Risk and Ambiguity Preferences and the Adoption of New Agricultural Technologies: Evidence from Field Experiments in Rural India

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Abstract

In this paper we conduct a series of field experiments in rural India in order to measure preferences related to risk, loss, and ambiguity. Disaggregating by data, we find that on average women are significantly more risk averse and loss averse than men, though the higher average risk aversion arises due to a greater share of women who are extremely risk averse. Through a series of two empirical examples, we demonstrate how these parameters affect decisions to adopt new agricultural technologies. By combining these results with a choice experiment over new and familiar rice seeds, we find that ambiguity averse individuals are far more likely to stick with seeds they are familiar with, while a greater degree of loss aversion generally suggests people are more willing to switch to a new variety.

JEL classification: O13, O33, C93

Keywords: uncertainty, Prospect Theory, technology adoption, India

1 Introduction

Despite the heralded benefits of new agricultural technologies relative to conventional technologies, widespread adoption of these new technologies is often a slow process. There have been many attempts to explain the process of technology adoption. For example, previous research has suggested that initially slow diffusion reflects various factors including initial supply-side constraints and differences in the option value of postponed investment in the new technology. Some factors that influence the decision-making process may not be directly observable. Patterns of technology adoption may be symptomatic or reflective of heterogeneity in individuals' preferences toward uncertainty. Such preferences affect the curvature of decision-makers' utility or value functions and may result in otherwise sub-optimal investments or production decisions. When it comes to new technologies, uncertainty arises due to both risk as well as ambiguity. Risk arises because, while almost all new agricultural technologies tout increases in mean productivity, many only perform optimally under certain conditions, such as with precise additions of complementary inputs. Deviations from these conditions may result in not only reduced yield benefits vis-á-vis the traditional technology, but also increased variance. Ambiguity, on the other hand, arises because new technologies are unknown and unproven in the minds of prospective adopters who generally do not know the yield distribution of the new technology. While this ambiguity makes it difficult to formulate profit expectations, farmers may also have an inherent disdain for insufficient information which may additionally influence behaviors. Combined, aversion to both risk and ambiguity may lead to production decisions that are incongruent with deterministic profit maximization.

In this paper, we analyze various behavioral parameters related to risk and ambiguity aversion collected through field experiments conducted in rural India. In analyzing these behavioral parameters, we relax some of the restrictive assumptions that are inherent in standard expected utility theory (EUT) and allow for more flexibility in describing individuals' decision-making calculus by incorporating aspects of prospect theory (PT). Our experimental design allows for the unique identification of several different parameters, accomplished over a series five experiments, each comprised of a set of choices between two options with different real payouts. Using gender-disaggregated experimental data, we demonstrate that women are both significantly more risk averse and loss averse than men. Contrary to some previous findings in different contexts, we find no significant evidence of ambiguity aversion.

The remainder of this paper is organized as follows. In Section 2, we review the literature on risk and ambiguity aversion, especially those studies that have utilized experimental methods to elicit these unobservable behavioral parameters. In Section 3 we introduce the latent behavioral parameters and discuss their measurement. In Section 4, we discuss the experimental design for our field experiments, as well as the supplemental data that is used in the proceeding analysis. In Section 5, we discuss some of the key results that arise from our experiments. In Section 6 we demonstrate the effects of these behavioral paramters on the adoption of new agricultural technologies. Finally, in Section 7 we offer some concluding comments.

