

Utility, Risk, and Demand for Incomplete Insurance: Lab Experiments with Guatemalan Cooperatives *

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Abstract

We play a series of incentivized laboratory games with risk-exposed cooperative-based coffee farmers in Guatemala to understand the demand for index-based rainfall insurance. We show that insurance demand goes up as increasingly severe risk makes insurance payouts more partial (payouts are smaller than losses), but demand is adversely affected by more complex risk structures in which payouts are probabilistic (it is possible that a shock occurs with no payout). We use numerical techniques to estimate a flexible utility function for each player and consequently can put exact dollar values on the magnitude of the behavioral response triggered by probabilistic insurance. Exploiting the group structure of the cooperative, we investigate the possibility of using group loss adjustment to smooth idiosyncratic risk. Our results suggest that consumers value probabilistic insurance using a prospect-style utility function that is concave both in probabilities and in income, and that group insurance mechanisms are unlikely to solve the issues of low demand that have bedeviled index insurance markets.

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1 Introduction

Given the pervasive role that risk plays in farming, improvements in the design of agricultural insurance could offer large potential welfare benefits. New types of index insurance, in which pay-outs are based on a pre-defined index (such as local rainfall), can provide insurance against aggregate shocks without creating moral hazard (Barnett and Mahul, 2007). From a perspective motivated by the Townsend (1994) model of village-level risk pooling, these products appear ideal in that they insure precisely the correlated shock that cannot be smoothed locally. Yet, almost universally these products have met with disappointing demand when introduced in the field (Cole et al., 2013). Uptake rates in pure index insurance products have typically been very low, and several studies have found that interlinking index insurance with credit products actually dampens the demand for credit (Giné and Yang, 2009; Banerjee, Duflo, and Hornbeck, 2014). Low demand for these apparently welfare-improving contracts is puzzling, and so a deeper understanding of consumer risk preferences is critical.

Despite the central importance of risk preferences in economics and the potential for insurance to solve risk-driven poverty traps (Brick and Visser, 2015), our understanding of the drivers of insurance demand remains incomplete. A well established feature of index insurance products is the issue of ‘basis risk’, which arises because the index is only imperfectly correlated with the risk it is meant to protect against (Barnett, Barrett, and Skees, 2008). The empirical literature on demand for incomplete insurance has focused on comparing the predictions of prospect theory (Kahneman and Tversky, 1979) to those of expected utility (EU) theory (Camerer, 2004; Cohen and Einav, 2007; Barseghyan et al., 2013). In this paper we bring the lens of prospect theory to bear in explaining index insurance demand, constructing a unique empirical environment in which we can estimate a utility curve for every individual in the study. This curve can be used to predict EU-driven demand over a variety of counterfactual risk scenarios, and we can compare this to the actual stated demand under that scenario.

We contrast models of decision making under risk using a set of controlled lab-in-the-field experiments conducted with a very risk-exposed group: cooperative-based smallholder coffee farmers in Guatemala. During the course of an incentivized day-long exercise, we presented farmers with a way of visualizing the weather-driven risks to their farms and recorded their willingness to pay (WTP) for an excess rainfall index insurance product across multiple scenarios. The payout and payout probability of the insurance was held constant, while attributes of the risk environment and the group contractual structure shifted. Payouts were incentivized, with the actual insurance purchase decision based on a Becker-DeGroot-Marschak lottery in prices and the stated WTP. The games were designed to help us under-

stand how the risk environment drives insurance demand by isolating conditions in which Expected Utility and behavioral models have testably distinct implications.¹

Basis risk can generate two separate forms of incompleteness which the behavioral literature suggests will have distinct effects on insurance demand. If an insurance contract is *partial*, then it covers only a part of the variation in the shock to income that occurs when the index pays out. Expected utility theory appears to explain demand for *partial* insurance relatively well (Wakker, Thaler, and Tversky, 1997). If insurance is *probabilistic*, then there is a chance that a shock occurs and the product fails to pay out. In our context of an excess rainfall index, variation in yields driven by excess rain leads to *partial* payout, and variation in yields driven by drought events not covered by the index lead to *probabilistic* payout. Insurance demand responds adversely to *probabilistic* risk for reasons that are both EU-driven and behavioral (Tversky and Kahneman, 1992). Even under EU theory, if it is possible that the most severe outcome can occur without a payout, then the insurance product loses its purity as a variance-reduction tool: the premium payment may now transfer income from bad states to good (Clarke, 2016). Insight from the behavioral literature, furthermore, suggests that demand will respond even more negatively to probabilistic risk than would be predicted by EU theory alone, in particular to small losses. A common way of representing this deviation from EU theory is to allow the objective function to feature decision weights which may differ from the objective probabilities of the events. Numerous experimental studies have suggested that people over-weight the likelihood of small probabilities, and thus have utility which is concave in probabilities (Yaari, 1987; Doherty and Eeckhoudt, 1995).

We present an environment in which we can study how demand responds to shifts in the risk environment. In a set of games focused on partial insurance, we vary the severity of the loss in the insured state, and thus trace out the marginal utility of income in a relatively straightforward way. WTP over seven games is used to estimate an individual-specific, two-parameter utility function. This utility function is then taken to a separate set of probabilistic games, in which we vary the severity and probability of a shock that occurs with no insurance payout. Using our individual-specific utility curves, we can simulate the WTP that they 'should' have for the probabilistic product under expected utility maximization. Deviations of actual WTP away from this EU prediction then provide a straightforward money-metric value for the component of demand that is driven by behavioral issues.

Our results provide important insights into the underlying structure of utility under

¹All probabilities in our games are explicitly defined, meaning that we study *risk* but not *uncertainty* (Ellsberg, 1961). These tightly framed games provide a context that provides a very straightforward way of thinking about how individuals weigh different outcomes in decision making, but they are not informative as to the related issues of ambiguity aversion (Fox and Tversky, 1995; Bryan, 2010) or the failure to reduce compound lotteries (Segal, 1990; Elabed and Carter, 2015)

risk. We confirm the low overall demand for index insurance; only 12% of our sample were willing to pay a price above actuarially fair in our base scenario. When we estimate utility curves we find an average coefficient of relative risk aversion of 5.8 and a modal utility function that has very close to constant absolute risk aversion. Introducing the probability of contract failure causes a substantial drop in WTP. When we decompose the demand into the component predicted by expected utility maximization and the 'behavioral' residual, we find the magnitude of the behavioral dampening in WTP responds strongly both to the probability and the magnitude of the shock. Adding a 1 in 21 chance of a small uninsured loss would have caused a \$.43 decrease in WTP under our expected utility estimation but actually resulted in a decrease of \$4.13, implying that almost 90% of the response to highlighting the possibility of small droughts is behavioral. Once we move to the largest shocks in which purchasing insurance increases the potential variability of income, we find that the EU-driven component more than explains the observed drop in WTP, and the behavioral component is trivial. Thus, neither the pure EU model nor the 'Dual' model that is linear in utility and non-linear in probabilities are consistent with our results. The behavioral welfare function among this group of Guatemalan coffee farmers is concave both in probabilities and in wealth.

From diagnosing the problem, we then move to test a solution posed by the literature to the problem of incomplete insurance, namely the use of group insurance contracts (Dercon et al., 2014). The premise is that an instance of payout can be used by the group membership as an opportunity to smooth the shocks they have experienced more completely than would be achieved by their respective individual index insurance payments (Dercon et al., 2006). By its nature, this group insurance mechanism lessens the extent to which insurance is partial, but only a broader risk pooling mechanism can help with the probabilistic states in which there is no insurance payment to be shared out (Ligon, Thomas, and Worrall, 2002). Exploiting the cooperative structure of the farmers in our study, we test the promise of the group solution to the partial insurance problem. Again, our individually estimated utility curves provide insight into the results. We vary the extent of risk pooling conducted by the cooperative with the payout, and compare how demand responds to insurance provided by group members rather than by the insurance company. We experiment with the risk heterogeneity of group members, and see how demand for risk pooling shifts once the shocks have been realized.

The analysis of group insurance is confirmatory in terms of basic mechanisms, but discouraging in terms of the commercial viability of group insurance as a way to solve basis risk. We find that individuals recognize and are willing to pay for the ability of the group to pool idiosyncratic risk. On the other hand, they only expect their groups to conduct about a quarter of the degree of risk sharing possible, and there is a secular dislike of the

group mechanism that roughly compensates for the degree of pooling they expect to occur. Heterogeneity is detrimental to the functioning of group insurance, although the elasticity of demand with respect to the expected transfer to other group members is half of what would be actuarially fair, implying that members display some willingness to redistribute income through risk pooling. By eliciting demand for pooling before and after the drawing of a random weather shock we demonstrate that even in the short-term environment of the lab, the ex-ante desire for pooling is undermined by issues of ex-post incentive compatibility.

What can we conclude about ways to improve index insurance design? WTP will be highest when the index is calibrated to pick up loss events with a probability very close to one, even if the magnitude of payouts does not match the magnitude of losses well. When uni-dimensional index insurance is extended into environments with complex multi-peril risks, demand is likely to be low. WTP will fall with both the severity and the probability of uncovered risk, providing sobering evidence that the uncertainty caused by global warming may actually hamper the demand for one of the primary risk-protecting tools at hand. This indicates that the development of multi-peril index insurance products, particularly those calibrated to cover the most severe shocks with very high probability, will be critical to stimulating demand.

The remainder of the paper is organized as follows: Section 2 provides the background and setting for the games, and a detailed description of the exercise. Section 3 uses the partial insurance games to estimate the best-fit utility function for the data, a control structure that is then used throughout the paper. Section 4 provides results on the probabilistic insurance games, Section 5 on the group insurance games. Section provides robustness checks, and Section 6 concludes.

2 Setting and Game Design

Coffee is by far the most important export sector in Guatemala, but yield in the coffee sector is highly variable with excess rainfall and hurricanes posing the primary source of weather risk exposure². In early 2010 we conducted a cooperative survey of the coffee sector in Guatemala. That survey attempted a census of every registered first-tier coffee cooperative in the country, and included data on 1,440 individuals from 120 cooperatives.

For this exercise, we then selected from that population the 71 cooperatives that reported being vulnerable to excess rainfall risk (the product that this project is intended to pilot) and devised a set of games to understand the nature of index insurance demand. For each of

²Work by Said, Afzal, and Turner (2015) suggests that risk-exposed groups may be more sensitive to risk than those who are less exposed.

the selected cooperatives we then attempted to draw in 10 individual members to participate in the day of laboratory experiments (the actual number that attended varies between 4 and 13, with 10 as the modal number). Invitations were sent to a randomly sampled group of members to attend, but if we did not have 10 players than we filled in the remaining players with any available cooperative members. The experimental sample is broadly representative of the overall cooperative membership on observable variables; 85% are male, average age in the late 40s (49.5 in study versus 48 overall among cooperative members), average of a 4th grade education (4 versus 3.6), a high fraction of individuals involved in cooperative governance (39% versus 36%), and smallholder production of coffee (95 quintals per year versus 85).

2.1 Protocol

The games were typically played in the cooperative offices. The survey team that ran the games was comprised of a *presenter* who ran the sessions and read the scripts, an *enumerator* who would sit with the subjects and help them fill in their sheets if they required assistance (25% of the respondents reported never having been to school), and two additional assistants. Upon arriving, subjects were walked through an intake survey asking a set of typical questions about household composition, wealth, education, risk exposure of the farm, as well as a set of behavioral questions focusing on risk aversion, ambiguity aversion, discounting, and present bias.

We then introduced farmers to excess rainfall insurance. Beginning from a schematic of the distribution of rainfall events over time, the process through which index insurance pays out based on the local rainfall station observation was explained³. The training materials emphasized the fact that the premium and payout are uniform within a village despite the fact that losses may be heterogenous. After this general introduction, farmers were introduced to a carefully designed graphical presentation of the scenarios that will be used throughout the day (see Figure 1 for examples of these graphics), which exhibit the different states of nature (normal, heavy, or excess rainfall), the probability of occurrence of these states, the levels of loss (0 for normal rainfall, 100 Quetzales (Q) for heavy rainfall, and Q2,000 to Q8,000 for excess rainfall), and the payment they would received if they choose to be insured.

