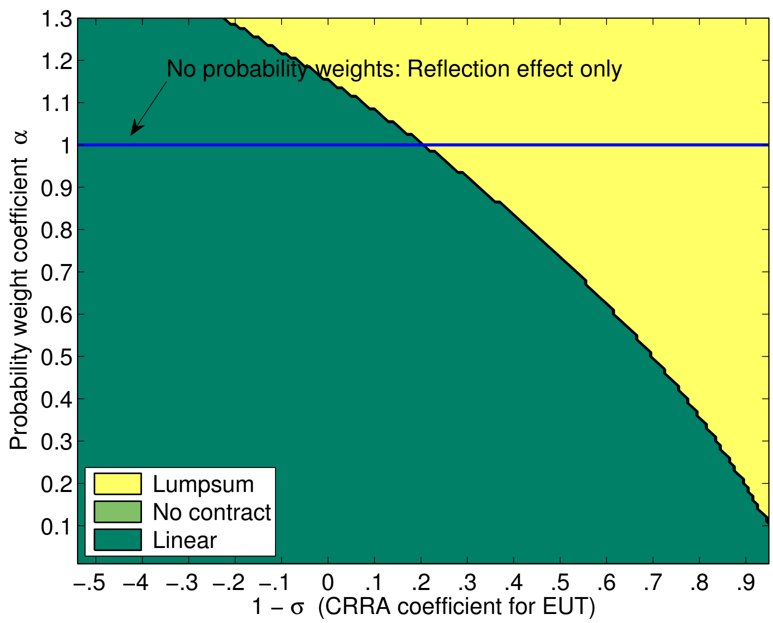


Figure 5 and 6 show how increasing λ above 1 makes the no insurance option less and less appealing, despite the reflection effect described above. This is intuitively sensible since, over negative outcomes, even as the utility function is convex, loss aversion increases disutility. Moving from figure 4 to figure 5 and then figure 6, we see how the linear contract becomes the preferred choice over an increasing range of parameters (α, σ). This is because loss aversion increasingly dominates the reflection effect to the point where, for those with high loss aversion (as figure 6 with $\lambda = 4$) all choose insurance (within the reasonable range of curvature and probability weighting here.) The lumpsum contract remains attractive to some agents with utility function with higher curvature because of higher convexity over negative outcomes, and increasingly so as α increases, because of the decreasing weight of small negative outcomes.

Figure 6: Insurance demand predictions with the reflection effect and high loss aversion ($\lambda = 4$).



In terms of policy, CPT might or might not matter in informing the design of crop insurance contracts, and might, or not, suggest non-EUT inspired contract designs, such as the lumpsum contract. This will depend on the empirical distribution of individual-specific preference parameters α, σ and λ, on objective features of revenue distributions with and without insurance, as well as the framing of the insurance contracts. In figure (2) for example, if revenues are framed as gross revenues and most people overweigh small probabilities ($\alpha < 1$,) the lumpsum contract would not be preferred but demand for the linear contract is higher than predicted without taking probability weighting into account. It follows that the first task of the empirical methodology was therefore to determine the distribution of CPT and EUT parameters for a sample of cotton farmers.

3 CPT and EUT parameters for Pisco cotton farmers

We have shown that CPT often predicts different choices in the context of a stylized example of revenue distributions with two possible insurance options. However, this matters only if, for a significant proportion of farmers, CPT preference parameters fall within ranges where EUT and CPT generate different predictions. To see whether this might be the case with a relevant farmer population, we presented a sample of cotton farmers in the Pisco Valley with a series of lottery choices designed to reveal the three CPT parameters described in the previous section, namely, curvature of the utility function (σ), probability weighting (α) and loss aversion (λ). This section first briefly describes the sample, and then details the elicitation procedure and the results for the three CPT parameters as well as the EUT constant relative risk aversion (CRRA) coefficient.

3.1 The sample

We conducted experimental games with a total of 480 cotton farmers in November and December 2011. Participants were selected as follows: Because farming in the Pisco valley depends on irrigation, all farmers are registered with a water-user organization (junta de usarios.) The valley is divided in 21 separate water distribution sectors. We geographically stratified sectors and selected 14 of them across the valley, so that land quality and terrain would be heterogenous across participants. In order to mitigate problems of self-selection, experiments took place at a time of low farming activity. We ran a total of 29 experimental sessions with an average of 16 participants per session. Upon arrival, each participant was paid a show-up fee of 20 NS, equivalent to half the daily agricultural wage rate in the valley. At the end of each session, participants were also paid their earning from the experiments. Following standard randomized lottery incentive procedures, one decision from each game (the TNC lotteries, insurance game over gross and net revenues) was randomly selected for payment.

Most of the sampled cotton farmers, 78%, were men. The average age is 53 year-old. A fourth of the sample is over 63 year-old while the first quartile is 44 years. On average, sample farmers completed eight years of education, but 40% completed at least 11 years, the threshold indicating high school graduation. The total area of farm land owned by households in the sample is 5.1 hectares on average, but when the area is weighted by household size, the mean is 1.7 hectare per adult. 37% of participants cultivate land they do not own.

We also asked participants about their usual cotton yields, their cotton harvest the *previous* season (harvested in May-July 2011) and their ongoing cotton season (not yet harvested at the time of the interviews.) The mean of their usual yield is 50 quintals per hectare. On average, the area planted in cotton the previous season was 4.7 hectares and the crop yielded 57 quintals of cotton per hectare[3]. For only 19% of participants, the last season's yield was below their usual average. Moreover, less than 10% of farmers described the previous season's harvest as a loss and, for another third of the sample, the yield was at least 20% above their own average. Therefore it seems that the previous cotton harvest was rather good. 79% of participant reported that their household had no other source of income outside farming. In sum, these descriptive statistics show that farming is a vital activity for all, but that the sample is heterogeneous, which will translate into heterogeneity of risk preferences.

3.2 Eliciting preference parameters with lotteries

Following Binswanger (1980), elicitation of risk preference with experimental procedures applied to non-traditional subject pools, such as farmers in developing countries

[3]There are few outliers: Seven participants reported a yield above 100 quintals per hectares for the previous season cotton crop, while 25 participants did not plant cotton at all that last season. For the ongoing season, only 13 participants had not planted cotton. Of those 13, four had also not planted cotton the last season, but three of these four had at least eight years of experience with cotton.

has been the subject of an abundant literature (Andersen et al. (2006),Cardenas and Carpenter (2008), Eckel and Grossman (2008), Harrison et al. (2005), Harrison and Rutström (2008)) These works all use variations of a multiple price list (MPL) along with a random incentive lottery mechanism which determines eventual payment to participants. Many tests of EUT against CPT also use MPL's and maximize a likelihood function in order to estimate structural models and test which better fits participants' decisions (Andersen et al., 2010). The most recent extension of that method is finite mixture models (Humphrey, 2000), which allow the data to fit both EUT and CPT at the same time, as opposed to looking for which is "best" (Harrison and Rutström (2009), Harrison et al. (2010), Galarza (2009), de Brauw et al. (2011), and Bocquého et al. (2011)). Instead of these methods, which estimate and test means or conditional means of CPT parameters, we replicate the procedure that Tanaka et al. (2010) (TCN) designed to elicit individual parameters. The authors use three series of decisions over MPL's in order to identify intervals for three CPT parameters for each individual in their sample of rural villagers in Vietnam.