2 Literature review

There is a rich literature studying the process of technology adoption. Among the factors linked with adoption include tenurial arrangements (Newbery, 1975; Bardhan, 1979), farm size (Feder et al., 1985; Weil, 1970), education (Foster and Rosenzweig, 1996; Huffman, 2001), credit constraints (Weil, 1970; Lowdermilk, 1972; Lipton, 1976; Feder and Umali, 1993; Dercon and Krishnan, 1996), social networks and social learning (Foster and Rosenzweig, 1995; Conley and Udry, 2010; Duflo et al., 2006), information constraints (Schutjer and Van der Veen, 1977; Fischer and Lindner, 1980), and risk (Sandmo, 1971; Srinivasan, 1972; Feder, 1980; Feder et al., 1985; Liu, 2013). Some studies (e.g., Sandmo, 1971; Srinivasan, 1972; Schutjer and Van der Veen, 1977; Feder, 1980) demonstrate the effects of risk in a theoretical setting. Sandmo (1971) was the first paper to demonstrate risk averse firms would systematically under-invest and under-produce in the absence of sufficient insurance. Srinivasan (1972) used a farming input use model to demonstrate that perceptions of risk, attributable to the uncertainty of weather conditions, lead small farmers to intensify the use of inputs so as to maximize the expected value of the utility of their income. Feder (1980) modeled agricultural production using a production function exhibiting both deterministic and stochastic input responses, with utility over farm income demonstrating constant relative risk aversion. He demonstrated that, while the optimal fertilzer/land ratio was independent of the degree of risk aversion, the optimal allocation of land to a modern variety was decreasing in the degree of risk aversion. In their survey of the literature related to technology adoption, Feder et al. (1985) note that risk aversion is one of the major hindrances towards the adoption of new technology. Risk aversion is a particularly signigicant barrier when it is coupled with other production constraints, credit constraints, inefficient farm size, unreliable supplies of farm inputs, and logistical complications. Despite efforts by governments and development organizations to remove the external constraints in farm production, the nonuniform adoption of new technologies demonstrates the extent to which risk considerations constrain farmers' production decisions.

When studying technology adoption, failing to account for risk preferences potentially introduces bias in the estimated effects of other determinants of adoption. Challenges arise in confronting this bias, however, in that risk preferences are not directly observed. Some authors have preferred to estimate risk effects econometrically (e.g., Just, 1974; Antle, 1983, 1989; Chavas and Holt, 1990, 1996; Holt and Moschini, 1992). This approach may be justified in developed countries where missing markets are sparse or where other potentially significant constraints affect production behavior, but such an approach is unlikely to be suitable in a developing country (Wik and Holden, 1998). Other researchers have attempted to elicit risk preferences through interview methods, though such methods are subject to potential interviewer bias. Starting with Binswanger (1980), many researchers have sought to elicit these otherwise unobservable behavioral characteristics through carefully constructed field experiments. Other examples of such experimental studies include Holt and Laury (2002), Liu (2008), Harrison et al. (2010), Tanaka et al. (2010),de Brauw and Eozenou (2011),Charness and Viceisza (2011). Some more studies like Miyata (2003); Wik et al. (2004); Vargas-Hill (2009) have also used both hypothetical and real payofffs in Indonesia, Zambia and Uganda respectively to identify the effects of risk aversion on production related decisions. Many of these have assumed that preferences conform to expected utility theory (EUT), though behavioral economists argue that observed behaviors often violate the standard axioms of EUT. One of the most oft-cited violations is the Allais Paradox (Allais, 1953), which demonstrates that observed choices between risky payoffs often violate the independence axiom of EUT. Kahneman and Tversky (1979) demonstrated that individuals' valuation of a particular prospect is conditioned by two subjective factors: the asset (or wealth) position of the individual that constitutes the individual's reference point, and the change in the asset position from that reference point represented by the prospect. This latter factor appears to have the greatest impact on decision making, leading individuals to under-weigh outcomes that were merely probable in comparison with outcomes that were obtained with certainty. This phenomenon, termed as 'certainty effect' contributed to risk aversion in choices involving sure gains and risk seeking in choices involving sure losses (see also Tversky and Kahneman, 1992). According to much of the observed evidence supporting prospect theory (or its later refinement, cumulative prospect theory) as an alternative to EUT, individuals tend to overweight the likelihood of low probability-high impact events and display aversion to losses, introducing additional behavioral parameters that should be estimated and considered when studying, for example, production decisions. These additional parameters showed that the value function for respondents was normally concave for gains, commonly convex for losses, with the curve being more steep for losses than gains when decision makers are loss averse (Figure 1). At the same time, they also found that decision weights were lower than the probabilities assigned to those values, except for the lower probability options. Harrison and Rutström (2009) made an attempt to evaluate both the EUT and PT in the same setting, defining a grand likelihood model that allowed each theory to co-exist and have different weights. Surprisingly, they found that both the theories accounted for roughly 50 percent of all the choices made. This mixture model concluded that one model could not overpower the other in some settings. This contrasts with Tanaka et al. (2010) and Liu (2013), who each reject EUT in favor of PT based on experimental results from Vietnam and China, respectively.