The monetary amounts involved in the scenarios were all framed to be consistent with the real profits and risks faced by typical smallholder coffee farmers in the Guatemalan context. Using one scenario as an example, farmers were asked to record their WTP, i.e., the maximum

³The index is based on cumulative rainfall over the fruiting and flowering period for coffee as measured at the nearest government-administered rainfall station.

price they would accept to buy the insurance, using a grid with price increments of Q20. Each farmer having recorded his WTP, the presenter announced a price for the insurance, which defined who was insured. A random weather event and its associated loss was drawn from a deck of cards. Each producer could complete his form and figure out his net income, and comparison was drawn between those that did and did not purchase the insurance. The exercise was repeated with the different possible weather cards. These explanations were followed by a short quiz, with 4 questions relative to the payout in different cases of rainfall observations and losses, and 2 questions on group insurance. Results on the basic concept of index insurance were good, with 59% of subjects having all 4 answers correct and 84% having at least 3 correct. On the group insurance 43% had both answers correct and 86% had at least one correct answer.

Subjects were then notified that one of the scenarios played during the course of the day would be chosen at random and they would be given financial payouts based on a randomly drawn shock and premium price given the WTP they had expressed in this scenario. The actual incentivized payouts were 0.7% of the framed financial amounts that were being presented in the scenarios, and the random selection of the actual premium price to be charged provides a Becker-DeGroot-Marschak mechanism to induce truthful revelation of WTP. As an example, an individual who would have lost half of a Q10,000 harvest due to excess rainfall in the selected scenario would be paid $.07 * 5,000 = Q35$ for the day if their WTP did not exceed the randomly drawn premium price, and $.07 * (5,000 + \text{payout} - \text{premium})$ if their WTP did exceed the premium price. Subjects were walked through three different examples to make sure they were understood, and a trial game was played all the way through to implied payment before we began recording WTP.

The heart of the day's exercises was a sequence of scenarios. All scenarios feature an excess rainfall index insurance product paying out a given amount (Q1,400) in case of excess rainfall losses, which always occurred with a 1 in 7 probability. The actuarially fair value of the insurance is therefore constant at Q200 across scenarios. For each scenario individuals are asked to record their willingness to pay for the insurance product as the nature and severity of losses, and the source of risk is varied. Data is recorded privately by each individual using a form that lists the games in the rows and then has columns with price increments of Q20; individuals were to circle the number that most closely approximates their WTP, or to write in the WTP if the number lies outside the range of values provided. Values were randomized to lie between Q40 and Q320 or Q80 and Q360 to test for bracketing effects. See on line Appendix D for the full set of scripts used during the day's exercises and a copy of the data entry form. The scenarios are described in the next two sections.

When being asked about individual insurance purchase decisions, the games were played

in an entirely individual manner without discussion between subjects. Similarly, in all of the group insurance games but one, decisions are made in a private and individual manner. The only exception to this is the Group Deliberation Exercise, described in Section 5.4, in which we first collected WTP for group insurance under a variety of loss adjustment scenarios, and then asked the members of the group to discuss together how they would actually handle loss adjustment. We therefore observe both an individual and a group decision for these scenarios, and finally we return to ask individuals privately about their WTP for group insurance once the group loss-adjustment rule has been decided upon.

2.2 Structure of the Games

The day's games consist of a series of 32 exercises grouped into four major clusters each of which focuses on a different issue (described in section 2.3).

The structure of the games is represented in Figure 2. In all scenarios, there is a set of states $s \in R$ in which a (excess rainfall) shock occurs and a payout is received if the subject is insured; the probability of each of these states is π_s . If R_s is the return in state s , c is the cost of insurance, and P is the payout, the payoff is R_s if uninsured and $R_s - c + P$ if insured. There is a set of states $s \in D$ in which a (heavy rainfall or drought) shock occurs and no payout is received; the probability of each of these states is ω_s and payoffs are D_s if uninsured and $D_s - c$ if insured. Then there is the state in which no shock occurs and no payout occurs; this will happen with frequency $1 - \sum_{s \in R} \pi_s - \sum_{s \in D} \omega_s$ and induces payoff K if uninsured and $K - c$ if insured.

Without insurance, an expected utility maximizer will have the following welfare:

$$EU_0 = \sum_{s \in R} \pi_s u(R_s) + \sum_{s \in D} \omega_s u(D_s) + (1 - \sum_{s \in R} \pi_s - \sum_{s \in D} \omega_s) u(K). \quad (1)$$

With insurance, expected utility is:

$$EU_I = \sum_{s \in R} \pi_s u(R_s + P - c) + \sum_{s \in D} \omega_s u(D_s - c) + (1 - \sum_{s \in R} \pi_s - \sum_{s \in D} \omega_s) u(K - c). \quad (2)$$

The WTP is the premium payment c that equalizes expected utility across these two options.

While the index insurance literature has typically referred to all variation in income that is not covered by the index as 'basis risk', there are sharply contrasting theoretical predictions surrounding increases in uncovered risk in insured states versus risk in uninsured states. As the severity of shocks in insured states increases (holding the payout constant), expected utility theory predicts that insurance will become more valuable because its ex-

pected marginal utility in the insured states rises. Thus, while the insurance product appears worse in the sense that it covers a smaller fraction of the risk, it should in fact yield a higher WTP. By contrast, increasing severity of shocks in the uninsured states increases the utility cost of paying the premium and should cause WTP to fall.

We can also contrast the expected utility environment, in which probabilities enter linearly, with the behavioral environment of prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). In that environment we replace the objective probabilities π_s with decision weights $\Omega(\pi_s)$, which have been found empirically to over-emphasize small probabilities and to underweight large probabilities.⁴ Two other benchmark cases that we will discuss are the ‘Dual’ model of Yaari (1987), in which the weights Ω are non-linear but the utility function $u(\cdot)$ is linear, and the rank dependent expected utility theory of Quiggin (1982), in which only unlikely outcomes that result in extreme changes in utility are overweighted. We return to a discussion of these cases in the results section.

2.3 Summary of Games

Risk Games. We begin by analyzing a set of experiments in which π_s and R_s were varied (I1-I7). These games vary the probability and severity of losses while keeping the insurance product fixed, and hence provide a very simple environment in which to understand marginal utility: what is people’s willingness to pay to transfer income from good states to bad ones as bad states become worse?

Drought Games. We then move to a set of games that vary ω_s and D_s (I8-I13). These provide variation in the likelihood and severity of an uninsured shock to income, labeled ‘drought’. The comparison between the response we would have predicted based on an expected utility model and the actual observed willingness to pay provides us with a measure of the extent to which the subject behavior follows prospect theory rather than expected utility.

Group Sharing Games. Next, we exploit the group structure of our environment to test the extent to which the groups can perform risk pooling and remove some of the idiosyncratic variation that exists across states of nature within R (G1-G6). Using the same risk scenarios as in the risk games I5-I7, we can cleanly identify their differential WTP for risk reductions when achieved through the group mechanism, as well as the amount of pooling that they expect their group to achieve. We conduct a semi-structured group deliberation exercise in which the groups discuss how they would conduct within-group loss adjustment in practice,

⁴We do not have the ability to test standard versus cumulative prospect theory, and hence do not emphasize the difference between these two theories in our presentation

and analyze the process and outcome of this deliberation using group-level characteristics (G12)

Group Heterogeneity Games. If some group members are chronically more exposed to downside shocks, then a pooling mechanism will involve an element of expected wealth transfer. How destructive is this form of inequality to the willingness to participate in a group pooling mechanism, and how asymmetric is this effect depending on whether one is the winner or the loser in this transfer are explored in these games (G7-G11).

A complete presentation of the different risk scenarios is given in Appendix A; scripts and graphics for each of the games are given in the online Appendix D, and more detail on each game is provided as it is discussed in the text.

3 Expected Utility and Demand for Partial Insurance

We estimate individual-specific utility functions using the variation in WTP in the ‘Risk’ games which vary how *partial* the insurance product is. The Risk games measure how WTP changes with the severity of the shock in the insured state, and hence provide a simple metric of the desire to move income from good states to bad as the bad state gets worse or more uncertain. Previous work has suggested that partial insurance demand conforms relatively well to expected utility theory (Wakker, Thaler, and Tversky, 1997)⁵, and so we use the Risk games to estimate utility functions.

3.1 Evidence of risk aversion and prudence

We first model risk aversion and prudence in our experimental context, examining how the demand for *partial* insurance responds to variation in risk in the risk games. These games all include three states of insurable risk with equal probability of occurrence π and income R_s equal to R , $R - \sigma$, and $R + \sigma$, respectively, one state with uninsured shock with probability ω and income D , and one state without shock with probability $(1 - 3\pi - \omega)$ and income K .

⁵The authors compare the WTP for three insurance contracts: A standard insurance with no deductible, a 0.99 partial insurance (which pays 99% of any claim), and a 0.99 probabilistic insurance (which pays the full claim 99% time). Under expected utility theory, the WTP for the partial and probabilistic insurance should be approximately 99% of the WTP for the standard insurance. Yet, they find the median ratio of the WTP for the probabilistic insurance to the standard insurance to be as low as 0.50, while it is 0.95 for the partial insurance. This leads them to conclude that demand for partial insurance conforms relatively well with expected utility, but not the demand for probabilistic insurance.

Under the expected utility model, the WTP is solution of:

$$\begin{aligned} EU_0 &\equiv \sum_s \pi u(R_s) + \omega u(D) + (1 - 3\pi - \omega)u(K) \\ &= \sum_s \pi u(R_s + P - wtp) + \omega u(D - wtp) + (1 - 3\pi - \omega)u(K - wtp) \equiv EU_I \end{aligned}$$

In the first three games we increase the severity of insured shocks (R) while keeping their distribution (σ) constant. In games I4 to I7, we keep R constant, and vary σ in multiple of Q1,000 from 0 to Q3,000.

Total differentiation of the solution equation gives:

$$\begin{aligned} \frac{dwtp}{dR} &= \frac{1}{EU'_I} \sum_s \pi [u'(R_s + P - wtp) - u'(R_s)] \\ \frac{dwtp}{d\sigma} &= \frac{1}{EU'_I} \pi [-u'(R - \sigma + P - wtp) + u'(R + \sigma + P - wtp) + u'(R - \sigma) - u'(R + \sigma)] \\ &\approx \frac{1}{EU'_I} \pi [u''(R + P - wtp) - u''(R)] 2\sigma \end{aligned}$$

The first expression confirms that demand falls with the severity of the shock when utility is concave. From the second expression, $\frac{dwtp}{d\sigma} = 0$ if u' is linear (i.e., u'' is constant). But if preferences also exhibit prudence ($u''' > 0$), wtp increases with σ .

Panel A of Table 1 presents the average WTP across the risk games. Column 1 shows that WTP increases as the severity of the shocks increases across games I1 to I3, indicating an overall risk aversion among all participants. WTP also increases as the variance in losses increases across games I4 to I7, suggesting the presence of an overall prudence in preference. Hence the behavior of participants in the risk games is consistent with risk aversion and prudence under expected utility theory.

We now proceed to fit an EU demand model for each individual using these risk games.

3.2 Estimating utility functions under EU

The objective of this section is to estimate a utility function for each player based on revealed willingness to pay for the incomplete insurance scheme in the seven individual games I1–I7. This approach is in spirit similar to Currim and Sarin (1989) and Currim and Sarin (1992) in which the authors calibrate individual behavioral models. The purpose of course is not to obtain precise parameters, but to allow for individual predictions for a different set of games, without resorting to a parametrization of heterogeneity.