As in TCN, our participants were successively presented with three arrays (table 2) of paired lottery options and asked to choose one option (A/C/E or B/D/F) per pair. Each lottery is a prospect of two monetary outcomes with constant probabilities within a series. Moreover, for series 1 and 2, the outcomes of the first option do not change, so the prospects of option A/C are exactly the same for each row of the first and second series. The outcomes are expressed in experimental monetary units, the Peso, which converted to 0.25 NS.[4]

Using a notation similar to Wakker (2010), we write options in series 1 as (40:0.3, 10), which describes a prospect with a 30% probability of getting 40 Pesos, a 70% probability

[4]This allowed us to keep the same lottery values as in TCN and keep whole numbers.

Table 2: TCN Lotteries.

Series 1	Option A		Option B	
	$p_1 = 0.3$	$p_2 = 0.7$	$p_3 = 1$	$p_4 = 0.9$
Row	Outcome 1	Outcome 2	Outcome x_3	Outcome 4
1	40	10	68	5
2	40	10	75	5
3	40	10	83	5
4	40	10	93	5
5	40	10	106	5
6	40	10	125	5
7	40	10	150	5
8	40	10	185	5
9	40	10	220	5
10	40	10	300	5
11	40	10	400	5
12	40	10	600	5

Series 2	Option C		Option D	
Probabilities	$p_5 = 0.9$	$p_6 = 0.1$	$p_7 = 0.7$	$p_8 = 0.3$
Row	Outcome 5	Outcome 6	Outcome x_7	Outcome 8
1	40	30	54	5
2	40	30	56	5
3	40	30	58	5
4	40	30	60	5
5	40	30	62	5
6	40	30	65	5
7	40	30	68	5
8	40	30	72	5
9	40	30	77	5
10	40	30	83	5
11	40	30	90	5
12	40	30	100	5
13	40	30	110	5
14	40	30	130	5

Series 3	Option E		Option F	
Probabilities	$p9 = 0.5$	$p_{10} = 0.5$	$p_{11} = 0.5$	$p12 = 0.5$
Row	Outcome 9	Outcome 10	Outcome x_{11}	Outcome 12
1	25	-4	30	-21
2	4	-4	30	-21
3	1	-4	30	-21
4	1	-4	30	-16
5	1	-8	30	-16
6	1	-8	30	-14
7	1	-8	30	-11

of getting 10 Pesos. Its expected value is 19 Pesos. The B options are (x_3:0.1, 5), where outcome x_3 has a probability of 10% and it increasingly increases from 68 in row 1 to 600 in12[5]. Hence the expected value of option B increases as one moves down from row 1 to 12. The lefthand side (A) prospect is the safest choice in that it has the least variance. However, its expected value is less than that of the righthand side (B) in rows 1 to 6. For row 6, the expected value of the righthand side prospect is 17 Pesos, and it increases to 19.5 Pesos in row 7. Hence only risk seeking farmers would choose option B in rows 1 through 6, and the most risk seeking always choose option B. The most risk averse farmers always choose option A. As in TCN, we enforced monotonicity within each series, making sure that one would never switch back to option A once they chose option B. This way, people who choose B in row 1 (the most risk seeking) can never switch back to A. It follows a higher switch row number corresponds to a greater degree of risk aversion.

The second series has the same structure as the first one, but option C is (40:0.9, 30), with an expected value of 39 Pesos, and option D is (x_7:0.7, 5), with x_7 increasing from 54 Pesos to 130 Pesos. In contrast to the first series, the expected value of option C is always less than that of option D, so that one does not need to be risk seeking to always choose option D in series 2.

Looking at choices made by our sample of farmers in the first two series, we find that 14.6% of participants never switched in either series 1 and 2. Taken at face value, this indicates a level of risk aversion so high that it is not at the boundary of either series. On the other end of the risk aversion spectrum, 7.3% of participants switched at the first row in both series 1 and series 2, which represents the least risk averse (or most risk seeking) option for either series.

[5]We truncated the last two rows from the TCN first series because we had to be risk averse with respect to our experimental budget.

In order to derive a unique combination of CPT parameters (α, σ) from each participant's choices in series 1 and 2, the expected utility of prospect A (C) is set to equal the utility of prospect B (D) corresponding to the switch rows in each series. With Rank Dependent probability weighting and CRRA utility $u(x) = x^\sigma$, for series 1 we have:

$$w(0.3, \alpha)\ 40^\sigma + (1 - w(0.3, \alpha))\ 10^\sigma = w(0.1, \alpha)\ x_3^\sigma + (1 - w(0.1, \alpha))\ 5^\sigma \tag{7}$$

and, for series 2:

$$w(0.9, \alpha)\ 40^\sigma + (1 - w(0.9, \alpha))\ 30^\sigma = +w(0.7, \alpha)\ x_7^\sigma + (1 - w(0.7, \alpha))\ 5^\sigma \tag{8}$$

Where $w(p, \alpha)$ is the Prelec probability weighing function with coefficient α defined in (3). x_3 and x_7 are the left hand side outcome of options B and D as defined above. This yields $12 \times 14 = 168$ combinations of (α, σ).

Given individual values of (σ, α) revealed in series 1 and 2, like TCN we assume the reflection effect modeled in (4), and we derive individual loss aversion parameters from the switch row in series 3, using the equality (9)[6]. Option E on the lefthand side has decreasing expected value, while option F on the righthand side has increasing expected value. While both options always have a 50% chance of a loss, the value of the loss in option F is always larger than that in option E. Hence series 3 is set up so that the higher the switch row, the more loss averse.

$$x_3^\sigma + \lambda\ x_4^\sigma = 30^\sigma + \lambda\ x_5^\sigma \tag{9}$$

[6]The probability weighting parameter is irrelevant because both RHS and LHS lotteries in series 3 are mixed prospects with equal probabilities at 50%. With Rand Dependent probability weighting over such prospects, with x_4 and x_5 negative, probability weighting cancels out.

The next section discusses descriptive statistics of the coefficients α, σ and λ obtained from the individual choices in these abstract lotteries for our sample of 480 Pisco farmers.

3.3 Pisco farmers' CPT and EUT preference parameters

We were particularly careful in the details of the script and presentation of the experiments[7]. In order to introduce the notion of probability in the context that farmers could better understand (Harrison et al., 2007) each session started with the insurance game, followed by the abstract TCN lotteries.

Table 3 shows summary statistics of the parameters calculated from choices in the three series. Starting with probability weighting and curvature of the utility function, the means for (σ, α) are (0.56, 0.71) which is close to values in TCN, who found $(0.59, 0.74)$ and $(0.63, 0.74)$ for their samples in the south and north of Vietnam respectively, and it is also close to $(0.49, 0.69)$ found when the same methodology was replicated with a sample of Chinese farmers (Liu, 2008). For our sample, the t-test on the mean of α shows that it is less than 1 and in the interval $[.68, .74]$ at the 99% confidence level, which is consistent with much of the empirical literature (Camerer, 2004). The consequence of taking into account the inverse-S shape of the probability weighting function, in the gain frame and all else being equal, means that more people in our sample are predicted to choose the linear contract than is predicted by EUT. Yet, in recent work in developing countries, Humphrey and Verschoor (2004) and de Brauw et al. (2011) find more support for S-shaped probability weighting ($\alpha > 1$), which is the case for 14% of the Pisco sample. As for curvature (σ), its mean and median are less than one (yet for 11% of farmers, $\sigma > 1$), which means that the utility function is concave over gains for

[7]Sessions were entirely scripted. After an introduction about the whole session, a training was conducted to get farmers familiar with our probability set up, where probabilities were represented by drawing tennis balls from a bag. The balls were also displayed next to each outcome, so as to be a tangible representation of each probability. In order to prevent an income effect through an experimental session, draws to decide payment for each part of the experiments were all conducted at the end of the session.

the average and the median farmer, like risk averse agents in the EUT context.