Risk, however, is not the only source of uncertainty that arises as a constraint to technology adoption; uncertainty may also rise in the form of ambiguity, what Ellsberg (1961)[657] defined as "a quality depending on the amount, type, reliability and 'unanimity' of information, and giving rise to one's degree of 'confidence' in an estimate of the relative likelihoods". Ellsberg (1961) used a series of novel experiments to demonstrate the effects of ambiguity on decision making, finding that decision makers had non-neutral attitude towards ambiguity. In situations of ambiguous information, respondents were found to be violating the Savage (1954) axioms for certain choices.

An extension of this analysis was done by Halevy (2007) to assess the association between ambiguity neutrality and reduction of compound objective lotteries. Their results were consistent with subjective expected utility model (SEU), as subjects who reduced compound lotteries were almost always ambiguity neutral, with almost the same number otherwise as well. More importantly, they observed that about half (35 percent) of the respondents exhibited ambiguity aversion (seeking) together with aversion (affinity) to mean. The impact of ambiguity on real life decision making and entrepreneurial innovation has been observed by (Rigotti et al., 2008), who observed that people with lower degrees of ambiguity aversion owned the most innovative firms. They measured ambiguity tolerance by the relative weight placed on the highest expectation, following an Arrow-Hurwicz measure, and observed that individuals evaluated prospects by calculating a weighted average of the highest and lowest expected returns, with respect to their probabilities.

3 Measurement of latent behavioral parameters

As an alternative to EUT, PT therefore allows for a greater degree of flexibility in characterizing behavioral responses to risky situations. PT does not reject EUT outright, but rather is a general model of decision making under uncertainty within which EUT is a specific case. Under PT, there are three important parameters that characterize individual behavior. The first parameter (σ) dictates the curvature of the prospect value function, and can be thought of as a measure of risk aversion. The second parameter (λ) characterizes loss aversion. The third parameter (α) captures the degree to which low probability outcomes are disproportionately weighted when valuing risky prospects. Together, these three parameters jointly characterize the valuation of risky prospects. Consider the simple case of a risky prospect with two outcomes, x and y, occurring with probabilities p and $q = 1 - p$, respectively. The value of the prospect can be written

$$U(x, y; p, q, \sigma, \alpha, \lambda) = \begin{cases} v(y) + w(p)\,[v(x) - v(y)] & \text{for } x > y > 0 \text{ or } x < y < 0 \\ w(p)v(x) + w(q)v(y) & \text{for } x < 0 < y \end{cases} \tag{1}$$

where

$$v(x) = \begin{cases} x^{\sigma} & \text{for } x > 0 \\ -\lambda(-x)^{\sigma} & \text{for } x < 0 \end{cases} \tag{2}$$

and $w(p)$ is a probability weighting function. We follow Tanaka et al. (2010) and Liu (2013) by using the axiomatically derived weighting function presented in Prelec (1998). This weighting function is written as $w(p)$ as $w(p) = \exp\left[-(-\ln p)^{\alpha}\right]$. Note that this functional form is flexible enough to allow for decisions to be consistent with EUT; all that must hold for such a case is $\alpha = 1$ and $\lambda = 1$. In that case, the only parameter that defines preferences is σ.