Preferences are characterized by the following utility function:

$$u(y; k, \beta) = -\frac{1}{k}e^{-k\frac{y^{1-\beta}}{1-\beta}} \quad (3)$$

Despite having only two parameters, this utility function is quite flexible. Absolute risk aversion $ARA = \beta\frac{1}{y} + ky^{-\beta}$ decreases with income for ($\beta > 0$ and $k > -y^{\beta-1}$) or ($\beta < 0$ and $k < -y^{\beta-1}$), and increases with income otherwise. It converges to the CRRA function $u(y) = -\frac{1}{k}y^{-k}$ with $RRA = k + 1$ when $\beta \rightarrow 1$, and is the CARA exponential utility $u = -\frac{1}{k}e^{-ky}$ with absolute risk aversion k when $\beta = 0$. Absolute risk aversion is an increasing function of k and (empirically) a decreasing function of β , and so are prudence ($\frac{u'''}{u''}$) and temperance ($-\frac{u''''}{u'''}).$

We simplify the expressions for EU given in (1) and (2) with a common notation for all states of nature. Each game g presented to the players is characterized by a set of probabilities p_x^g for the states of nature with income x and payout P_x^g that the insurance will pay if the player is insured (this includes 0 for the uninsured shocks). In a given game, the expected utility with and without insurance for an individual with preference parameters (k, β) are:

$$\begin{aligned} EU_0^g(k, \beta) &\equiv \sum_x p_x^g u(x; k, \beta) \\ EU_I^g(k, \beta, \delta) &\equiv \sum_x p_x^g u(x + \delta P_x^g - c; k, \beta) \end{aligned}$$

where $\delta \in [0, 1]$ is a trust parameter that the agent places on the insurance payout. The addition of the parameter δ is prompted by the fact that observed willingness to pay was in most cases inferior to the fair price, which is not conceivable with a standard utility function. Our utility estimates are thus identified from variation between games, but not by the overall average expected WTP. The willingness to pay is the solution

$$wtp(g, \theta) = (c : EU_I^g - EU_0^g = 0) \quad (4)$$

where $\theta = (k, \beta, \delta)$ denotes the vector of parameters of the model.

3.3 Econometric method

We proceed now with the estimation of a vector of parameters θ for each individual. We assume that there is some additive measurement error on the willingness to pay, such that

the observed willingness to pay by a given individual wtp_g is:

$$wtp_g = wtp(g, \theta) + \epsilon_g \quad g = 1, \dots, 7 \quad (5)$$

We also assume the usual regularity conditions on the error ϵ_g such that our estimator is consistent and efficient. Let $\mathbf{X}(\theta)_{G \times 3}$ denote the matrix with characteristic element $\partial wtp(g, \theta) / \partial \theta_j$, $j = 1, 2, 3$. For each individual, we use a non-linear least squares estimator:

$$\hat{\theta} = \arg \min_{\theta \in \Theta} \sum_{g=1}^G (wtp_g - wtp(g, \theta))^2 \quad (6)$$

implying that $\hat{\theta}$ must satisfy the first order conditions

$$-2\mathbf{X}(\hat{\theta})^T (\mathbf{wtp} - \mathbf{wtp}(\mathbf{g}, \hat{\theta})) = \mathbf{0}$$

Equation (6) describes a typical non-linear least squares problem, except that in addition to being nonlinear, the function $wtp(g, \theta)$ is only defined implicitly by equation (4). Thus, the derivatives with respect to θ that define the moment equations, and that are critical to any gradient-based solution algorithm, require application of the implicit function theorem at each trial value of θ .

3.4 Estimated preferences and predicted WTP

We start by estimating a unique utility function for all 674 players. Results for the parameters, with robust standard errors clustered at the individual level in parentheses, are reported in Table 2, col. 1. The utility function exhibits risk aversion and some prudence, with absolute risk aversion only slightly decreasing over the range of values of income, from 0.80 to 0.73, implying that relative risk aversion increases very steeply from 1.6 (for the worst income equal to 20% of the normal income) to 7.3 when there is no negative shock to income.

We next proceed with the estimation of θ for each individual player. Since we rely on a very small number of observations for each player (at most 7, and less for the 61 players that did not play all 7 games), estimated parameters can take some extreme values. We therefore report the median and the lowest and highest 5th percentile of the estimated parameters in Table 2, col. 2-4. We see large variations in estimated parameters across individuals, reflecting heterogeneity in preferences.⁶

⁶The small number of observations imply that standard errors on parameters are extremely high, and the

The estimated utility functions are shown in Figure 3. Using these estimated parameters we can compute for each individual predicted utility and all of its derivatives at any level of income. Among all participants 76% exhibit prudence and 10% have an almost quadratic utility function.

For each individual with parameter $\hat{\theta}$, we can compute the predicted WTP, $\widehat{wtp}(g', \hat{\theta})$ that the player ought to have for any game g' . As above, this is the solution to (4) for that particular game characterized by $p_x^{g'}$, $P_x^{g'}$. The process converged for 621 players for the first 3 games and 666 players for all other games.

Since measures of risk aversion and \widehat{wtp} will be used as regressors in the analysis of the observed WTP in games, we will need some measure of precision on these predicted values to correct the standard errors in the estimations. This is done by implementing a wild bootstrap of the whole procedure using the 6-point distribution proposed by Webb (2013).⁷ With equal probability, the residual for each observation is multiplied by $\pm\sqrt{0.5}$, ± 1 , or $\pm\sqrt{1.5}$. For each replicate we then re-estimate the parameters, and in turn compute the predicted $\widehat{wtp}(g', \hat{\theta})$ and measure of risk aversion. The wild bootstrap here assumes that errors are independent across observations, but allows them to be heteroskedastic and non-normal. Notice that because it is computationally intensive to repeat the gradient-based search for each bootstrap replicate, the bootstrap parameter estimates rely on a grid search method. The bootstrapped values will be directly used in the estimations that use risk aversion or \widehat{wtp} as regressors.

4 Demand for Probabilistic Insurance

With these explicit utility functions in hand we now proceed to the analysis of WTP for a set of *probabilistic* insurance games. Our goal is to decompose the response to probabilistic risk into an EU and a behavioral component, using the precise measure of what the WTP ‘should’ be if agents were standard expected utility maximizers. The estimated demand is a dollar-value WTP under expected utility theory, and the difference between this amount and the observed WTP provides a monetary estimate of the extent to which decreases in demand for probabilistic insurance are driven by behavioral concerns. This context is particularly straightforward because all probabilities are objectively known, and because the Drought games simply relabel and reweight the same outcome space that was used to estimate WTP in the Risk games.

quality of fit of the estimation, measured by $SSR_{i,q} = \sum_{g=1}^7 (wtp_g - wtp(g, \theta_q))^2$, very good.

⁷With fewer than 10 observations, the 6-point distribution by Webb is recommended over the more common 2-point distribution (Cameron, Gelbach, and Miller, 2011).

4.1 Comparing the demand for probabilistic and partial insurance

To investigate how this source of uninsured risk drives demand, we include a state of loss not protected by the insurance, which we label ‘drought’, and vary both the severity and the probability of the drought loss.⁸ Because these scenarios feature variation in the probability that the insurance contract fails to perform, they correspond to varying *probabilistic* insurance, while the previous scenarios isolated the differences in WTP that arise from the extent to which the insurance is *partial*.

The drought games all include one state of insurable excess rainfall with probability $\pi = 1/7$ and income $R = 50\%$ of potential income K , one state of uninsurable drought shock with probability ω and income D , in addition to the small risk of heavy rainfall and the remaining state of no shock. The non-drought states are the same as implemented in one of the risk games (I4), which can serve as reference for the demand for insurance in absence of uninsurable states. The six drought games vary the probability and intensity of the drought risk, while maintaining constant the probability and intensity of the excess rainfall risk. They began with a framing of a mild drought risk, one which was both unlikely to occur ($\omega = 1/21$) and small (loss equal to 20% of potential income). The magnitude of the drought-induced loss was then increased to 40% and 80% of potential income, and the likelihood of the risk was increased to 1/7, for each shock magnitude level. Critically, at the potential 80% loss the drought-induced outcome becomes the worst outcome that can obtain. This has strong negative effects on predicted WTP (because the product has the possibility of moving income from worse states to better states where marginal utility of income is lowest).

Both partial insurance and probabilistic insurance are incomplete in the sense that they leave the insured person with a residual variance in income even after payouts have occurred. An increase in risk however affects the demand for insurance in a fundamentally different way. With partial insurance, transfers always occur in states of shocks and hence become even more valuable when the severity of the shock increases, as we have shown in section 3.1. In contrast, when the risk is uninsurable, the demand for insurance decreases with the severity of the risk, as the marginal utility cost of paying the premium increases. Since the insurance product is invariant across all games, these two cases correspond to increasing an uninsurable risk that is positively and negatively correlated with the insured risk, respectively (Eeckhoudt, Gollier, and Schlesinger, 1996; Gollier and Pratt, 1996).

⁸In essence, all insurance that cover specific sources of risks are probabilistic. The labeling of the uninsured risk as drought was purposefully chosen to highlight this sort of uninsured risk, rather than those unrelated to weather, or to a risk of non-compliance by the insurance company, which would involve other issues beside the existence of uninsured states of the world.

We verify these basic relationships in Table 3 by regressing WTP on the standard deviation of residual risk after insurance. In order to assess whether there is a behavioral aspect to the demand for probabilistic risk, we run the regression for both the observed WTP and the WTP predicted with the EU model. Column 1 shows that the predicted WTP displays the expected relationships; a small probabilistic risk leads to a small decrease in predicted WTP, and more severe shocks in insured states drives up WTP while shocks in uninsured states drive it down. Column 2 shows that, as a result, predicted WTP falls by \$3.59 when farmers face a mild drought risk, and by \$18.80 when they face a risk so severe as to make it possible that the worst state of nature is uninsured.

Columns 3 and 4 repeat the previous analysis but using the actual WTP observed across games. While the signs of the responses are consistent, the magnitudes display quite a distinct pattern. Actual WTP proves to be very sensitive to small amounts of drought risk, and then to display little additional sensitivity to the magnitude or likelihood of risk posed by drought (column 4). This indicates that there is a secular dislike of probabilistic insurance that manifests itself even when the actual probability of contract non-performance is minimal. To understand how actual and predicted WTP relate to each other, Column 5 runs a regression explaining the former while including the latter as a control variable, and Column 6 uses the simple difference between the two as dependent variable.

The patterns estimated in Table 3 are represented visually in Figure 4. The clear story emerging from these two ways of analyzing the data is that there is a response to small probabilistic risk that cannot be squared with our expected utility predictions, and if anything the surprise in the response to very large probabilistic risk is that the actual WTP displays less of a decrease than we might expect. Hence, we can conclude very clearly that there is a behavioral puzzle in demand that decreases as the probabilistic nature of the insurance is magnified.

The literature on probabilistic insurance has compared the demand for insurance when the payout is probabilistic with the standard case of full insurance (Camerer (2004)). In particular, Wakker, Thaler, and Tversky (1997) show that when the probability of contract failure is small the WTP under EU should be roughly discounted by the probability of contract failure. We conduct a different but closely related exercise, amplifying the probability of an uninsured loss (and thus shifting the underlying risk profile) while holding the insurance features fixed. We show in Appendix B that under EU the introduction of a small uninsurable shock induces a reduction in WTP that is approximately proportional to the probability ω of the shock, that is:

$$\Delta wtp \simeq \frac{[u'(K) - u'(K - wtp)](K - D)}{\pi u'(R - wtp + P) + (1 - \pi)u'(K - wtp)} \omega < 0$$

We can refer again to Table 1 to observe how demand is affected by a small probability risk. Games I4, I8, and I11 only differ in the drought risk, with no drought in I4, and a small drought risk with probabilities $1/21$ in I8 and $1/7$ in I11. Column 2 shows that predicted WTP falls from its value in I4 by \$0.43 in I8, and by \$1.24 in I11. Change in WTP is thus proportional to the probability of uninsured risk as expected from theory when utility is concave in income and probabilities enter linearly in the EU model. Column 1 shows the actual changes; here by contrast there is a strong response to a very small increase in probabilities, and then a lower-than-proportional response to increasing the risk further. WTP falls by \$4.13, almost 10 times more than under EU, when the probability of drought is set at $1/21$, but the decrease in WTP only doubles to \$8.50 when the probability of drought is tripled from here. Increasing the magnitude of loss in uninsured states while holding probabilities constant leads to a further decrease in WTP for insurance, a fact that is consistent with concave utility. Consequently, the decision criterion must be concave in income, but non-linear and concave in probabilities over the state space studied here. This result is directly inconsistent with the ‘dual’ theory of Yaari (1987), and also with the rank dependent expected utility theory of Quiggin (1982), since the distortion to decisionmaking (relative to EU) disappears as the magnitude of the low-probability shock increases.