Table 3: EUT and CPT parameters for the Pisco farmers.

	Variable	Mean	Median	Min	Max	sd
EUT	ρ (curvature)	.69	.62	.21	1.7	.44
CPT	σ (curvature)	.56	.5	.05	1.5	.41
	α (probability weighting)	.71	.65	.05	1.3	.27
	λ (loss aversion)	4.2	2.3	1	12	4.1

Because there is no theoretical foundation for one to be loss seeking, we censor the values of λ at one[8] so that participants who switch at the first row are defined as *not* loss averse and assigned $\lambda = 1$. This is the case for 19% of the sample. The mean of λ is 4.2, closer to 3.47 in Liu (2008) than the value in TCN (2.63). Furthermore, the median of λ is 2.87, which is close to 2.5 found in Tversky and Kahneman (1992). This evidence for loss aversion is also consistent with empirical findings with other methodological approaches (Gaechter et al., 2007).

In order to compare predictions from both models, we also derive a EUT curvature parameter from farmers' choices in the first two TCN lotteries. We use the same Bernouilli utility functional form as in TCN ($u(x) = x^\sigma$) which, in EUT, gives a CRRA coefficient equal to $1 - \sigma$. We set $\alpha = 1$ in equations (7) and (8) and get two midpoint parameters for each farmer. We define a parameter ρ as the average of these two values for each farmer. The mean of ρ is 0.69 and its median 0.62, translating into risk aversion and equivalent to CRRA coefficients of 0.31 and 0.38 for the average and median farmer, respectively (20% of the sample is risk seeking). The mean CRRA coefficient is in the lower range of findings in the empirical literature in developing countries: In the review

[8]This calibration is different from that of TCN and Liu (2008).

of empirical work in developing countries by Cardenas and Carpenter (2008), CRRA coefficients are between 0.05 and 2.57. In more recent work, Harrison et al. (2010) find an average CRRA coefficient of 0.54 with 531 subjects from poor areas of Ethiopia, India and Uganda, while Brick et al. (2012) find an average CRRA coefficient of 0.39 with South African fishermen.

4 Implications of the empirical CPT parameters on insurance demand

Thanks to the elicited individual EUT and CPT parameters, we can now make predictions about each individual's preferred option in the insurance games. For each of gross and net revenue framing, we calculate each participant's expected utility from the three options in table 1 and determine which one is theoretically preferred, under EUT and under CPT. Recall that a farmer's favorite choice under EUT depends on the single parameter $1-\rho$, the coefficient of constant relative risk aversion. Under EUT, any farmer with values of $1-\rho > 0.39$ is predicted to purchase the linear contract while those with $1-\rho < 0.39$ would prefer no insurance, regardless of whether the outcomes are framed as gross or net revenues. The lumpsum contract would never be chosen under EUT. In our sample, half (237/480) have $1-\rho > 0.39$ are thus predicted to chose the linear contract and the other half (243/480) does not insure.

Predictions under CPT are more complicated for two reasons. First, under a given frame, some parameter ranges deliver a prediction of demand for the lumpsum contract. Second, for some parameter ranges, a given individual's choice may change across the gross and net revenue frames. Table 4 presents the CPT predictions for insurance demand under each frame.

Table 4: Farmers' CPT predicted choices, gross by net revenue frames.

			Net revenues		
			No insurance	Lumpsum	Linear
		Total	34	277	169
Gross	No insurance	119	**33**	58	28
	Lumpsum	0	0	0	0
	Linear	361	1	219	**141**

Over gross revenues, half of farmers in our sample are predicted to choose the linear contract in a EUT world, whereas (table 4) 75% (361/480) are predicted to do so with CPT. The remainder 25% (119/480) chose not to insure in CPT, while the lumpsum contract is never preferred to either the linear or the no insurance options, with either model. When the frame is net revenues, however, 58% (277/480) of farmers chose lumpsum contract, while fewer (141/480) choose the linear contract. Yet overall changing frame to net revenues increases insurance demand by 24% with a total of 446 farmers choosing insurance instead of 361. Only 7% (34/480) do not insure under the net revenue frame.

In order to explore some policy implications of CPT, we evaluate predictions if farmers are only given one insurance option, the lumpsum contract, instead of the linear contract which is the only insurance option which is preferred over gross revenues. Under gross revenues, if offered only the option to chose between no insurance and the lumpsum contract, insurance demand decreases by 19% under EUT because 46 of those predicted to choose the linear contract do not want the lumpsum contract and now choose no insurance insurance instead. This is consistent with the fact that the revenue distribution with the lumpsum contract is a mean preserving spread of the distribution under the linear option. Similarly under CPT, 59 of those predicted to choose the linear contract instead choose no insurance if only offered the lumpsum contract, or a 16%

decrease in demand.

Turning to the effect of offering only one insurance option in a net revenues frame, table 5 shows how insurance demand would decrease. The largest decrease is when offering the linear contract only (case 2) , where demand decreases by 51% (from 446 to 217), while the decrease is only 8% (from 446 to 411) when offering the lumpsum contract only (case 3). Hence in the CPT world, if constrained to offer one contract only, lumpsum has the highest demand when prospects are framed as net revenues, whereas when prospects are framed as gross revenues, the highest demand is when the linear contract is the only option offered.

Table 5: Predicted choices with net revenue frame.

			Case 2		Case 3	
			No insurance	Lumpsum	No insurance	Linear
Case 1	Total	480	69	411	263	217
	No insurance	34	34	0	34	0
	Lumpsum	277	0	277	226	48
	Linear	169	35	134	0	169

In sum, identifying which framework (EUT or CPT) is consistent with farmers' choices is important as it has implications for contract design and marketing. This is important for insurance suppliers, who require enough uptake to offer insurance to farmers, but it also matters for community welfare if farmers make welfare enhancing production decisions when they are less exposed to risk. Given the distribution of preference parameters in our sample, if we are in a EUT world, predicted demand is less than that predicted by CPT when this crop insurance is marketed in a gains frame, regardless of which type of contract is offered. In a CPT world, using net revenues greatly increases predicted demand, but this is conditional on offering the lumpsum contact alone or along with the linear contract.

5 Insurance decisions framed in a crop context

The next empirical test is to observe actual choices when the insurance options are presented to farmers and to compare choices with the predictions from the EUT and the CPT models described above. In order to do that, we designed insurance games where farmers were shown the revenue distributions in table 1. Actual payments were 1 NS for each 1,000 experimental NS. Hence the real expected payout from choosing the option without insurance is 21 NS, approximately equivalent to half the daily agricultural wage. Farmers where successively presented with the same options twice, first framed as gross revenues, then framed as net revenues, in order to see how choices changed according to framing over gains or over mixed prospects.

A way to create the feeling of loss in the net revenues framing, within an ethical experimental setting, was to give people a voucher. In order to generate an endowment effect, this voucher was described as something they had earned for the time they had "worked" with us up to that point. Later, at the time of the mixed prospect decision, they were told that they would have to pay off any incurred crop losses with the voucher money.

Table 6: Farmers' actual choices, gross by net revenue frames.

			Net revenues		
			No insurance	Lumpsum	Linear
		Total	119	138	223
Gross	No insurance	147	**82**	30	35
	Lumpsum	160	18	**78**	64
	Linear	173	19	30	**124**

The first striking result from farmers' choices (table 6) is that a third of the sample chose the lumpsum contract when prospects were framed as gross revenues, which is consistent with neither the EUT nor the CPT model. A possible policy implication is that there is something salient in this contract structure, such as the simplicity of a single, constant, indemnity level, that makes it appealing. Note that the demand for the lumpsum contract actually decreases when prospects are framed as net revenues.