Ambiguity may be a particularly troublesome constraint to technology production, since it inhibits the ability to properly formulate expectations about the benefits of one technology vis-á-vis another. Consider a technology with production exhibiting stochastic returns varying on the utilization of inputs (e.g., Just and Pope, 1979). Let output arising from this technology be written as

$$y = f(x) + h(x)\varepsilon \tag{3}$$

where f is the deterministic input response (production) function and h is a function that perturbs the effect of a random disturbance (ε) on total output arising from the technology, conditional upon the level of the aggregate input used (x). We can write ex post profits as $\pi(x, \varepsilon, p, r) = p\left[f(x) + h(x)\varepsilon\right] - rx$. For simplification, let us assume unitary input and output prices, and further assume that f is a known, deterministic production component. If it is assumed that smallholder producers maximize the expected utility of profits, and further assumed von Neumann-Morgenstern utility functions consistent with Arrow-Pratt definitions of risk aversion, then producers would choose input level to maximize $EU(\pi(x; \varepsilon))$. If this were a new technology, then it can reasonably be assumed that the distribution of the uncertainty arising from the technology is unknown and conditioned by a knowledge (or ambiguity) parameter ν, with a conditional distribution denoted by $F(\varepsilon|\nu)$. The conditional distribution affects the expected output from the technology, such that, for a given level of input, $E(y) = f(x) + h(x)E_{\nu}E_{\varepsilon|\nu}(\varepsilon|\nu)$, and expected utility of profits would be $E_{\varepsilon|\nu}U(\pi(x;\varepsilon))$. Klibanoff et al. (2005) defined a function ϕ that captures aversion to ambiguity, such that expected utility is lower under ambiguity than when ambiguity is absent. This function behaves just like a von Neumann-Morgenstern utility function over risky outcomes. The function ϕ is strictly increasing in the degree of ambiguity, and aversion to ambiguity implies concavity in ϕ. Under these enhancements, the producer's maximization problem consists of choosing the input level x^* that maximizes $\Theta(x) \equiv E_{\nu}\phi\left[E_{\varepsilon|\nu}U(\pi(x;\varepsilon))\right]$, subject to feasibility. The indirect expected utility is $V(x) = E_{\nu}\phi\left[E_{\varepsilon|\nu}U(\pi(x^*,\varepsilon))\right]$. By Jensen's Inequality, we know that $V(x) \leq \phi\left[E_{\nu}E_{\varepsilon|\nu}U(\pi(x^*,\varepsilon))\right]$. Following the input choice–but before the realization of any stochastic events–the ex ante expected utility is $\mu(x) = E_{\nu}E_{\varepsilon|\nu}U(\pi(x;\varepsilon))$. We therefore have $\phi\left[\mu(x)\right] \geq V(x)$, such that $V(x) = \phi[\mu(x) - \varsigma(x)]$, where $\varsigma(x)$ is an uncertainty premium, representing the total amount that producers would be willing to pay to resolve all uncertainty (both risk and ambiguity) in their decision making process. This total uncertainty premium can be decomposed into portions attributable to both risk and uncertainty. Suppose that ambiguity has been resolved. Then we can define a certain equivalent payment $\varsigma_a(x)$ that satisfies $\Theta(x) = \phi\left[E_{\varepsilon|E\nu}U(x;\varepsilon) - \varsigma_a(x)\right]$. The certainty equivalent payment $\varsigma_a(x)$ represents the maximum amount producers would be willing to pay to alleviate ambiguity, replacing ν with its expected value $E\nu$. The risk premium can be computed as the difference between the total uncertainty premium $\varsigma(x)$ and the ambiguity premium ς_a: $\varsigma_r(x) = \varsigma(x) - \varsigma_r(x)$. Barham et al. (2012) have shown how this formulation can be used to estimate ambiguity aversion.

There are other methods for measuring ambiguity aversion. Engle-Warnick et al. (2007) framed experiments to capture willingness to pay to avoid ambiguity. They offer a series of five choices between two bets, but the outcomes of the choices are different, for one of them gives payoffs with a probability of 50-50, which for the other bet is unknown, thereby introducing ambiguity. The payoffs in this case are hypothetical and may not reflect the individuals' real willingness to pay. Anagol et al. (2008) conducted real experiments with children on Halloween to observe the effects of ambiguity. The children were asked to pick a favorite color between red and blue and they also had to choose a bowl from which a dice would be pulled out, and if it matched the child's chosen color, they won a candy. The introduction of ambiguity in this regards was brought about by covering one of the bowls with a towel so the kids were not sure of the distribution of red and blue dice. Moore and Eckel (2006) used the Holt-Laury style table where the respondent had to choose between winning an amount with a 45-50 percent probability and a fixed sum. The fixed sum increases as one proceeds with the questions. This continues till they attain the switching point. They did 20 sets of 20 decisions like this, with unsure probabilities, unsure prizes, and both. They also did another 20 sets of 20 decisions on the loss domain. They observed that subjects displayed ambiguity aversion in both the gain and loss domains. However, unlike the gain domain, where ambiguity is displayed in both the probability and amount of outcomes, ambiguity aversion in the loss domain was driven by the size of the ambiguity.