4.2 Explaining the behavioral aversion to probabilistic insurance

The primary violation of expected utility theory uncovered above is the excessive response to very small drought risks. We can form a very straightforward monetary measure of this excess response by taking the difference between the predicted and actual WTP in the mild drought scenarios. Then taking this as a dependent variable, we can seek to understand the determinants of the behavioral over-response to mild drought risk. The core question we try to answer is the following: is this excess response a function of behavioral attributes of the individual, or does it relate to a real risk exposure in their farming activities that makes drought risk more salient or dissuasive for farmers so exposed?

To address this question, we bring to bear two sets of covariates. The first are behavioral attributes of the individual, including risk aversion (average risk aversion computed from the individual-specific utility functions estimated above over the range of states), ambiguity aversion (measured on a 1-5 scale using the typical survey measure of ambiguity aversion), and an index of trust built from four questions asking about the extent to which individuals trust their fellow cooperative members. To explain actual risk exposure we rely on a set of survey questions asked at the beginning of the day of games as to what are the main risks facing the output on subjects’ farms. We asked about excess rainfall, drought, strong wind,

or disease, and we characterize each risk as being relevant at all or being the dominant source of risk for each farmer.

Table 4 presents the results of this exercise. Column 1 shows the simple means of each right-hand side variable. Column 2 uses only the behavioral attributes, and finds that all three of these variables have very strong relationships with the behavioral aversion to probabilistic insurance in the direction that we would expect. The risk averse, for whom insurance is more important overall, are less likely to see large drops in demand as a result of the small drought risk. Similarly, those with a high trust index are less put off by the presence of drought risk and maintain demand. The ambiguity averse, on the other hand show much larger drops in demand when faced with the possibility of mild drought. This latter fact is particularly relevant in that it suggests that the simple survey question eliciting ambiguity aversion does indeed capture relevant information in predicting economically relevant parameters.⁹

Columns 3-5 of Table 4 include the actual risk exposure of the farmers to test whether these can explain the over-reaction to small drought risks. Not only is drought exposure insignificant in both specifications, and not only does a joint F-test of all four measures of risk exposure prove insignificant both for ‘some’ and for ‘main’ risk, but the point estimates on the behavioral parameters are almost completely unchanged. Even when we dummy out each level of each risk we find the behavioral determinants of this over-reaction to be very robust. Consequently, our results show very clearly that this over-response to small risks is driven by the behavioral attributes of the decision-maker and is not driven by the actual exposure to risk.

4.3 Risk aversion and demand for insurance against severe risk

We now focus on the response to the ‘worst state’ drought risk, because the literature on demand for index insurance has paid particular attention to this specific type of contract non-performance as a candidate explanation for low demand. As shown by Clarke (2016), the possibility of the worst state being uninsured can introduce non-monotonicity into the relationship between risk aversion and insurance demand. The drop in WTP for insurance that features this worst possibility should be particularly pronounced among those with high risk aversion. Similarly, the Maximin Expected Utility framework used by Gilboa and Schmeidler (1989) and Bryan (2010) evokes a pessimism in which decisionmakers fixate on the worst thing that could possibly happen in making insurance purchase decisions, another

⁹To verify that the results are not simply driven by differential understanding of the game, we added controls for the level of education and the result on the quiz of understanding of the rainfall insurance administered to the farmers at the end of the training session. The results were essentially unaffected.

context in which the effect of these extreme tail risks would be accentuated.

To investigate this, we use data from all the drought games and the risk game with the same insurable risk but no drought, distinguishing among the drought games between the severe drought where the drought loss is worse than the rainfall loss and mild drought for the other cases. We interact dummies for mild drought and severe drought with the measure of risk aversion to study the extent to which WTP drops differentially with the risk of severe drought for the most risk averse.

Consistent with the argument in Clarke (2016), Column 1 of Table 5 shows that while mild drought risk leads to differentially higher predicted WTP among the more risk averse, this relationship flips over and the ‘worst possible’ severe drought leads to a substantial and negative differential effect. In sharp contrast to this, Column 2 illustrates that the patterns of actual WTP are reversed: WTP in the most risk-exposed uninsured scenarios is highest for the most risk averse, even though the premium must be paid in this state. Thus the non-monotonicity in demand over risk aversion as the severity of probabilistic risk increases is not observed in actual WTP.

In conclusion, while the overall aversion to insurance featuring large probabilistic risk is largely in line with expected utility theory (Table 3), the mechanism of high risk aversion leading to large drops in WTP does not appear to be the operative one.

5 Demand for Group Insurance

The promise of insuring groups (rather than individuals) is the possibility that superior information held by group members allows payouts to be adjusted to reflect the actual losses experienced. Because the smoothing opportunity in group index insurance only occurs in the context of a payout, we model only this scenario in our games and hence study the way in which the group mechanism can make index insurance less *partial*. In principle this can permit superior smoothing, and index insurance for aggregate risk can be thought of as complementary to group insurance for idiosyncratic risk (Dercon et al., 2014).

Despite this potential, there are at least four factors that could play against group insurance. First, the group negotiation process is not frictionless, and thus distrust or social costs may make group negotiation an unattractive way to provide smoothing. Second, individuals may simply not find it credible that the group will conduct this smoothing after the fact, meaning that the group fails to live up to its potential as a risk pooling mechanism. Third, while risk pooling may be easy to maintain when group members face homogenous risks, in reality certain individuals are likely chronically more exposed to risk than others, meaning that loss adjustment will de facto be a transfer mechanism from the less exposed to the more

exposed. Finally, there is the well-known dissonance between the ex-ante desire to pool risk (prior to the realization of shocks) and the willingness to carry through with the transfers necessary for pooling once the shock outcomes have been observed. We now present the results of experimental games intended to isolate the relative importance of each of these four mechanisms.

The group games present risk scenarios that are similar to those of the risk games I5 to I7, where excess rainfall experienced at the group level may lead to three possible levels of idiosyncratic losses of R , $R - \sigma$ and $R + \sigma$, where R now represents the average loss in the group. Should the group be insured, the aggregate payout will be Q1,400 times the number of insured members. This aggregate payout can then be either equally shared among members, or attributed according to experienced losses.¹⁰

5.1 The demand for group loss adjustment

Before eliciting WTP for group insurance we explained this modality to players, and facilitated a discussion in which we explicitly presented the potential for group loss adjustment through unequal sharing of the group payout. We begin our analysis of group WTP with the results from several tightly framed scenarios in which the within group loss adjustment was specified. The graphic for group game G4, with $\sigma = Q1,000$, is represented in Figure 1, panel c. Participants were asked to consider each of the three scenarios indicated in the payout rows: one that featured group insurance with no loss adjustment, one with a moderate degree of loss adjustment, and one with complete sharing. Similar group games with $\sigma = Q2,000$ and $Q3,000$ were also played. Notice that the ability to loss adjust is capped by the size of the payout, so that ‘complete sharing’ is replaced by ‘maximum possible degree of loss adjustment’; when insurance is partial then the ability to loss adjust is similarly incomplete. The benchmark case in which no loss adjustment is conducted is exactly comparable to the individual games I5-I7, meaning that the difference in WTP comes from a ‘pure’ preference for the group modality itself. Our fitted utility curves are again useful, because they allow a very precise measure of what individuals *should* be willing to pay if the response to risk protection provided by the group were identical to risk protection coming from the insurance company, as in the individual risk games.

¹⁰Note that the group insurance games are played individually. Each subject is presented a scenario (such as G4 in Figure 1c), representing the distribution of shocks in the group, and the rule of allocation of the payout that would prevail should excess rainfall trigger a payout. The subject is asked what would be his WTP for such an insurance. The game does not require any coordination with the other participants, although it was clearly framed as a potential group insurance for the cooperative to which they all belong, meaning that whatever trust or reservation they have with regard to their cooperative could influence their decision in the game.

Column 1 of Table 6 shows the predicted WTP for group insurance under the three potential levels of risk pooling, as compared to the baseline individual insurance game, for the games of low variance (low σ). By construction, the predicted WTP in the ‘no loss adjustment’ scenario is identical to the individual game. The third row of Column 1 shows that the maximal possible risk pooling achievable by the group ought to increase WTP by \$7.19. Column 2 provides three fundamental insights into the demand for group risk pooling. The first row illustrates that when farmers are presented with a group index insurance product that is precisely comparable to an individual equivalent, WTP is \$5.21 *lower*. This provides the pure preference for group insurance, and shows that all things equal there is a dislike of the group modality, and farmers would prefer to be insured individually. We can also compare the changes in the WTP coefficients across the rows of Columns 1 and 2, and here we see that the increase in actual WTP for group insurance as loss adjustment increases to its maximum is \$6.07 (.86+5.21), while the predicted WTP increases by slightly more than a dollar more than this. Hence, risk protection that arises from group loss adjustment is slightly less attractive than risk protection that is provided by the insurance company. Finally, while the group becomes more attractive as its degree of loss adjustment increases, the secular dislike of the group mechanism is sufficiently strong that farmers are basically indifferent between even the maximally risk pooling group insurance mechanism and individual insurance. Column 3 pulls all games with low, medium, and high variances in risk, and shows that this result is very stable even when we increase the degree of variance in losses.

What is the origin of this dislike of group insurance? One obvious explanation is that farmers simply do not understand the group game. To test this, we use the score that individual obtained on 2 questions relative to group insurance in the quiz taken at the end of the training session. In Column 4 of Table 6, we interact this test score with a dummy for the group games. While individuals with better understanding of group insurance have a higher WTP, even those with the maximum test score of 2 have a reduction in WTP of \$4.65 (highly significant with a standard error of 0.67). The next possible interpretation is that farmers do not trust their groups. To test this, we exploit our trust index (which is a composite of four questions about the degree of trust among members of their cooperative¹¹). In Column 5 of Table 6, we interact this trust index with a dummy for the group games. While high-trust individuals do indeed have significantly higher demand for group insurance,

¹¹The questions ask whether the cooperative members trust each other, whether the interest of all members are equally considered when decisions are made, whether rules are respected in decision making, and whether decision making is transparent. For each of these questions, farmers could choose “Strongly disagree”, “Disagree”, “Agree”, “Strongly Agree”, which we coded 1 to 4. The index is the normalized sum of the 4 scores.

the magnitude of this effect is small (93 cents) and hence it would appear that distrust can account for at most about one fifth of the secular dislike of the group mechanism. Column 6 shows that trust does not alter WTP for the group modality as the level of environmental risk increases. Hence, while trust is not inconsequential, it cannot appear to explain the magnitude of the preference for individual insurance.

5.2 The expected degree of loss adjustment by groups

Having understood how much the groups are willing to pay for loss adjustment, we want to understand the actual degree of loss adjustment that the players expect from their groups. In other words, not *can* they loss-adjust but *will* they loss-adjust? Column 7 of Table 6 shows the results of an exercise conducted before the explicit presentation of loss adjustment rules was conducted, in which we asked WTP for a group insurance with the degree of loss-adjustment left unstipulated.¹² By comparing WTP in this game to those in which loss-adjustment was stipulated, we can measure expectations over pooling in a very exact way. The coefficient on this unstipulated game is -\$3.62, relative to a coefficient of -\$2.23 for a group insurance with moderate pooling and of -\$5.20 with no pooling. The implication is that the cooperative members expect that their groups would conduct a fraction of the possible degree of loss adjustment of idiosyncratic risk (corresponding to approximately a quarter of the idiosyncratic risk). Column 8 pools data from all three risk scenarios and arrives at very similar conclusions. Finally, we can ask whether a lack of group trust effects the extent of pooling that the members expect from the group. This is accomplished in Column 9 by interacting group trust with a dummy for the game in which the sharing rule was not stipulated; here we see an insignificant effect suggesting that trust is not the driver of expected loss adjustment.