Comparing choices shown in table 6 with CPT predictions in table 4, a first observation is that more people are consistent in their choice across framing than is predicted in CPT: 56% (82/147) of those who chose no insurance when prospects were framed as gains, did the same over mixed prospects, as well as 49% (78/160) for the lumpsum option and 72% (124/173) for the linear insurance option. Hence for most people, framing had no effect, as assumed in EUT. However, in either frame, more farmers chose insurance than is predicted by EUT, which could be consistent with probability weighting. Furthermore, the fact that fewer people choose no insurance over mixed prospect is consistent with loss aversion, although more farmers (25%) choose not to insure in the mixed prospect frame than is predicted by CPT.

In sum, these descriptive statistics do not point to one model or the other. While we see an effect of the reference point and possibly loss aversion, which is not consistent with EUT, it is not clear that it is consistent with CPT either. The next section turns to statistical tests and regression analysis to more precisely compare how each model fits the data.

6 Statistical analysis

6.1 Independence test

Contingency tables (table 7 for the gross revenues frame and table 8 for the net revenues frame) help organize the data in two dimensions by breaking down each choice by predictions for each individual. Looking, for example, at the column for no insurance predictions under CPT, in table 7, we see that out of the 119 participants predicted by the CPT model to choose no insurance over gains, only 24 indeed chose no insurance, while 49 others chose the lumpsum option and 46 chose the linear insurance. Looking at the diagonals suggests that neither model is a good fit for choices in the gross revenue frame. Only 142/480 choices are consistent with EUT predictions and only 151/480 are consistent with CPT predictions. Over net revenues, table 8 indicates that the CPT model is still not a good fit (157/48), while, surprisingly, the EUT model seems to fare a little better (171/480). An independence test gives a statistical dimension to these observations.

Table 7: CPT and EUT contingency tables, with gross revenues frame.

		Predictions						
		EUT			CPT			
		N	S	L	N	S	L	Total
Choices	No insurance (N)	**59**	0	88	**24**	0	123	147
	Lumpsum (S)	94	0	66	49	0	111	160
	Linear (L)	90	0	**83**	46	0	**127**	173
	Total	243	0	237	119	0	361	480

Table 8: CPT and EUT contingency tables, over net revenues.

		Predictions						
		EUT			CPT			
		N	S	L	N	S	L	Total
Choices	No insurance (N)	**55**	0	64	**5**	73	41	119
	Lumpsum (S)	81	0	57	10	**76**	52	138
	Linear (L)	107	0	**116**	19	128	**76**	223
	Total	243	0	237	34	277	169	480

An independence test compares the distribution of cells $O_{i,j}$ in a contingency table to frequencies E_{ij}, where i is for rows (choices) and j for columns (predictions). Frequencies are defined as the total of observed choices, weighted by the proportion of predicted choices. Continuing with the same example, 24 ($O_{i,j}$) is compared to the sum of participants who chose no contract ($147 = \sum_i O_{i,j} = n_{j,.}$) times the sum of those who are predicted to do so ($119 = \sum_j O_{i,j} = n_{i,.}$) divided by the sample size ($N = 480$). Hence the frequency $E_{ij} = \frac{n_{i,.}n_{.,j}}{N} = 36.4$. The null hypothesis of the independence test is that the distribution of choices across predictions is not significantly different from the distribution of expected frequencies:

$$H_0 : O_{i,j} = E_{ij} \quad \forall i, j$$

$$H_1 : O_{i,j} \neq E_{ij} \text{ for at least one } i, j$$

The test statistic, $\chi^2 = \sum_i \sum_j (O_{ij} - E_{ij})^2 / E_{ij} \sim \chi^2_{1-\alpha,df}$ is reported in the last row of the table 9 and each row reports the percentage value of $(O_{ij} - E_{ij})^2/E_{ij}$ for each option.

Table 9: Independence test for the whole sample.

	Gross revenues		Net revenues			
	EUT	RDU	EUT	CPT	Reflection	Loss aversion
No insurance (N)	-21%	-34%	-9%	-41%	-9%	-3%
Lumpsum (S)	NA	NA	NA	-5%	-18%	-5%
Linear (L)	-3%	-2%	5%	-3%	NA	1%
χ^2	10.8***	8.3**	5.1*	2.8	7.42**	1.1

*** Rejects H_0 at 1%, **Rejects H_0 at 5%, * Rejects H_0 at 10%;

The independence tests confirm that neither model is a good fit for any decision. Worse, the first column shows that the distribution of predictions from the EUT model is statistically not independent of choices, but it is so in the opposite direction from the model's predictions. In other words, since EUT preferences are monotonic in risk aversion, this means that the relationship between choices and risk aversion is significant, but opposite of that predicted by EUT: The less risk averse farmers are, the less likely they are to choose no insurance. For CPT, we also have negatively significant distributional result over gains. Regression analysis, pursued in the next section, allows for finer results, controlling for co-variates as well as permitting a direct interpretation of coefficients as the strength of predictions for each insurance option.

6.2 Regression framework

The contingency tables above and the independence test only provide a statistical test for the fit of the whole distribution of choices and they do not take into account any information on farmers beyond their predicted and observed choices. A regression framework allows to control for observed individual characteristics, session fixed effects, and get a statistical test of a coefficient for the fit of choices for each insurance option.

We model participants' decisions in the insurance game as a system of linear probability equations indexed by each option c, and where the dependent variable y_{ic} is a binary variable equal to 1 when the C^F option is chosen. The subscript c denotes each choice $C^F = N, S, L$, with frame $F =$ Mixed, Gains, and options $N =$ no insurance, S=lumpsum, and L=linear. Hence there is one system of six equations for each of the expected utility models:

$$Pr[y_{ic} = 1] = \alpha_c + \gamma_c pred_{ic} + \mathbf{x_i}'\beta_c + \mathbf{s_i}'\delta_c + u_{ic} \tag{10}$$

The categorical variable $pred_{ic}$ is equal to 1 if participant i is predicted to choose option C^F with EUT or CPT. $\mathbf{x_i}$ is a vector of individual observable characteristics, and $\mathbf{s_i}$ is a vector of session fixed effects. The errors u_{ic} are potentially correlated across equations c. The Seemingly Unrelated Regression estimator accounts for this correlation and performs a Feasible Generalized Least Square estimation of the system, which exploits this correlation in order to increase efficiency.

The coefficients $\hat{\gamma_c}$ and their significance, estimated for each expected utility model separately, have a straightforward interpretation: Do predictions from the model, for each choice and each frame, show a positive and significant correlation with actual choices? This approach does not pin one model against another, but allows either model, or both, to yield correct predictions. This is the idea behind the mixed log likelihood models such as those estimated by Harrison and Rutström (2009)) A positive coefficient corresponds to an increase in the probability that a farmer's choice is what is predicted by the model.

We also want to know how the models fare when they are directly compared with one another. For this we run the "horse race" specification (11) with predictions eut_{ic} and cpt_{ic} from both models together in each regression line of the system, where variables eut_{ic} and cpt_{ic} are as in model (10). We now have two coefficients γ_{1c} and γ_{2c}, whose interpretation is different from γ_c in (10). Because the prediction variables are binary, a positive (negative) coefficient now means that a given prediction increases (decreases) the probability that a farmer actually makes the predicted choice, when the models' predictions are different. Hence the sum of the coefficients γ_{1c} and γ_{2c} is the average shift in probability that farmers make a given choice, when both models predict it.

$$Pr[y_{ic} = 1] = \alpha_c + \gamma_{1c} eut_{ic} + \gamma_{2c} cpt_{ic} + \mathbf{x_i'}\beta_c + \mathbf{s_i'}\delta_c + u_{ic} \tag{11}$$

Tables 10 and 11 show regression results for coefficients γ_c, γ_{1c}, γ_{2c} with bootstrapped standard errors, clustered by session, for model (10) and (11), respectively.