Our measure of ambiguity aversion is different from the measure of Klibanoff et al. (2005), Engle-Warnick et al. (2007), and others. We consider a simple specification for which ambiguity aversion is specified as the ratio of two log utilities. Consider an ambiguity aversion parameter θ, such that, all other things equal, utility of a lottery is lower with ambiguity than without.[1] Without ambiguity, utility over the lottery is given by equation (3). If there is ambiguity (in the sense of unknown probabilities of x and y), then we can write the transformed utility function as

$$U(x, y; \hat{p}, \hat{q}, \sigma, \alpha, \lambda) = [w(\hat{p})v(x) + w(\hat{q})v(y)]^{\theta} \tag{4}$$

where $\hat{p}$ and $\hat{q}$ are now subjective probabilities. For ambiguity averse individuals, $\theta < 1$; for ambiguity neutral, $\theta = 1$; and for ambiguity seeking individuals, $\theta > 1$. In the following section, we introduce the experimental design and describe how this ambiguity aversion coefficient is measured in practice.

4 Experimental design and data

For this study, we used a series of lottery-based experiments to elicit the latent behavioral characteristics introduced in Section 3. The experiments used in this study were modified from Tanaka et al. (2010) in their study of Vietnamese households.[2] This experimental design has several key

[1]If, on the other hand, individuals are ambiguity seeking, utility will be higher under ambiguity than without it.
[2]This experimental design was also used by Liu (2013) in her study of Chinese cotton farmers.

advantages over some other experimental designs. First, as previously noted, it is general enough to allow for preferences to be consistent with EUT. Second, it has already been tested among individuals in different developing countries, and so is simple enough for relatively uneducated individuals in these settings to comprehend. Our experiments maintain the general design of the Tanaka et al. (2010) and Liu (2013) experiments, with slight modifications to the payouts as well as some additional simplifications to increase the probability of comprehension. Notably, contrary to Tanaka et al. (2010), most of our experiments involve choices between a certain payment and a risky prospect. This significantly simplifies the choices participants face, as well as simplifying the estimation of risk premia. In these experiments, chips numbered 1-10 are divided into "winning" and "losing" chips, such that chips 1–p are winning chips, while chips $(p + 1)$–10 are "losing" chips, and p varies from one experiment to the other.

We designed two experiments to estimate the two parameters central to PT: the probability weighting parameter (α) and the parameter describing value function curvature (σ). In each of these two experiments, respondents are presented with 14 choice scenarios and are asked to choose between two options. Option (A) is a riskless option while Option (B) is a risky option with both a "winning" and a "losing" draw. In the first of these two experiments, the riskless option always pays Rs. 10, while the risky option pays a "losing" award of Rs. 5 with a probability of 0.9 and a "winning" award of increasing magnitude with probability of 0.1. The second experiment has a similar structure, but with a higher riskless payout (Rs. 40), a higher probability of "winning" the risky draw (0.7), and a more gradual increase in the "winning" payouts with subsequent rounds. The payoff schedules for these two experiments are shown in Tables 1 and 2.