These results provide a mostly negative picture of the demand for group insurance. While farmers do have a strong WTP for loss adjustment via the group mechanism and they do expect their groups to conduct some loss adjustment, these positives are overwhelmed by a set of counteracting factors. They only expect their groups to loss adjust one quarter of the potential idiosyncratic variation, and on the whole there is a dislike of the group that is roughly equal in magnitude to the WTP for the maximum extent of risk reduction that group loss pooling can achieve. The WTP for marginal risk reduction achieved through group loss adjustment is less than what it would be if this protection was provided by the insurance company. Group trust decreases the magnitude of the penalty levied on group insurance products, but the mechanism for this is neither the extent nor the credibility of

¹²Because these two games were always played in the same order within the overall randomization we cannot control for the possibility of sequencing effects between these games.

loss adjustment to be conducted by the group.

5.3 The effect of heterogeneity in expected losses

Having considered so far the implications of mean-zero idiosyncratic risk on the demand for group insurance we now address the effect that asymmetric loss exposure may have on demand. This is a critical issue because this asymmetry introduces a dimension of expected transfer into the loss adjustment mechanism. If certain people are subject to more extreme shocks (because, for example, they are insuring steep or flood-exposed farmland) then loss adjustment will systematically entail a transfer of payouts towards these more exposed individuals and away from those who are less exposed to risk. This alters the actuarially fair premium. The greater the heterogeneity within a group in the exposure to these shocks, the more difficult we would expect group contracting to be.

To investigate this, we introduced five scenarios in which the group was presented as being composed of heterogeneous members with different risk exposure. While idiosyncratic losses could still be $R - \sigma$, R and $R + \sigma$, where σ was maintained constant at Q2,000, and the average loss in the group was R , some members had a higher probability of smaller losses $R - \sigma$, and others a higher probability of higher losses $R + \sigma$. In the example represented in panel d of Figure 1, the player face a relatively less risky environment than average, with the probability of low loss (of Q2,000) equal to $6/84$, while the probability of high loss is $2/84$. Across the five games, the probability of low loss varies from $8/84$ to $6/84$, $4/84$, $2/84$, and 0 , with the complementary probability for high losses. Throughout we maintained that there would be partial risk pooling, and gave concrete amounts to be pooled for each scenario. These five games give the basic dislike of heterogeneity, and the change in WTP as the expected losses to that individual change.

In the first game, we merely presented the issue of heterogeneity, but the player's exposure to risk is the same as the average in the group (probabilities for high and low losses are equal). Results in Table 7, column 1 that simply framing the group as consisting of heterogeneous membership drives down WTP by \$6.54, an amount greater than the overall penalty to group insurance. We then place the individual in different parts of the expected loss distribution, meaning that group loss adjustment would predictably serve as a transfer to or from that individual of the difference between net expected payout and the group average. Players with higher probability of low losses will on average transfer a higher amount to the group, and players with higher probability of high losses will be net receiver. As a way of understanding what this move in expected payouts should have done to demand, again utilize our utility structure to predict WTP. Column 2 shows that predicted WTP from the utility models

should have decreased by \$1.21 for each marginal dollar to be transferred (this number is less than negative one because the money is transferred in the worst states), while column 3 shows that the actual WTP drops by only \$.60. Thus, at the margin, the demand disutility of making transfers to other group members is only half of what it is when the transfers are to the insurance company. Columns 4 and 5 repeat this analysis showing each cell of the game separately; the results indicate that the divergence between the two types of WTP is particularly pronounced when an individual is the one least exposed to shocks.

The takeaway from this analysis is that while group heterogeneity depresses demand for group insurance, and individuals do respond in the predicted way to their own shock exposure relative to the rest of the group, these individuals are only half as unwilling to transfer money to each other to reduce inequality as they are to lose money to the insurance company.

5.4 Willingness to loss adjust after shocks are realized.

Having conducted tightly framed exercises on group loss adjustment, we now try to understand decisions over loss adjustment in a more natural deliberative context. The actual decision over group loss adjustment requires an aggregation of individual preferences into a group decision, and the successful implementation of group insurance requires that those individual who suffered less severe shocks remain willing to pool after these losses have been realized. To try to simulate these steps in a laboratory context, we conducted a sequenced ‘group deliberation exercise’.

We first presented the idea that groups could loss adjust, framed the pros (better risk protection) and the cons (tensions within the group), and asked players as individuals what degree of loss adjustment they would prefer (1 = none, 2 = moderate, 3 = as much as possible) if they were obtaining group insurance. We then asked them to discuss and decide upon this issue as a group, and recorded the outcome. Finally, we attempted to mimic the incentive to renege on group risk sharing by asking each individual to draw an actual rainfall shock (and thus a level of income) and to vote again on the group risk pooling decision. These three outcomes (pre-deliberation individual preference, group choice, and post-shock individual preference) provide a window directly into the desirability of this theoretically central feature of group insurance.

Column 1 of Table 8 shows that players that are risk averse or ambiguity averse have a lower preference for sharing, although the point estimates are small. The group decision, explained in Column 2, shows that groups with more women and with less educated members reach agreement on a higher level of risk pooling after deliberation. The core point of

the exercise, however, is illustrated in Column 3. Even in this contrived environment in which individuals are asked to state their preference twice over a very short period of time and with only a small sum of money at stake, we find evidence that the ex-post incentive incompatibility of risk pooling will prove problematic. Individuals who draw large negative shocks pivot to desire greater pooling, and those who draw small shocks desire less pooling. The extent to which preferences for sharing are altered in this interval provides an application of withdrawing the Rawlsian Veil of Ignorance, as agents who had previously not understood their exact position in a shock redistribution now know what they personally stand to win or lose. The magnitude of the change in behavior provides some evidence for the extent to which the inability to writing binding contracts will pose a constraint on pooling agreements that must be ex-post incentive compatible.

The coefficients on the desired degree of risk sharing can be taken back to the coefficients from Table 6 in which the expected degree of risk pooling is estimated. Across all three exercises, participants report wanting ‘moderate’ risk sharing (50% of potential), and yet they expect that the groups will only provide 25% of the potential risk sharing. Given our evidence that the dynamic consistency of risk sharing is a problem in practice, the expectation that actual risk pooling will come in below the level desired may be well justified.

6 Robustness Checks

Our study included features designed to test the robustness of our results to three study effects that might threaten internal validity: bracketing effects, framing effects, and game ordering effects.

6.1 Bracketing effects

The brackets for the WTP worksheets were randomized at the cooperative level; half of the respondents spent the day using sheets that presented values between Q40 and Q320, and the other half between Q80 and Q360. This lets us examine the extent to which the framing of the price altered the resulting WTP. The price bracketing did not lead to large variation in WTP (the \$6.35 difference between the ‘high’ and ‘low’ brackets led to an insignificant \$1.90 difference in average WTP), and the marginal effect of risk variation across the high and low bracket groups is very similar.

6.2 Framing effects

There are important ways in which the usual analogy of lab behavior to real-world actions breaks down in the study of insurance. Firstly, to understand insurance we must understand the effects of very large swings in income, and these cannot be replicated in the lab. Secondly, the core utility motivation of insurance is based on downside risk, and this cannot ethically be recreated in the lab (one can alter payouts but cannot confiscate income from experimental subjects). For our results to be meaningful, it must be the case that the magnitude of the responses are driven by the very large risks around which the exercises were framed, rather than the relatively small benefits provided by the incentives to play. Despite this, the use of games to explore insurance-related questions has nonetheless been expanding, from early papers such as Binswanger (1980) to a more recent set of studies (Lybbert et al., 2009; McPeak, Chantarat, and Mude, 2010; Charness, Gneezy, and Imas, 2013; Norton et al., 2014; Elabed and Carter, 2015). The stated purpose of these field studies has been mixed; some have intended to use the games only as a tool for teaching potential customers about insurance, some have seen it as a marketing exercise to build demand, and others have sought to learn about the nature of demand from these exercises.

To study this, at one point in the day we stripped off the framing completely and elicited WTP to insure the small upside risk induced by the actual payments in the experiments (I14-I16). In this analysis we would hope to see some WTP for insurance in the unframed games; a lack of demand for insurance would suggest that the stakes were not large enough to induce risk aversion. We would also hope to see higher WTP in the scenarios framed as large losses, suggesting outcomes spread further out the distribution of the individual's utility curve. Figure 5 and Table 9 present this comparison, beginning with predicted WTP as a simple way of showing what individuals should have been willing to pay for an insurance product that effectively protects them against a very small upside risk. Given the small amounts of money in play, had individuals shifted completely to the unframed outcomes they would have been willing to pay only 21 cents for the unframed insurance, relative to \$29.42 for the framed insurance. Instead, we see in columns 3 and 4 that actual WTP in the unframed scenarios was on average \$19.50, and the framing increased this by an additional \$9.79. Column 2 shows that all of the response to the severity of the shock should have come in the framed shocks only, while Column 4 shows that in actuality the framing only doubled the marginal response to variance relative to the unframed scenarios.

These results are consistent with substantial framing effects, and indeed suggest that we were unable to completely remove the framing in the 'unframed' games. A sample that was willing to pay \$29 to protect themselves against risks with framed standard deviation of \$282 and an actuarially fair price of \$31.73 were willing to pay \$20 to insure themselves against

unframed risks with a standard deviation of \$1.97 and an actuarially fair price of \$1.40. Thus while our results indicate that framing is effective, we clearly failed to completely unframe the decision during these three rounds. We nonetheless take these results as confirming the idea that the analysis of framed games does capture risk aversion over quantities substantially larger than those actually at risk.

6.3 Game ordering effects

We randomized the order of the games to the maximum extent possible. While the marketing exercises were always first and last, the ‘real values’ previous to last, and the ‘deliberation’ round last within the group games, we randomized the ordering of the individual (I) and group (G) games, as well as the ordering of the games within the risk games set (I1-I7), as well as the ordering of group with rule (G4-G6) and group heterogeneity (G7-G11) games, leading to 8 possible ordering cells for the day’s games (Appendix C Table 1).

Results of an analysis of these ordering effects is reported in Appendix C Table 2. Using fixed effects for games to identify the ordering parameter only off of the randomized timing, we find that having a game come later in the day by one exercise lowered WTP by \$.52 per exercise. In line with this, players like whichever of the (Group, Individual) games they saw first, and so the overall sign on the group versus individual choice depends on the order in which the game was played. Given the randomization of ordering, the overall effect measured by the study drops out this heterogeneity and measures the average impact across orderings, but the magnitude of the ordering effect in the group-individual comparison is large. In Appendix C Table 3 we show that the drought effect is slightly stronger when the individual games are played first in the day, by \$1.76, over the decline of \$6.83 when individual games are played in the second half of the day; again the \$7.71 is the average over all subjects. The overall takeaway from the Drought (Probabilistic) table is unchanged. We also re-estimate the WTP for group loss adjustment results with game ordering effects; we interact the loss adjustment variables from Columns 1 and 2 of Table 6 with a dummy for ‘group-games-played-after-individual-games’. Again we see the large overall effect of the group game going second, but the differential results across loss adjustment rules are very similar regardless of the order in which they came. The group with no loss adjustment effect is -\$3.1 if group games are played first and -\$7.41 if individual games are played first), but the same for all levels of loss adjustment, meaning that the WTP for loss adjustment reported in Table 6 is unaffected by game ordering (Appendix C Table 4).

Overall, the study does not appear to have suffered from substantial bracketing effects, players are responding strongly to the framing of large losses, and the main results are robust

to ordering effects.