6.3 Results

The main regression results on coefficients γ_{1c}, γ_{2c}, and γ_c, in tables 10 and 11, confirm the independence test results. Neither model makes accurate predictions. Full regression are reported in tables 16 and 17 in the appendix.

Table 10: Comparing results in separate regression systems (10).

		N^G	S^G	L^G	N^M	S^M	L^M
EUT	$\gamma_\mathbf{c}$	-0.10***	–	-0.10***	-0.02	–	-0.02
		(0.028)		(0.028)	(0.024)		(0.022)
CPT	$\gamma_\mathbf{c}$	-0.08	–	-0.08	-0.04*	-0.04*	-0.04**
		(0.057)		(0.057)	(0.021)	(0.022)	(0.019)

*** p<0.01, ** p<0.05, * p<0.1;
G=gains, M=mixed prospects; N = no insurance, S=lumpsum, L=linear

Table 11: One system of six equations with both model predictions (11).

		N^G	S^G	L^G	N^M	S^M	L^M
EUT	$\gamma_\mathbf{1c}$	-0.08**	–	-0.08**	-0.03	–	-0.03
		(0.033)		(0.033)	(0.025)		(0.023)
CPT	$\gamma_\mathbf{2c}$	-0.05	–	-0.05	-0.04*	-0.03	-0.03*
		(0.061)		(0.061)	(0.020)	(0.023)	(0.019)

*** p<0.01, ** p<0.05, * p<0.1;
G=gains, M=mixed prospects; N = no insurance, S=lumpsum, L=linear

Under the gross revenues frame, only EUT makes significant predictions, but in the wrong direction, with respect to the predicted relationship between risk aversion and insurance preferences. The coefficient in table 10 for farmers predicted to not insure tells that they are 10% less likely to do so (or, symmetrically, they are more likely to choose the linear contract.) This is confirmed in the horse race specification in table 11.

This inverse relationship between risk aversion and insurance preferences is not consistent with theory, but similar to other recent empirical findings about the relationship between crop insurance and risk aversion in developing countries (Gine et al. (2008), Cole et al. (2013) and Hill et al. (2013a)).

This EUT result, however, does not hold under the net revenues frame, where no EUT prediction is significant. The CPT model, on the other hand, does make weakly significant predictions under the net revenues frame, but also in the wrong direction. Note however that this might be driven by the fact that only 5 of the 34 participants predicted to choose no insurance did so (table 8). Furthermore, because of the many features at play in CPT, this negative result cannot be interpreted directly in terms of a relationship between insurance preferences and risk aversion.

It could be that, although the overall result does not support CPT, some features of CPT are still important in our context. The lack of significance of CPT predictions in the gross revenues frame, in both specification (10) and (11), is evidence against probability weighting. In order to test the two other features of CPT, the reflection effect and loss aversion, we test predictions for "partial CPT models". First we test a partial CPT model with the reflection effect only, that is the model in equations (5) and (6), but constraining $\lambda = \alpha = 1$. Then, in order to see if loss aversion is a significant feature, we relax the constraint on λ but maintain no probability weighting ($\alpha = 1$). We run independence tests, whose results are in table 9, and regression models (10) and (11) where cpt_{ic} are individual choice predictions for the partial CPT models, and whose results are in tables 12 and 13.

Note that, over gains, the reflection-only CPT model is the same as the EUT model, since there is no probability weighting. Hence the two models only differ over mixed

Table 12: CPT with reflection effect only.

Separate regression systems

		N^G	S^G	L^G	N^M	S^M	L^M
EUT	$\gamma_{\mathbf{c}}$	-0.10***	–	-0.10***	-0.02	–	-0.02
		(0.028)	–	(0.028)	(0.024)	–	(0.022)
CPT	$\gamma_{\mathbf{c}}$	-0.10***	–	-0.10***	-0.05*	-0.05*	–
		(0.025)	–	(0.025)	(0.03)	(0.03)	–

Horse race

		N^G	S^G	L^G	N^M	S^M	L^M
EUT	$\gamma_{\mathbf{1c}}$	–	–	–	0.01		0.01
		–	–	–	(0.022)		(0.02)
CPT	$\gamma_{\mathbf{2c}}$	–		–	-0.08**	-0.08**	–
		–	–	–	(0.037)	(0.038)	–

*** p<0.01, ** p<0.05, * p<0.1;
G=gains, M=mixed prospects; N = no insurance, S=lumpsum, L=linear

prospect, for net revenues. Both the independence test results in the penultimate column in table 9 and the regression results in table 12 show that this model makes significant predictions, but again in the wrong direction. Contrary to EUT, there is no direct relationship with risk aversion because our CPT model imposes that the curvature over gains mirror that of losses.

Comparing figures 2 and 4 at the threshold where $\alpha = 1$, we can compare insurance predictions from the EUT model and from the reflection-only CPT model, under the net revenues frame. Reflection-only CPT increases the curvature threshold σ above which farmers are predicted not to ensure (more people take insurance), those who do insure take the less risk reducing insurance option (the lumpsum contract.) Table 6 shows that this is far from the case, since 223 farmers choose the linear option. The significant negative result therefore hinges on the remainder of the sample who chose either the

Table 13: CPT with reflection effect and loss aversion only.

		N^G	S^G	L^G	N^M	S^M	L^M
		Separate regression systems					
EUT	$\gamma_{\mathbf{c}}$	-0.10***	–	-0.10***	-0.02	–	-0.02
		(0.028)	–	(0.028)	(0.024)	–	(0.022)
CPT	$\gamma_{\mathbf{c}}$	-0.09***	–	-0.08***	0.01	-0.01	
		(0.024)	–	(0.024)	(0.032)	(0.021)	–
		Horse race					
		N^G	S^G	L^G	N^M	S^M	L^M
EUT	$\gamma_{\mathbf{1c}}$	–	–	–	-0.03	–	-0.03
		–	–	–	(0.025)	–	(0.022)
CPT	$\gamma_{\mathbf{2c}}$	–	–		0	-0.01	–
		–	–	–	(0.007)	(0.006)	–

*** p<0.01, ** p<0.05, * p<0.1;
G=gains, M=mixed prospects; N = no insurance, S=lumpsum, L=linear

lumpsum option or no insurance. For these, the relationship between insurance preference and curvature is the opposite of what is predicted by the model: they are 5% more likely to choose the other, not predicted, option.

Lastly, the last columns in table 9 and regressions in table 13 show that adding loss aversion to the reflection-only CPT model does not yield any significant positive predictions. In sum, neither probability weighting nor loss aversion are significant features for predicting crop insurance choices with the stylized yield distribution and contract options in the Pisco valley context. The remainder of the model, the reflection-only model makes significantly wrong predictions, suggesting a flipped relationship with risk aversion, as with the EUT model. The next section looks at this relationship and hypotheses that might elucidate it.

6.4 Education and new technologies

There is empirical evidence (Gine and Yang, 2009) that education is positively correlated with crop insurance demand, which is also the case with our data. Indeed, a closer look at the data shows that results vary when the sample is split into two groups according to who graduated from high school and who did not. We therefore replicate the analysis but split the sample between farmers who graduated from high school and those who did not.