Since both the riskless payoff and the payoff arising from the "losing" draw are fixed, and since the payoffs from the "winning" draw are monotonically increasing in each successive round, we should observe respondents switching their preferences from the riskless option to the risky option at most one time.[3] To further enforce monotonic preferences, we follow Tanaka et al. (2010) and capture information only on the switching round in each experiment. These switching

[3]It should be noted, however, that respondents were not forced to switch. In conducting the experiments, several examples were given prior to eliciting responses. In one of these examples, the riskless option is chosen throughout, while in another example, the risky option is preferred in all rounds.

rounds are useful in identifying the underlying behavioral parameters, since the switching round is interpreted as the round at which the individual is indifferent between the two options. The two parameters are simultaneously determined, so in each of the experiments a given switching round is potentially consistent with several different combinations of behavioral parameters. As such, these two experiments are carefully designed so that the pair of switching rounds from the two experiments (in tandem) uniquely identifies the parameter tuple for which the respondents' choices are consistent under PT.

A third experiment is designed to estimate the loss aversion λ. In this experiment, respondents are presented with seven choice scenarios, each comprised of two lotteries. In each lottery, there is a "winning" draw with a positive payout and a "losing" draw with a negative payout. The payoff schedule for this experiment is presented in Table 4. The "winning" and "losing" payouts vary from round to round, but are specified in such a way that enables estimation of a range of possible loss aversion coefficients for each respondent. For each of the two lotteries, the probabilities of "winning" and "losing" are equivalent, so the probability weighting function applied to both "winning" and "losing" payouts in each of the lotteries is the same, and further drops out of consideration when estimating the loss aversion parameter for a particular switching round. For example, suppose an individual switched from Option A to Option B in round j. Then we assume that the utility derived from Option A in round j is the same as the utility derived from Option B in round j. Let $x_{j,A}$ and $x_{j,B}$ be the "winning" payoffs in round j corresponding to Options A and B, respectively, and let $y_{j,A}$ and $y_{j,B}$ be the corresponding "losing" payoffs. Then we can set the utility of the two prospects equal to one another:

$$w(p_A)v(x_{j,A}) + w(1 - p_A)v(y_{j,A}) = w(p_B)v(x_{j,B}) + w(1 - p_B)v(y_{j,B}) \tag{5}$$

where p_A and p_B are the probability of a "winning" draw in each of the two lotteries. Since $p_A = p_B = 0.5$, we can substitute in p for all probabilities. This then becomes

$$w(p)\left[v(x_{j,A}) + v(y_{j,A})\right] = w(p)\left[v(x_{j,B}) + v(y_{j,B})\right] \tag{6}$$

which reduces to

$$v(x_{j,A}) + v(y_{j,A}) = v(x_{j,B}) + v(y_{j,B}) \tag{7}$$

Then, for $x_{j,k} > 0$ and $y_{j,k} < 0$, this becomes

$$x_{j,A}^{\sigma} - \lambda_j(-y_{j,A})^{\sigma} = x_{j,B}^{\sigma} - \lambda_j(-y_{j,B})^{\sigma} \tag{8}$$

where λ_j is the loss aversion parameter associated with switching from Option B to Option A in round j. Clearly, λ_j is a function of σ, so an estimate for the upper bound of $\lambda_j(\sigma)$ is given by

$$\lambda_j(\sigma) = \frac{x_{j,A}^{\sigma} - x_{j,B}^{\sigma}}{(-y_{j,A})^{\sigma} - (-y_{j,B})^{\sigma}} \tag{9}$$

Table 5 provides a range of estimates for λ for different values of σ consistent with switching from Option A to Option B in each of the seven rounds.

The final two experiments aim to measure ambiguity aversion. Each present respondents with a series of 11 choices over potential monetary outcomes, where each choice includes a riskless option of Rs. 20 and a risky option with both a “winning” draw and a “losing” draw. The winning draw is constant across all 11 rounds (Rs. 40), but the “losing” draw declines in value in each subsequent round, so the objective expected value of the lottery declines from one round to the next. The payout schedule for these two experiments is shown in Table 6. In the first of these two experiments, respondents do not have any information regarding the distribution of “winning” and “losing” draws in the lottery option, so both risk and ambiguity are present. In the second of these experiments, respondents face the same set of choices, but with additional information regarding the distribution of “winning” and “losing” draws in the risky option. With ambiguity resolved, respondents are generally willing to switch from the risky to the riskless alternative at a later round, demonstrating ambiguity aversion as a constraint to maximizing otherwise expected utility. While the discussion of these two experiments follows the discussions of all other experiments, these were actually the first two conducted (in the order discussed here), so as to minimize the potential that subjective expectations would be biased by prior experiences.