7 Conclusion and Discussion

Using a set of artefactual field experiments, we investigate the demand for index insurance among coffee farmers in Guatemala. Willingness to Pay is in general lower than the actuarially fair rate, which is an initial piece of evidence that partial insurance products do not generate the kind of demand that we would expect from risk-averse agents if offered perfect insurance. We use the lab context to decompose the potential reasons that insurance products may meet with limited demand, and to investigate one promising modality to stimulate demand.

Our study provides several novel perspectives on how people respond to risk. First, we can explicitly estimate utility functions from the demand for risk reduction that we believe is well explained by EU theory. This permits us to harness the EU model to predict WTP in a wide variety of counterfactual scenarios, and provides an unusually direct way of decomposing insurance demand. We confirm the very strong role that uncovered sources of risk play in undermining WTP, and find the drivers of this response to be complex. When the magnitude of uncovered losses is high, EU responds strongly to the risk and behavioral explanations appear to play very little role in driving the drop in demand. In contrast, even very small and low-probability uncovered risks have strong effects on WTP. In these cases the EU model would predict only very modest shifts in WTP, and so we find that roughly 90% of the response to small probabilistic risk is behavioral. A prospect-style utility function where the decision criterion is concave in both wealth and probabilities is consistent with these results.

We verify the mechanisms underlying group insurance, but fail to provide much hope that such products will prove commercially viable. Farmers understand the risk pooling benefits of loss adjustment, and indeed they expect their cooperatives would provide about a quarter of the possible degree of risk pooling. Despite this, there is a secular dislike of the group mechanisms, increasing in the degree of distrust of the cooperative, that makes even a fully loss-adjusted group insurance product only just equal to individual insurance. Given the expected degree of loss adjustment, the average individual would prefer individual insurance to group. Heterogeneity in the group further damages the desire to use the group mechanism to cross-insure. Demand disutility when agents are asked to transfer money to fellow group members is only half of what it is when transferring to the insurance company, but they are also willing to pay 18% more to purchase risk protection from the company than through group risk pooling. Hence, while we verify that the underlying mechanisms that

make group insurance potentially attractive are indeed at play, in the end in this context they are insufficient to compensate for the overall dislike of the group mechanism.

In summary our results isolate several reasons for the low demand that index insurance products have met in the developing world. Integral to the nature of the use of an index is that the insured quantity is not the outcome of direct interest to the agent. Index insurance will struggle to generate demand in environments with multiple risks, and group insurance does not appear to be an attractive way to overcome this hurdle. While insurance demand would rise if climate change caused more severe or more variable shocks in the dimension captured by the index, even a very small increase in risks not covered by the index prove highly detrimental to demand. As uninsured shocks become larger and more likely behavioral explanations become less important, but only because even Expected Utility models predict such large decreases in WTP in these scenarios. This study therefore reinforces the need to push index insurance products to cover multi-peril risks, as can be achieved with more sophisticated indexes, or to find ways of going directly towards indemnifying the losses themselves.

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Tables

Table 1: Summary Statistics on WTP by Game

Game	Description	Actual Willingness to Pay	Predicted EU Willingness to Pay
Panel A: Variation in Insured Risk		(1)	(2)
I1	Risk, small shock	24.38	22.73
I2	Risk, med shock	29.51	29.92
I3	Risk, large shock	33.87	35.02
I4	Risk, base (no variability)	25.72	28.49
I5	Risk, some variability	29.10	29.41
I6	Risk, med variability	32.31	31.42
I7	Risk, large variability	35.58	33.40
Panel B: Variation in Uninsured Risk			
I4	No drought	25.72	28.49
I8	Drought, rare & small	21.59	28.05
I9	Drought, rare & med	18.71	26.48
I10	Drought, rare & worst	15.58	12.36
I11	Drought, freq & small	17.22	27.24
I12	Drought, freq & med	14.26	23.50
I13	Drought, freq & worst	11.72	9.86

All figures are in US Dollars.

Table 2: Estimated Parameters

Parameters	Overall utility	Individual utilities		
	Coeff. (se)	Median	Lowest 5%	Highest 5%
$\hat{\beta}$	0.042 (0.120)	.720	-.959	3.64
\hat{k}	0.801 (0.194)	.849	-4.033	50.500
$\hat{\delta}$	0.156 (0.004)	.217	.0737	1.0347

Table 3: Willingness to Pay in Presence of Drought

Dependent Variable: WTP, US \$.	Predicted WTP		Actual WTP			Difference Actual WTP - Predicted WTP
	(1)	(2)	(3)	(4)	(5)	(6)
Any Drought	-7.71*** (0.2240)		-14.03*** (0.4160)			
Residual SD of Income in Drought Games	-79.33*** (2.6280)		-31.10*** (1.14)			
Residual SD of Income in Risk Games	62.32*** (2.1190)		55.41*** (2.05)			
Mild Drought		-3.59*** (0.11)		-12.02*** (0.38)	-10.03*** (0.35)	-8.44*** (0.34)
Drought Inducing the Worst Possible State		-18.80*** (0.60)		-16.31*** (0.45)	-5.87*** (0.62)	2.48*** (0.58)
Predicted WTP					0.56*** (0.03)	
Constant	31.91*** (0.17)	30.00*** (0.12)	31.73*** (0.23)	30.03*** (0.19)	13.36*** (0.79)	0.05 (0.17)
Observations	8,523	8,523	8,547	8,547	8,517	8,517
R-squared	0.795	0.771	0.74	0.704	0.775	0.41

*** p<0.01, ** p<0.05, * p<0.1. Regressions use fixed effects at the individual level, and standard errors are clustered at the individual level. Regressions use games I1-I13.

Table 4: Deviation from EU Behavior when Facing Low Uninsured Risk

	Mean (sd)	Reduction in WTP under mild drought games Mean value of (Predicted WTP - Actual WTP) in USD			
	(1)	(2)	(3)	(4)	(5)
Behavioral characteristics					
Risk Aversion	5.76 (0.80)	-0.88*** (0.34)	-0.81** (0.35)	-0.86** (0.35)	-0.87** (0.36)
Ambiguity Aversion	2.2 (1.17)	0.83*** (0.32)	0.85*** (0.32)	0.82*** (0.33)	0.87*** (0.34)
Trust Index	-0.01 (1.00)	-1.00*** (0.31)	-0.95*** (0.32)	-0.95*** (0.31)	-0.88*** (0.32)
Perceived Risk Exposure	(Some risk)		(Some risk)	(Main risk)	
Excess Rainfall	0.91 (0.29)		-0.10 (1.15)	0.41 (1.90)	Dummy variables for each level of each risk
Drought	0.17 (0.38)		-0.04 (0.89)	2.20 (2.48)	
Strong Wind	0.24 (0.43)		1.52* (0.79)	3.66 (2.91)	
Disease	0.60 (0.49)		-0.94 (0.71)	0.71 (2.29)	
Constant		11.65*** (2.47)	11.50*** (2.68)	11.02*** (3.08)	
Observations	644	644	644	644	644
R-squared		0.036	0.047	0.041	0.064
F_stat. for exposure to risk variables			1.737	0.782	1.089

*** p<0.01, ** p<0.05, * p<0.1. Risk aversion is the estimated average risk aversion based on the individual-specific utility model. Ambiguity aversion is an indicator from 1 to 5 based on the standard survey question. Trust index is a normalized index of four questions related to trust in the coop. The risk variables are constructed from responses to the question: Does (Excess rainfall / Drought / Strong Wind / Diseases) represent a risk to your coffee production? Potential answers are: the highest risk, 2nd highest risk, 3rd highest risk, 4th highest risk, no risk. In columns 1 and 3, the risk variable is set to 0 if answer is no risk, 1 otherwise. In column 4 the risk is set to 1 if it is the highest risk. In column 5, there is one variable per type of risk and rank. Standard errors on behavioral characteristics bootstrapped from 300 iterations in each of which risk aversion is re-calculated to account for the prediction error of the estimated right-hand side variable.

Table 5: Willingness to Pay and Risk Aversion

Dependent Variable: Willingness to Pay, US\$	Predicted WTP	Actual WTP
	(1)	(2)
Risk aversion * Mild Drought	0.15* (0.10)	0.33 (0.54)
Risk aversion * Severe Drought	-6.83*** (0.93)	0.7 (0.61)
Risk Aversion	0.99 (0.67)	1.73** (0.70)
Mild Drought	-3.01*** (0.58)	-9.69*** (3.20)
Severe Drought	21.95*** (5.46)	-16.12*** (3.61)
Constant	22.80*** (3.90)	15.75*** (3.85)
Observations	4662	4686
R-squared	0.319	0.142

*** p<0.01, ** p<0.05, * p<0.1. Regressions are estimated using games I4 and I8-I13. Standard errors bootstrapped from 300 iterations in each of which risk aversion is re-calculated to account for the prediction error of the estimated right-hand side variable.

Table 6: Willingness to Pay for Group Insurance

Dependent Variable: Willingness to Pay, US\$	Amount of Loss Adjustment Conducted by Group			Understanding of Group Insurance	Trust in Group		Amount of Loss Adjustment Expected from Group		
	Predicted WTP	Actual WTP	Actual WTP	Actual WTP	Actual WTP	Actual WTP	Actual WTP	Actual WTP	Actual WTP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Group with No Loss Adjustment	0 (0.00)	-5.21*** (0.52)	-5.45*** (0.47)	-6.95*** (1.12)	-5.52*** (0.47)	-5.52*** (0.47)	-5.20*** (0.50)	-5.20*** (0.46)	-5.27*** (0.46)
Group with Moderate Loss Adjustment	2.11*** (0.10)	-2.25*** (0.53)	-2.17*** (0.48)	-3.68*** (1.11)	-2.25*** (0.49)	-2.25*** (0.49)	-2.23*** (0.51)	-2.15*** (0.48)	-2.24*** (0.48)
Group with Maximal Loss Adjustment	7.19*** (0.35)	0.86 (0.56)	0.06 (0.49)	-1.45 (1.12)	-0.05 (0.49)	-0.05 (0.49)	0.87 (0.54)	0.07 (0.48)	-0.04 (0.48)
Medium Variance in Loss Game			2.85*** (0.16)	2.85*** (0.16)	2.81*** (0.16)	2.82*** (0.16)		3.10*** (0.16)	3.07*** (0.16)
High Variance in Loss Game			5.84*** (0.23)	5.84*** (0.23)	5.91*** (0.23)	5.91*** (0.23)		6.32*** (0.24)	6.38*** (0.25)
Test Score * Group Game				1.15 (0.75)					
Trust in Group * Group Game					0.93* (0.51)	0.90* (0.52)			0.93* (0.50)
Trust * Group * Moderate Loss Adjustment						0.1 (0.22)			
Trust * Group * Maximal Loss Adjustment						0.02 (0.32)			
Sharing Rule Not Stipulated							-3.62** (1.42)	-2.89* (1.53)	-2.92* (1.55)
Trust * Group * Sharing Not Stipulated									-0.72 (1.16)
Constant	29.62*** (0.11)	29.27*** (0.38)	29.50*** (0.34)	29.56*** (0.34)	29.43*** (0.35)	29.43*** (0.35)	29.22*** (0.44)	29.21*** (0.50)	29.18*** (0.52)
Observations	2664	2646	6610	6594	6463	6463	3306	8590	8413
R-squared	0.954	0.744	0.695	0.695	0.685	0.685	0.417	0.392	0.386
Games used	I5, G4abc	I5, G4abc	I5-I7, G4-G6	I5-I7, G4-G6	I5-I7, G4-G6	I5-I7, G4-G6	I5, G1, G4abc	I5, G1-G6	I5, G1-G6

*** p<0.01, ** p<0.05, * p<0.1. Regressions include fixed effects at the individual level, and standard errors are clustered at the individual level.
 Note: Games G1, G2, and G3 present the same risk profiles as I5, I6, and I7, respectively, as do G4, G5, and G6, all with same expected loss but varying variance in loss. In G1-G3, the rule of allocation of the group payout is not specified. In G4, G5, and G6, the rule of allocation is specified with no loss adjustment (a), partial loss adjustment (b), or maximum loss adjustment (c) in the group. Columns 1-2 only use the games with low variance in loss, columns 3-6 use all three levels of loss variance. Columns 7-9 also include the three games G1-G3 in which the rule of allocation is not specified. The test score variable is equal to the number of correct answers on the two questions of understanding of group insurance.