The independence tests for the sub sample of high school graduates (table 14) shows that none of the distributions of predictions is significantly different from frequencies, which is partially due to the small size of the sample (N=193.) Yet the observed choices are now in the right direction for the EUT predictions, but not for CPT predictions. The SUR specifications in (10) and (11) are now augmented with a variable that interacts the prediction variable $pred_{ic}$ and the binary education variable (equal to 1 for non high school graduates.) Hence the coefficients γ_{1c}, γ_{2c}, and γ_c in table 15 are for the sample of farmers who graduated from high school.

Table 14: Independence test for high school graduates.

	Gross revenues		Net revenues			
	EUT	RDU	EUT	CPT	Reflection	Loss aversion
No	9%	-8%	6%	none	-1%	-20%
Lumpsum	NA	NA	NA	-10%	-21%	-7%
Linear	7%	-2%	8%	-9%	NA	-35%
χ^2	1.2	0.3	3.3	3.6	4.2	4.6

*** Rejects H_0 at 1%, **Rejects H_0 at 5%, * Rejects H_0 at 10%;

The independence test tells that we cannot reject the null hypothesis that choices and either EUT or CPT predictions are independent, but this could be because of the small sample size. Regression results support the EUT model for high school graduates but reject CPT. Table 15 indicates that the EUT results from the full model are reversed for high school graduates. The separate-models regressions show that they are 7% more likely to choose no insurance or the linear option when predicted to do so by the EUT model. This result is even stronger in the horserace model. The results for the CPT model, however, are still not good. Regression results in table 15 show nothing significant under the gross revenues frame and significant but negative results under the net revenues frame.[9]

Table 15: High school graduates.

		Separate regression systems					
		N^G	S^G	L^G	N^M	S^M	L^M
EUT	$\gamma_{\mathbf{c}}$	0.07***	–	0.07***	0.06**	–	0.06**
		(0.025)		(0.025)	(0.025)		(0.023)
CPT	$\gamma_{\mathbf{c}}$	-0.02	–	-0.02	-0.08**	-0.08**	-0.08**
		(0.049)		(0.049)	(0.034)	(0.037)	(0.033)
		Horse race					
		N^G	S^G	L^G	N^M	S^M	L^M
EUT	$\gamma_{\mathbf{1c}}$	0.11**	–	0.11***	0.05*	–	0.05**
		(0.043)		(0.043)	(0.027)		(0.024)
CPT	$\gamma_{\mathbf{2c}}$	-0.08	–	-0.09	-0.09***	-0.08**	-0.08***
		(0.063)		(0.062)	(0.029)	(0.035)	(0.030)

*** p<0.01, ** p<0.05, * p<0.1;
G=gains, M=mixed prospects; N = no insurance, S=lumpsum, L=linear

The result for high school graduate is rather clearcut: The CPT model does not explain farmers' decisions, while farmers predicted to choose a linear contract or no contract in the EUT model, under both the net and the gross revenue frame, are significantly more likely to actually do so in our experimental games, by a factor of 6 to 7 %.

[9] For completeness, we also tested (not reported here) partial CPT models for the high school graduate subsample and find no positive evidence for them either.

It is harder to explain, however, why farmers who are less educated show a significantly negative relationship between insurance demand and risk aversion.

It has been suggested (Gine et al. (2008), Cole et al. (2013) and Hill et al. (2013a)) that the negative relationship between risk aversions and insurance preferences may be explained by the fact that insurance is a new technology. In practice, this hypothesis can imply that insurance is associated with lack of trust of contract compliance by the insurance provider. This cannot be the case in our setting since there is no reason for farmers to trust that experimental payments for the no insurance option would be made and not feel the same way about either insurance options. Another related explanation is that the new technology is confusing to uneducated farmers and hence there is an additional risk associated to the confusion, which can explain a negative relationship between demand for a new technology and risk aversion. This interpretation also does not apply to our experimental setting, where *the whole setting* is new and there is no reason why the outcome distribution without insurance would be more confusing than that for the two insurance options. If all was confusing, choices from farmers who did not graduate from high school would be only noise and would not be significant.

Another, untested, behavioral hypothesis is that the framing dominated what it contained. In other words, uneducated farmers did not pay attention to what was explained to them, but only their labels. The framed experimental script was very careful in making the experimental farm revenues tangible to farmers by explaining to them in detail how these revenues were generated for a five hectare plot not unlike their own. Hence they could relate to that framing. Even if it did not require more cognitive abilities to understand the revenue distributions with insurance, the insurance was presented as the new item, the new technology which, in itself, only because of its label, could have been perceived as unknown and risky. In other words, the safe options was what they were told is like their farm, whereas paying attention, and maybe even trying, the other options required more risk tolerance.

7 Conclusion

Which expected utility model economists use to inform policy can have deep implications for poor farmers in the developing world. Because crop risk is a limiting factor for farmers who strive to rise out of poverty, properly understanding and modeling their risk behavior is essential to designing instruments to help them cope with it.

The first question this paper answers is whether the CPT model can better inform the design of crop insurance for farmers, through an example. The general answer depends on farmers' beliefs about the distribution of their crop returns and what their reference point is. In our example, where the probability distribution includes some small probabilities of low crop yields and associated returns, we show that the CPT model increases the range of parameters where agents are predicted to choose insurance. This is conditional on offering two types of contracts, one of which, the lumpsum contract, has features that make it more attractive to a CPT agent, whereas it is not as attractive to an EUT agent relative to a standard linear contract. Furthermore, we show that framing matters, in that the framing of revenues as net revenues, where revenues are negative when investment is not recouped, also increases the range of parameters over which agents choose insurance.

The second set of questions pertains to the empirical implications of the model. Are farmers' preferences better described by CPT, and, if so, how does the model predict their insurance choices? Furthermore, do predictions, derived from parameters elicited in a context free game, map out to choices framed as insurance decisions? Given the set of individual CPT parameters determined in the lottery game, we find a 75% predicted demand for insurance in the gross revenues framing with CPT, whereas the predicted demand is only 50% with EUT. In predictions from the CPT model for our sample of cotton farmers, we find that both the framing and the design of the contract are important. Insurance demand increases significantly (24%) when insurance options are presented as net revenues and when the lumpsum contract is offered. This, however, did not translate in actual choices in the framed experiments, where demand is 70% in the gross revenues frame, and 75% in the net revenues frame, or an increase of only 8% with net revenues.

The last question is whether either model significantly explains farmers' decisions. The statistical and regression analyses point to another policy aspect related to presenting insurance to farmers. Over the whole sample, we find a negative relationship between predictions for each option, in either the EUT or CPT model, and actual choices. This suggests a negative relationship between risk aversion and willingness to insure. This negative relationship disappears when separating out non high school graduates. Indeed, farmers who graduate from high school are significantly more likely to choose insurance when predicted to do so by the EUT model (not so by the CPT model.)

In sum, we show that modeling farmers' preferences with the CPT model has important contract design and marketing implications but that, although our sample shows heterogeneity of CPT parameters, CPT does not have prediction power for choices in a framed setting. EUT does make significant choice predictions, but only for high school graduates. The significant negative relationship for farmers who did not graduate suggests that their risk aversion applies to insurance itself, as an uncertain new technology.