In each of these final two experiments, we gather information on the round at which the participant switches from preferring the lottery to preferring the certain payment. At this switching round, it is assumed that the utility derived from each of the two options are equivalent. Let us first assume that decisions are made with proper knowledge regarding the distribution of "winning" and "losing" draws in the lottery. So, for example, for an individual switching from preferring the lottery to preferring the certain payment in round j, $U(x_A) = U(x_{j,B}, y_{j,B}; p, q)$.[4] As introduced in Section 3, ambiguity aversion is captured by an additional parameter that augments utility. In such a case, ambiguity only arises in Option B, so for an individual switching from the lottery to the riskless option in round k, $U(x_A) = [U(x_{k,B}, y_{k,B}; \hat{p}, \hat{q})]^{\theta}$. Given that the utility of the lottery in both cases is equivalent to $U(x_A)$, so the utility of the lotteries in the two experiments have the same certainty equivalent utility. We can write

$$U(x_{j,B}, y_{j,B}; p, q, \alpha, \sigma, \lambda) = [U(x_{k,B}, y_{k,B}; \hat{p}, \hat{q}, \alpha, \sigma, \lambda)]^{\theta} \tag{10}$$

Taking logarithms of both sides, we have

$$\ln U(x_{j,B}, y_{j,B}; p, q, \alpha, \sigma, \lambda) = \theta \ln U(x_{k,B}, y_{k,B}; \hat{p}, \hat{q}, \alpha, \sigma, \lambda) \tag{11}$$

This gives us an estimate of our ambiguity aversion measure:

$$\theta = \frac{\ln U(x_{j,B}, y_{j,B}; p, q, \alpha, \sigma, \lambda)}{\ln U(x_{k,B}, y_{k,B}; \hat{p}, \hat{q}, \alpha, \sigma, \lambda)} \tag{12}$$

In general, estimating θ requires information on σ, α, and λ, as well as the subjective probabilities assigned to the "winning" and "losing" draws from the lottery.[5] Estimates of σ, α, and λ can be obtained from the previous experiments and can be used in estimating utility. A naïve assumption that $\hat{p} = \hat{q} = 0.5$ seems like a reasonable approximation, but this may result in biased estimates

[4] Since the payout from Option A is a fixed payment across all rounds, we have suppressed the switching round subscript j.

[5] In the case of our experiments, there are no potential losses, so knowledge of λ is not needed to estimate θ.

of the ambiguity aversion parameter if participants systematically deviate from this assumption. Alternatively, we may ascertain ex post information regarding the participant's assumption about this distribution. This is done through a follow up question which asks respondents to guess how many of the chips are "winning" chips. While this gives some information on participants' subjective probabilities, it may not actually reflect the true subjective probability that was used when evaluating options. In our analysis, we followed both of these approaches.

To reduce hypothetical bias and provide incentives to elicit appropriate responses, actual payments were made for a randomly selected round among the five experiments described above. Participants were told in advance that they would be compensated based on the results of their choices and, where applicable, the results of the specified lottery. After the participant provided responses to all questions from these experiments, enumerators randomly selected a round from a bag of chips labeled 1-57.[6] Based on the round selected, participants were paid either the riskless payout corresponding to that round or the payout resulting from the lottery, in which enumerators randomly selected a chip numbered 1-10 from a separate bag. While experiment three has loss potential under both lotteries, participants were not asked to submit money if there was a losing draw from the lottery; instead, they merely did not win any money. The average earnings from the experiments was Rs. 30, with men earning Rs. 32 on average and women earning Rs. 28 on average.