Table 7: Group Heterogeneity

Dependent Variable: Willingness to Pay, US\$	Homogenous		Heterogeneous vs. Group		Heterogeneous vs. Group	
	Predicted WTP	Actual WTP	Predicted WTP	Actual WTP	Predicted WTP	Actual WTP
	(1)	(2)	(3)	(4)	(5)	(6)
Group is Heterogeneous	-6.54*** (0.65)					
Expected Transfer to Others		-1.21*** (0.03)	-0.60*** (0.02)			
High transfer provider				-26.78*** (0.68)	-7.17*** (0.35)	
Low transfer provider				-5.01*** (0.23)	-3.86*** (0.27)	
Low transfer receiver				3.79*** (0.22)	4.52*** (0.28)	
High transfer receiver				7.07*** (0.43)	8.28*** (0.42)	
Constant	33.10*** (0.31)	42.19*** 0.00	26.74*** 0.00	46.37*** (0.18)	26.38*** (0.17)	
Observations	1252	3330	2990	3330	2990	
R-squared	0.791	0.848	0.817	0.899	0.818	
Games Used:	G6b & G7	G7-G11	G7-G11	G7-G11	G7-G11	

*** p<0.01, ** p<0.05, * p<0.1. Regressions include fixed effects at the individual level, and standard errors are clustered at the individual level.

Table 8: Group Deliberation

	Initial Individual Preference for Sharing	Group Decision on Sharing	Final Sharing Preference for Sharing
	(1=none, 2=moderate, 3=maximum possible)	(1=none, 2=moderate, 3=maximum possible)	In Difference from Group Decision
	(1)	(2)	(3)
Loss Shock Drawn after Deliberation ('000 US dollars)	-0.0109 (0.07)	-0.9055 (0.66)	0.0568*
Female	0.1258 (0.09)	1.2967** (0.54)	-0.0465 (0.04)
Education	-0.0084 (0.01)	-0.0745* (0.04)	0.0042 (0.00)
Wealth	-0.0398 (0.06)	0.3876 (0.42)	-0.0188 (0.03)
Trust in Cooperative	-0.0186 (0.03)	0.0722 (0.15)	0.0115 (0.02)
Utility-based Risk Aversion	-0.0804** (0.03)	0.4145* (0.22)	-0.0308 (0.03)
Ambiguity Aversion	-0.0510** (0.02)	-0.1168 (0.15)	0.0297*** (0.01)
Constant	2.7018*** (0.25)	-0.4691 (1.80)	0.1166 (0.20)
Mean of Dependent Variable	1.98	2.01	0.00
Observations	610	68	610
R-squared	0.024	0.174	0.026

*** p<0.01, ** p<0.05, * p<0.1. Regressions are clustered at the group level; Column 3 includes group fixed effects. The dependent variable in column 1 is the preference expressed before deliberation. Column 3 reports on the group decision as function of mean value of the indicated independent variables in the group. In column 3, the dependent variable is the difference between the preference for sharing after having drawn individual shocks and the agreed upon group choice.

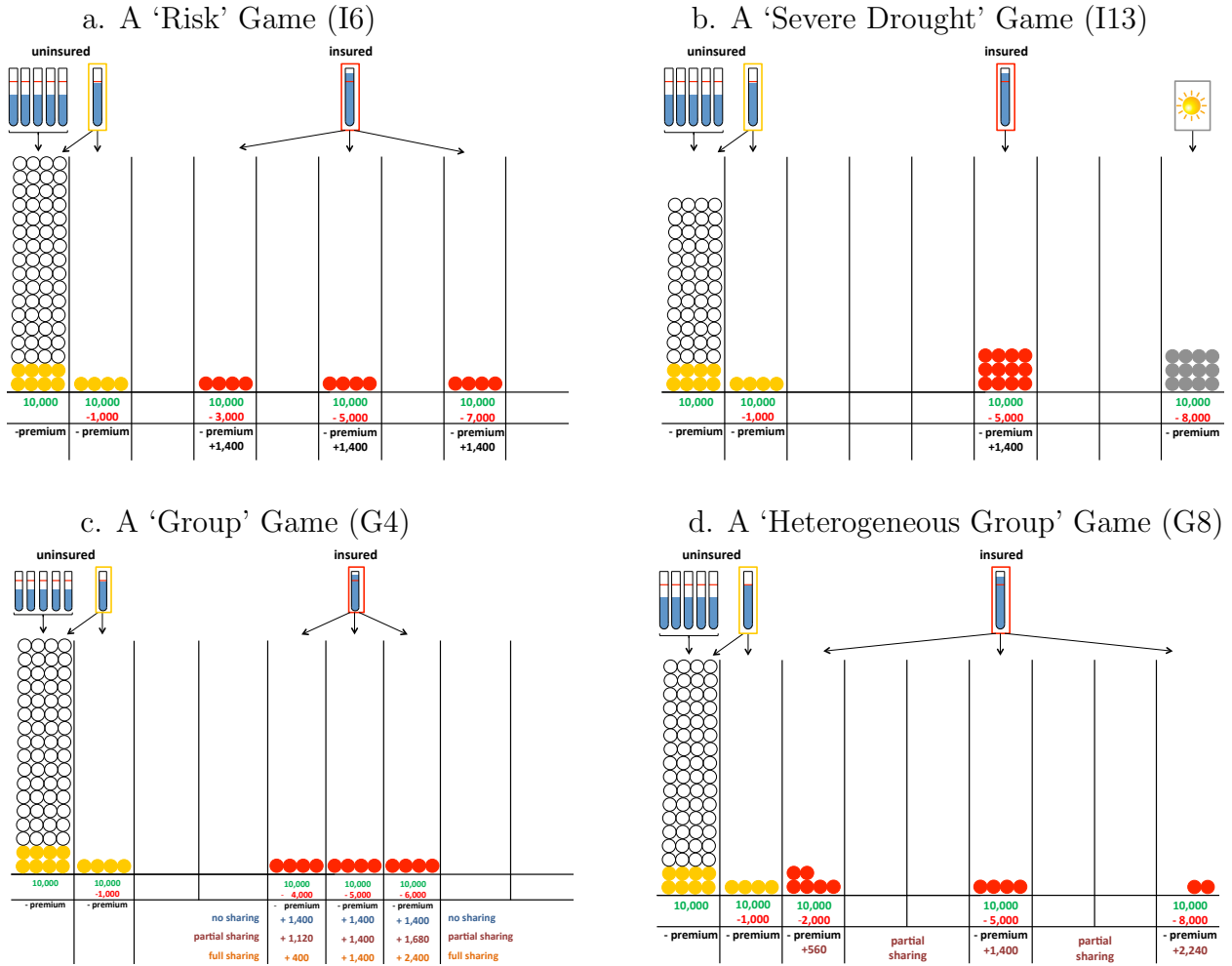
Table 9: WTP in Unframed Games

Dependent Variable: Willingness to Pay, US\$	Predicted WTP		Actual WTP	
	(1)	(2)	(3)	(4)
Framed	29.21*** (0.58)	22.95*** (0.56)	9.79*** (0.70)	7.72*** (0.66)
Framed * Medium Insured Shock		6.95*** (0.27)		2.29*** (0.45)
Framed * Large Insured Shock		11.85*** (0.44)		3.92*** (0.54)
Medium Insured Shock		0.03 (0.02)		2.50*** (0.26)
Large Insured Shock		0.07*** (0.02)		5.29*** (0.38)
Constant	0.21 (0.28)	0.18 (0.28)	19.50*** (0.35)	16.90*** (0.34)
Observations	3885	3885	3864	3864
R-squared	0.83	0.869	0.598	0.653

*** p<0.01, ** p<0.05, * p<0.1. Regressions include fixed effects at the individual level, and standard errors are clustered at the individual level. Regressions used games I1-I3 and I14-I16.

Figures

Figure 1: Examples of Representations Used in Games

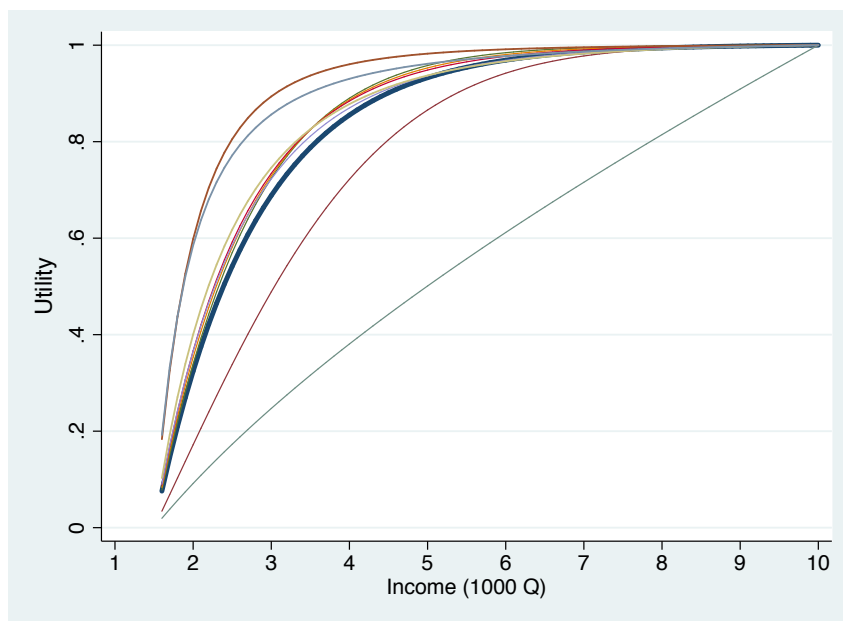


Note: Columns represent different states of nature. On the left, the state of nature with no loss shows an income of Q10,000, while the other columns represent states with losses ranging from Q1,000 to Q8,000. Circles indicate frequencies, with 4 circles representing an event with probability of 1/21. The pictogram (rain gauge or sun) and the color of the circles indicate weather events: white circle represent normal rainfall, yellow circles heavy rainfall below the threshold for insurance payout, red circles excess rainfall covered by the insurance, and grey circles incidence of drought. Panel a represents a scenario in which normal rainfall occurs with probability 5/7, heavy rainfall with either no loss or Q1,000 loss with probability 1/7, and excessive rainfall with losses of Q3,000, Q5,000, or Q7,000, each with probability of 1/21. In panel b, the scenario includes a potential loss of Q5,000 with probability 1/7 due to excess rainfall, a potential drought loss of Q8,000 with probability 1/7, and either normal or heavy rainfall with probability 5/7. Panel c shows a group game, with alternative rules of risk sharing. Panel d shows the case of a low risk person in a heterogeneous group with partial risk pooling. If the individual is insured, payment of premium occurs in all states of nature, and the payout of Q1,400 occurs in states of excess rainfall in individual games and of the indicated amount for the group risk pooling scenarios.

Figure 2: State Space and Payoffs in Games

		Payout Occurs		
		Yes	No	
Shock Occurs	Yes	Prob. of each state:	π_s	ω_s
		Returns in each state: (uninsured; insured)	$R_s; R_s - c + P$	$D_s; D_s - c$
	No	Probability:	\emptyset	$1 - \sum_s \pi_s - \sum_s \omega_s$
		Returns: (uninsured; insured)	\emptyset	$K; K - c$

Figure 3: Estimated Individual Utility Functions



Note: Utility curves are shown for the different deciles of their distribution, when individuals are ranked according to their risk aversion at the mid-point of the income range. The thick curve is the estimated aggregate utility curve.