8 Appendix

Table 16: Full regression results for prediction fit of EUT (model (10))

	NG	**SG**	**LG**	**NM**	**SM**	**LM**
No insurance prediction	-0.10***			-0.02		
	[0.028]			[0.024]		
Linear contract prediction			-0.10***			-0.02
			[0.028]			[0.022]
Female	0.04	0.03	-0.06	0	0.02	-0.02
	[0.032]	[0.040]	[0.046]	[0.038]	[0.058]	[0.054]
43 y-o. or less	0	0.01	-0.01	-0.06	0.08	-0.02
	[0.025]	[0.041]	[0.055]	[0.068]	[0.064]	[0.018]
Between 44 and 63 y-o.	-0.09***	0.03	0.06*	-0.10**	0.08***	0.02
	[0.023]	[0.035]	[0.031]	[0.041]	[0.024]	[0.034]
High school graduate	-0.14***	-0.03	0.18***	-0.1	-0.13***	0.23***
	[0.025]	[0.038]	[0.029]	[0.067]	[0.039]	[0.050]
Other business size	0.02	-0.07**	0.05***	-0.02	0	0.03
	[0.015]	[0.028]	[0.014]	[0.015]	[0.027]	[0.040]
Number employed outside ag.	-0.05	0.11**	-0.06*	0.02	0	-0.01
	[0.038]	[0.048]	[0.032]	[0.039]	[0.050]	[0.017]
Ag. land owned per adult	-0.02	0.01	0.01	0	0	0.01
	[0.018]	[0.014]	[0.010]	[0.018]	[0.009]	[0.015]
Normal cotton yield	-0.00*	0.00*	0	-0.00***	0	0.00*
	[0.001]	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]
Total area planted last crop	0	0.01	-0.01*	-0.01	0.01	0
	[0.003]	[0.007]	[0.006]	[0.004]	[0.004]	[0.008]
Low yield last crop	0.01	-0.10***	0.09**	0.02	-0.13***	0.11
	[0.066]	[0.026]	[0.043]	[0.056]	[0.026]	[0.069]
Loss in last cotton crop	-0.13***	0.14***	-0.01	-0.11***	0.12**	0
	[0.033]	[0.050]	[0.024]	[0.021]	[0.046]	[0.030]
Cultivates land not owned	-0.01	-0.02	0.04	-0.06***	-0.02	0.08***
	[0.038]	[0.030]	[0.065]	[0.017]	[0.017]	[0.024]
Heard of index insurance	-0.08***	0.01	0.07	-0.07***	0.03	0.05**
	[0.019]	[0.030]	[0.042]	[0.018]	[0.033]	[0.023]
Observations	476	476	476	476	476	476
R-squared	0.081	0.053	0.078	0.08	0.052	0.092

*** p<0.01, ** p<0.05, * p<0.1;

G=gains, M=mixed prospects; N = no insurance, S=lumpsum, L=linear

Table 17: Full regression results for prediction fit of CPT (model (11))

	NG	**SG**	**LG**	**NM**	**SM**	**LM**
NG prediction	-0.08					
	[0.057]					
LG prediction			-0.08			
			[0.057]			
NM prediction				-0.04*		
				[0.021]		
SM prediction					-0.04*	
					[0.022]	
LM prediction						-0.04**
						[0.019]
Female	0.04	0.03	-0.07*	0	0.02	-0.02
	[0.027]	[0.040]	[0.042]	[0.038]	[0.060]	[0.054]
43 y-o. or less	0.01	0.01	-0.01	-0.06	0.09	-0.03
	[0.027]	[0.041]	[0.054]	[0.072]	[0.057]	[0.020]
Between 44 and 63 y-o.	-0.09***	0.03	0.05	-0.10**	0.08***	0.02
	[0.020]	[0.035]	[0.036]	[0.040]	[0.023]	[0.034]
High school graduate	-0.14***	-0.03	0.17***	-0.1	-0.13***	0.23***
	[0.025]	[0.038]	[0.032]	[0.065]	[0.040]	[0.049]
Other business size	0.02*	-0.07**	0.05***	-0.02	0	0.03
	[0.013]	[0.028]	[0.014]	[0.016]	[0.026]	[0.039]
Number employed outside ag.	-0.05	0.11**	-0.06*	0.02	0	-0.01
	[0.038]	[0.048]	[0.032]	[0.039]	[0.051]	[0.017]
Ag. land owned per adult	-0.02	0.01	0.01	0	0	0.01
	[0.017]	[0.014]	[0.008]	[0.018]	[0.009]	[0.016]
Normal cotton yield	-0.00*	0.00*	0	-0.00***	0	0.00*
	[0.001]	[0.002]	[0.001]	[0.000]	[0.001]	[0.001]
Total area planted last crop	0	0.01	-0.01*	-0.01	0.01	0
	[0.003]	[0.007]	[0.006]	[0.004]	[0.005]	[0.009]
Low yield last crop	0	-0.10***	0.10***	0.02	-0.13***	0.11*
	[0.058]	[0.026]	[0.037]	[0.055]	[0.024]	[0.065]
Loss in last cotton crop	-0.11***	0.14***	-0.02	-0.11***	0.11**	0
	[0.030]	[0.050]	[0.022]	[0.021]	[0.048]	[0.033]
Cultivates land not owned	-0.02	-0.02	0.04	-0.06***	-0.02	0.08***
	[0.036]	[0.030]	[0.063]	[0.016]	[0.018]	[0.023]
Heard of index insurance	-0.08***	0.01	0.07	-0.07***	0.02	0.05**
	[0.016]	[0.030]	[0.042]	[0.017]	[0.033]	[0.023]
Observations	476	476	476	476	476	476
R-squared	0.075	0.053	0.082	0.08	0.053	0.093

*** p<0.01, ** p<0.05, * p<0.1;

G=gains, M=mixed prospects; N = no insurance, S=lumpsum, L=linear

References

Andersen, S., Harrison, G., Lau, M., and Rutström, E. (2006). Elicitation using multiple price list formats. *Experimental Economics*, 9(4):383–405.

Andersen, S., Harrison, G. W., Lau, M. I., and Rutström, E. E. (2010). Behavioral econometrics for psychologists. *Journal of Economic Psychology*, 31(4):553–576.

Barnett, B. J., Barrett, C. B., and Skees, J. R. (2008). Poverty traps and index-based risk transfer products. *World Development*, 36(10):1766–1785.

Barseghyan, L., Molinari, F., O'Donoghue, T., and Teitelbaum, J. C. (2013). The nature of risk preferences: Evidence from insurance choices. *The American Economic Review*, 103(6):2499–2529.

Binswanger, H. (1980). Attitudes toward risk: Experimental measurement in rural India. *American Journal of Agricultural Economics*, 62(3):395–407.

Bocquého, G., Jacquet, F., and Reynaud, A. (2011). Expected utility or prospect theory maximizers.

Boucher, S. and Delpierre, M. (2013). The impact of index-based insurance on informal risk-sharing networks. In *2013 Annual Meeting, August 4-6, 2013, Washington, DC*, number 150440. Agricultural and Applied Economics Association.

Boucher, S. R., Carter, M. R., and Guirkinger, C. (2008). Risk rationing and wealth effects in credit markets: Theory and implications for agricultural development. *American Journal of Agricultural Economics*, 90(2):409–423.

Boucher, S. R. and Mullally, C. (2010). Evaluating impact of index insurance on cotton farmers in Peru. In Winters, P., Salazar, M., and Maffioli, A., editors, *Designing impact evaluations for agricultural projects*. Inter-American Development Bank.

Brick, K., Visser, M., and Burns, J. (2012). Risk aversion: experimental evidence from South African fishing communities. *American Journal of Agricultural Economics*, 94(1):133–52.

Cai, H., Chen, Y., Fang, H., and Zhou, L.-A. (2009). Microinsurance, trust and economic development: Evidence from a randomized natural field experiment.

Camerer, C. (2004). Prospect theory in the wild: Evidence from the field. In Camerer, C., editor, *Advances in Behavioral Economics*.

Camerer, C. and Loewenstein, G. (2004). Behavioral economics: Past, present and future. In Camerer, C., Loewenstein, G., and Rabin, M., editors, *Advances in Behavioral Economics*. Princeton University Press.

Cardenas, J. C. and Carpenter, J. (2008). Behavioural development economics: Lessons from field labs in the developing world. *Journal of Development Studies*, 44(3):311–38.

Carter, M., Little, P., Mogues, T., and Negatu, W. (2007a). Poverty traps and natural disasters in Ethiopia and Honduras. *World Development*, 35(5):835–856.

Carter, M. R., Galarza, F., and Boucher, S. R. (2007b). Underwriting area-based yield insurance to crowd-in credit supply and demand. *Savings and Development*, pages 335–362.

Carter, M. R. and Lybbert, T. J. (2012). Consumption versus asset smoothing: testing the implications of poverty trap theory in Burkina Faso. *Journal of Development Economics*, 99(2):255–264.

Chantarat, S., Mude, A. G., Barrett, C. B., and Carter, M. R. (2012). Designing index-based livestock insurance for managing asset risk in Northern Kenya. *Journal of Risk and Insurance*.

Clarke, D., Mahul, O., Rao, K. N., and Verma, N. (2012). Weather based crop insurance in India. *World Bank Policy Research Working Paper*, (5985).

Clarke, D. J. (2011). *A theory of rational demand for index insurance.* Department of Economics, University of Oxford.

Cole, S., Giné, X., Tobacman, J., Topalova, P., Townsend, R., and Vickery, J. (2013). Barriers to household risk management: evidence from India. *American Economic Journal: Applied Economics*, 5(1):104–35.

de Bock, O. and Gelade, W. (2012). The demand for microinsurance: A literature review. *Research Paper*, (26).

de Brauw, A., Eozenou, P., Gilligan, D., and Meenakshi, J. (2011). Measuring risk attitudes among Mozambican farmers.

Dercon, S. (2006). Risk, growth and poverty: What do we know, what do we need to know. Department of Economics, Oxford University.

Dercon, S., Gunning, J. W., and Zeitlin, A. (2011). The demand for insurance under limited credibility: Evidence from Kenya. In *International Development Conference, DIAL*.

Dercon, S., Hill, R., Clarke, D., Outes-Leon, I., and Taffesse, A. (2014). Offering rainfall insurance to informal insurance groups: evidence from a field experiment in Ethiopia. *Journal of Development Economics*, 106:132–43.

Eckel, C. and Grossman, P. (2008). Forecasting risk attitudes: An experimental study using actual and forecast gamble choices. *Journal of Economic Behavior & Organization*, 68(1):1–17.

Elabed, G. and Carter, M. R. (2013). Basis risk and compound-risk aversion: Evidence from a wtp experiment in Mali. In *2013 Annual Meeting, August 4-6, 2013, Washington, DC*, number 150353. Agricultural and Applied Economics Association.

Gaechter, S., Johnson, E., and Herrmann, A. (2007). Individual-level loss aversion in risky and riskless choice. Technical report, Working Paper. University of Nottingham.

Galarza, F. (2009). Choices under risk in rural Peru. University of Wisconsin-Madisson.

Gelade, W. (2011). The demand for index-based microinsurances: The importance of contract design. University of Namur.

Gine, X., Townsend, R., and Vickery, J. (2008). Patterns of rainfall insurance participation in rural india. *The World Bank Economic Review*, 22(3):539–566.

Gine, X. and Yang, D. (2009). Insurance, credit, and technology adoption: Field experimental evidence. *Journal of Development Economics*, 89:1–11.

Harrison, G., Humphrey, S., and Verschoor, A. (2010). Choice under uncertainty: Evidence from Ethiopia, India and Uganda. *The Economic Journal*, 120(543):80–104.

Harrison, G., Lau, M., Rutström, E., and Sullivan, M. (2005). Eliciting risk and time preferences using field experiments: Some methodological issues. In Carpenter, J., Harrison, G., and List, J., editors, *Field Experiments in Economics*, volume 10 of *Research in Experimental Economics*, pages 125–218. Emerald Group Publishing Limited.

Harrison, G., List, J., and Towe, C. (2007). Naturally occurring preferences and exogenous laboratory experiments: A case study of risk aversion. *Econometrica*, 75(2):433–458.

Harrison, G. and Rutström, E. (2008). Risk aversion in the laboratory. In Cox, J. and Harrison, G., editors, *Risk Aversion in Experiments*, volume 12 of *Research in Experimental Economics*. Emerald Group Publishing Limited.

Harrison, G. and Rutström, E. (2009). Expected utility theory and prospect theory: One wedding and a decent funeral. *Experimental Economics*, 12(2):133–158.

Hazell, P., Anderson, J., Balzer, N., Clemmensen, A. H., Hess, U., and Rispoli, F. (2010). The potential for scale and sustainability in weather index insurance for agriculture and rural livelihoods. Technical report.

Hill, R. V., Hoddinott, J., and Kumar, N. (2013a). Adoption of weather-index insurance: Learning from willingness to pay among a panel of households in rural Ethiopia. *Agricultural Economics*, 44:385–98.

Hill, R. V., Robles, M., and Ceballos, F. (2013b). Demand for weather hedges in India: An empirical exploration of theoretical predictions.

Hoddinott, J. (2006). Shocks and their consequences across and within households in rural Zimbabwe. *The Journal of Development Studies*, 42(2):301–321.

Humphrey, S. J. (2000). The common consequence effect: testing a unified explanation of recent mixed evidence. *Journal of Economic Behavior & Organization*, 41(3):239–262.

Humphrey, S. J. and Verschoor, A. (2004). The probability weighting function: Experimental evidence from Uganda, India and Ethiopia. *Economics Letters*, 84(3):419–425.

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

Kahneman, D. and Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica: Journal of the Econometric Society*, pages 263–291.

Kremer, M., Lee, J., Robinson, J., and Rostapshova, O. (2013). Behavioral biases and firm behavior: evidence from Kenyan retail shops. *The American Economic Review*, 103(3):362–368.

Liu, E. M. (2008). Time to change what to sow: Risk preferences and technology adoption decisions of cotton farmers in China. *Review of Economics and Statistics*, (0).

Mahul, O. and Stutley, C. J. (2010). *Government support to agricultural insurance: Challenges and options for developing countries*. World Bank Publications.

Miranda, M. (1991). Area-yield crop insurance reconsidered. *American Journal of Agricultural Economics*, 73(2):233–242.

Miranda, M. J. and Farrin, K. (2012). Index insurance for developing countries. *Applied Economic Perspectives and Policy*, 34(3):391–427.

Mobarak, A. and Rosenzweig, M. (2012). Selling formal insurance to the informally insured. *Yale University Economic Growth Center Discussion Paper*, (1007).

Prelec, D. (1998). The probability weighting function. *Econometrica*, 66(3):497–527.

Quiggin, J. (1991). Comparative statics for rank-dependent expected utility theory. *Journal of Risk and Uncertainty*, 4(4):339–350.

Quiggin, J. (1993). *Generalized expected utility theory: The rank dependent model*. Springer.

Starmer, C. (2000). Developments in non-expected utility theory: The hunt for a descriptive theory of choice under risk. *Journal of Economic Literature*, 38(2):332–82.

Tanaka, T., Camerer, C., and Nguyen, Q. (2010). Risk and time preferences: Linking experimental and household survey data from Vietnam. *The American Economic Review*, 100(1):557–71.

Thaler, R. (1999). Mental accounting matters. *Journal of Behavioral Decision Making*, 12(3):183–206.

Tversky, A. and Kahneman, D. (1981). The framing of decisions and the psychology of choice. *Science*, 211(4481):453.

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

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