Figure 4: Actual versus Estimated WTP in Risk and Drought Games

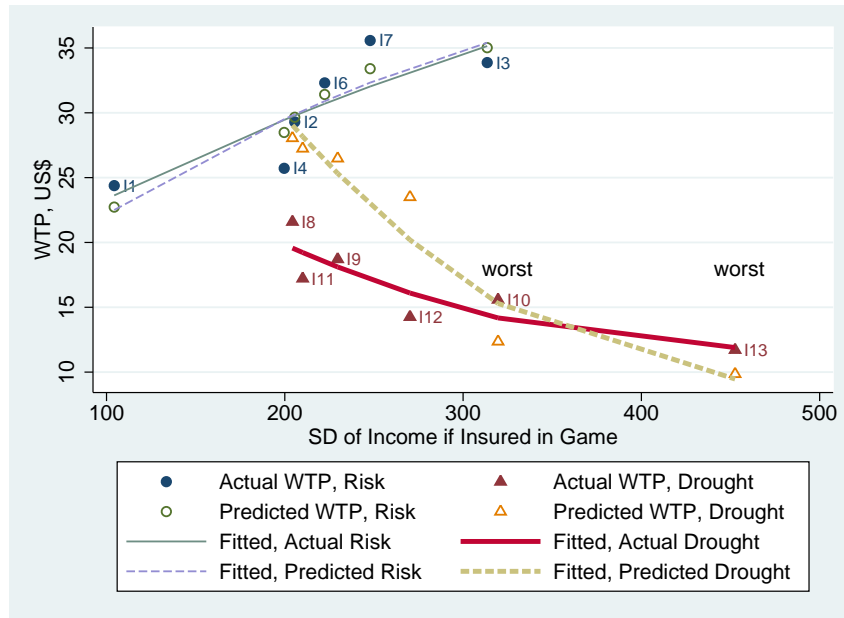
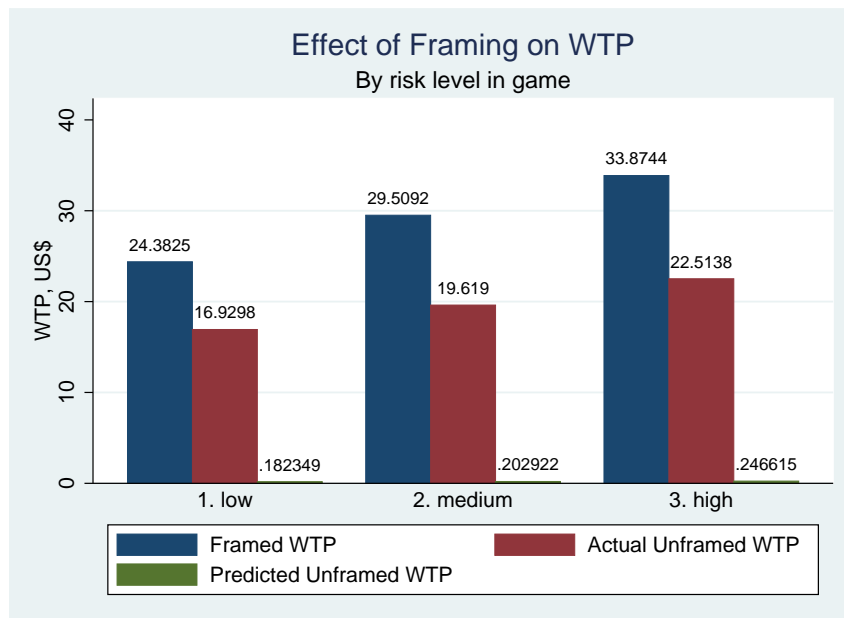


Figure 5: Actual and Predicted Demand in the Unframed Games



Appendix A - List of All Games

Table A.1: Distribution of States in Different Games

Games	Probabilities of Occurrence of States (*100)								
	Shocks (in Quetzales)								
	0	1,000	2,000	3,000	4,000	5,000	6,000	7,000	8,000
I1	80.95	4.76	4.76	4.76	4.76				
I2	80.95	4.76			4.76	4.76	4.76		
I3	80.95	4.76					4.76	4.76	4.76
I4	80.95	4.76				14.29			
I5	80.95	4.76			4.76	4.76	4.76		
I6	80.95	4.76		4.76		4.76		4.76	
I7	80.95	4.76	4.76			4.76			4.76
I8	76.19	4.76	4.76			14.29			
I9	76.19	4.76			4.76	14.29			
I10	76.19	4.76				14.29			4.76
I11	66.67	4.76	14.29			14.29			
I12	66.67	4.76			14.29	14.29			
I13	66.67	4.76				14.29			14.29
I14	80.95	4.76	4.76	4.76	4.76				
I15	80.95	4.76			4.76	4.76	4.76		
I16	80.95	4.76					4.76	4.76	4.76
G1	80.95	4.76			4.76	4.76	4.76		
G2	80.95	4.76		4.76		4.76		4.76	
G3	80.95	4.76	4.76			4.76			4.76
G4a	80.95	4.76			4.76	4.76	4.76		
G4b	80.95	4.76			4.76	4.76	4.76		
G4c	80.95	4.76			4.76	4.76	4.76		
G5b	80.95	4.76		4.76		4.76		4.76	
G5c	80.95	4.76		4.76		4.76		4.76	
G6b	80.95	4.76	4.76			4.76			4.76
G6c	80.95	4.76	4.76			4.76			4.76
G7	80.95	4.76	4.76			4.76			4.76
G8	80.95	4.76	7.14			4.76			2.38
G9	80.95	4.76	9.52			4.76			
G10	80.95	4.76	2.38			4.76			7.14
G11	80.95	4.76				4.76			9.52
G12	80.95	4.76	4.76			4.76			4.76

Income without shock is Q10,000. Cells with grey background are not covered by the insurance.

Appendix B - Change in WTP due to a small uninsurable shock in EU model

Simplify the model to include only one state with insurable shock (income R with probability π) and one state of uninsurable shock (income D with probability ω). In absence of uninsurable shock, the WTP wtp is defined by:

$$\pi u(R) + (1 - \pi)u(K) = \pi u(R + P - wtp) + (1 - \pi)u(K - wtp).$$

With an uninsurable shock $K - D$, the WTP wtp^* is defined by:

$$\pi u(R) + \omega u(D) + (1 - \pi - \omega)u(K) = \pi u(R + P - wtp^*) + \omega u(D - wtp^*) + (1 - \pi - \omega)u(K - wtp^*).$$

We derive a first order approximation for a small shock ($K - D$) and the corresponding small change in WTP. Subtracting these two expressions gives:

$$\begin{aligned} \omega [u(D) - u(K)] &= \pi [u(R - wtp^* + P) - u(R - wtp + P)] \\ &\quad + (1 - \pi) [u(K - wtp^*) - u(K - wtp)] \\ &\quad + (\omega) [u(D - wtp^*) - u(K - wtp^*)] \\ \omega [u'(K)(D - K) + o(K - D)] &= -\pi u'(R - wtp + P)\Delta wtp + o(\Delta wtp) \\ &\quad - (1 - \pi)u'(K - wtp)\Delta wtp + o(\Delta wtp) \\ &\quad - \omega [u'(K - wtp) + o(\Delta wtp)](K - D) + o(K - D) \end{aligned}$$

where $\Delta wtp = wtp^* - wtp$ and $o(z)$ indicates any function $f(z)$ such that $\lim_{z \rightarrow 0} f(z)/z = 0$. This gives:

$$\Delta wtp \simeq \frac{[u'(K) - u'(K - wtp)](K - D)}{\pi u'(R - wtp + P) + (1 - \pi)u'(K - wtp)} \omega < 0$$

This shows that in the EU model, the introduction of a small uninsurable shock induces a reduction in WTP that is approximately proportional to the probability ω of the shock.

Appendix C - Game Ordering

Table C.1: Game Ordering

Title of the Games:	Numbers in Base Order:	Alternative Ordering of the Games							
		1	2	3	4	5	6	7	8
MKTING: Before		1	1	1	1	1	1	1	1
IND: Risk, Expected Loss	I1-I3	2	3	2	3	6	7	6	7
IND: Risk, Variance in Loss	I4-I7	3	2	3	2	7	6	7	6
IND: Drought	I8-I13	4	4	4	4	8	8	8	8
GRP: Without Allocation Rules	G1-G3	5	5	5	5	2	2	2	2
GRP: With Allocation Rules	G4-G6	6	6	7	7	3	3	4	4
GRP: Heterogeneity	G7-G11	7	7	6	6	4	4	3	3
GRP: Deliberation	G12-G13	8	8	8	8	5	5	5	5
IND: Unframed	I14-I16	9	9	9	9	9	9	9	9
MKTING: After		10	10	10	10	10	10	10	10

Table C.2: Effect of Game Ordering

Dependent Variable: Willingness to Pay, US\$	Bracketing	Time Trend	Sequencing of Group Game	Sequencing of SDL and Heterogeneity Games
	(1)	(2)	(3)	(4)
High Price Bracketing (bracket higher by \$6.35)	1.90 (1.23)			
Order of Game		-0.52*** (0.12)		
Group Game * Group Game after Individual Game			-5.12*** (0.77)	-5.20*** (0.77)
Group Game			1.71*** (0.52)	4.11*** (0.56)
Standard Deviation of Loss * SDL after EL Game				-0.58 (0.67)
SDL Game				2.14*** (0.43)
Heterogeneity Game * Het Game after Correlation Game				0.14 (0.63)
Heterogeneity Game				-3.34*** (0.44)
Constant	23.77*** (0.91)	26.18*** (0.70)	31.08*** (1.07)	28.80*** (0.26)
Observations	674	17,948	12,017	12,017
R-squared	0.014	0.412	0.514	0.526

*** p<0.01, ** p<0.05, * p<0.1. Regression in column 1 uses game I1 only, it is cross-sectional at the individual level and standard errors are clustered at the cooperative level. Regressions in columns 2-4 include fixed effects at the individual level, and standard errors are clustered at the individual level. Regression in column 2 use all individual and group games, it includes fixed effects for each specific game, so the trend is measured for the same game played in different places in the sequence. Column 3-4 include individual games I1-I7 and group games with specified rules of allocation G4-G11.

Table C.3: Robustness of Drought Effect to Game Ordering

Dependent Variable: WTP, US \$.	Predicted WTP	Actual WTP	Difference Actual WTP - Predicted WTP
	(1)	(3)	(6)
Any Drought	-6.83*** (0.32)	-12.76*** (0.52)	
Any Drought x Ind. Game Before	-1.76*** (0.52)	-2.54*** (0.80)	
Residual SD of Income in Drought Games	-79.63*** (2.66)	-31.22*** (1.15)	
Residual SD of Income in Risk Games	62.79*** (2.17)	55.81*** (2.10)	
Mild Drought			-7.58*** (0.44)
Mild Drought x Ind. Game Before			-1.71** (0.69)
Drought Inducing the Worst Possible State			1.92** (0.79)
Worstt x Ind. Game Before			1.11 (1.16)
Constant	31.88*** (0.17)	31.68*** (0.23)	0.04 (0.17)
Observations	8,355	8,385	8,355
R-squared	0.794	0.739	0.414

*** p<0.01, ** p<0.05, * p<0.1. Regressions are estimated using games I1-I13. There are fixed effects at the individual level, and standard errors are clustered at the individual level.

Table C.4: Robustness of Group Effect to Game Ordering

Dependent Variable: WTP, US \$.	Predicted WTP	Actual WTP
	(1)	(2)
Group with No Loss Adjustment	0 (0.00)	-3.08*** (0.68)
Group with Moderate Loss Adjustment	1.93*** (0.14)	0.06 (0.68)
Group with Maximal Loss Adjustment	6.54*** (0.47)	3.33*** (0.72)
Group with No Loss Adjustment * Group after	0 (0.00)	-4.33*** (1.02)
Group with Moderate Loss Adjustment * Group after	0.47** (0.20)	-4.74*** (1.03)
Group with Maximal Loss Adjustment * Group after	1.68** (0.69)	-5.12*** (1.09)
Constant	29.41*** (0.11)	29.14*** (0.38)
Observations	2,616	2,625
R-squared	0.954	0.743

*** p<0.01, ** p<0.05, * p<0.1. Regressions include fixed effects at the individual level, and standard errors are clustered at the individual level.