These experiments were conducted along with a household survey in three districts in the state of Bihar, India. Bihar lies in the eastern Indo-Gangetic plain, bordering Nepal to the north, Uttar Pradesh to the west, Jharkhand to the south, and West Bengal to the east (see Figure 2). Although roughly 90 percent of the state's population live in rural areas (compared with only 72 percent at the national level), Bihar has the highest population density of any state in India, with an estimated 1,104 persons per square kilometer as of 2011. Bihar also has the lowest state-wise per capita income in India, with per capita incomes only 35 percent the national average in 2009-10 (Government of Bihar, 2012).

Our sample consists of observations from rice-producing households in rural Bihar. We used

[6]There are 14 rounds in each of the first two experiments, 7 in the third experiment, and 11 in each of the final two experiments, resulting in a total of 57 rounds.

a multi-stage sampling approach to form our survey sample. In the first stage, we selected three districts heavily dependent upon rice production in which to sample households: Bhojpur, Madhubani, and Nawada. These three districts provide a great deal of heterogeneity, not least in terms of geography and agro-ecology. In the second stage, we selected 16 high rice producing blocks across the three districts. The number of blocks drawn from each district is proportional to the share of rice production attributable to each district. Seven blocks were selected from Bhojpur, three from Nawada, and six from Madhubani. Within each of these blocks, we randomly selected two villages from which to draw households. From these villages, we randomly selected 18 rice growing households from village rosters prepared by enumerators through door to door listing. We interviewed the head male and head female within each household, both to provide some general observations regarding risk preferences between men and women, and also more specific analysis of differences between men and women within the same household.[7] We restricted our sample to those men and women who provided consistent responses to the risk and ambiguity questions. For example, if the respondent indicated that they preferred the riskless option in all rounds of one experiment, it is reasonably assumed that they should not prefer the risky option in all rounds of other experiments. Responses contrary to this basic assumption were deemed inconsistent and were subsequently dropped from analysis, since such inconsistencies likely either arise from enumerator error or respondents' failure to fully understand the options they are presented with, either of which have the potential to bias the results.[8] In addition, there were some respondents whose switching rounds were not consistent with reasonable values for σ or α. These observations were subsequently dropped from analysis. In all, our sample consists of 392 observations on men and 325 observations on women. Since some observations were deemed inconsistent and were dropped, we do not necessarily have balanced observations on men and women from the same households. Nevertheless, our data do contain information on men and women from 249 households.

[7] It is worth noting that there were both male and female enumerators involved in the survey, with male enumerators conducting surveys with male respondents, and female enumerators with female respondents.

[8] Stricter definitions of consistency could have been used, such as assuming that individuals who preferred the riskless option in all rounds during one experiment should prefer the riskless option in all rounds during other experiments, or that individuals who preferred the risky option in all rounds of one experiment should prefer the risky option in all rounds of other experiments. It was deemed that these definitions of consistent statement of preferences was too restrictive.

5 Results

Based on analysis of the first two experiments, we estimate average values for (σ, α) of (0.58, 0.73) for men, and (0.52, 0.73) for women. These estimates are quite similar to those reported in Tanaka et al. (2010) and Liu (2013) for their samples of Vietnamese households and Chinese farmers, respectively.[9] Our estimates of α for both men and women are significantly different from 1, with a p-value of 0.053 for men and 0.064 for women. With these values significantly different from 1, we reject EUT in favor of inverted-S shaped probability weighting. From the third experiment, we estimate an average loss aversion parameter of $\lambda = 4.99$ for men and $\lambda = 5.97$ for women.[10]

We compared the mean values for these estimated parameters across the male and female subsamples, and generally found the mean behavioral parameter values to be different between men and women. Table 7 reports the estimated sample means and standard deviations for each of the parameters, as well as a t-statistic testing the null hypothesis that the sample means are equal. We reject this null for σ and λ, but reject this null for α. Contrary to the findings in Tanaka et al. (2010), these results indicate that women are significantly more risk averse than men. This finding is consistent with many other studies conducted both in laboratory settings as well as in the field (see, e.g., the review in Eckel and Grossman, 2008). We also that women are significantly more averse to losses than men are.

Figure 3 plots the kernel density estimates of the distribution of σ differentiated by gender. For both men and women, the distribution of σ is roughly bimodal, with a density corresponding to what could be called a low σ sample segment and a density corresponding to what could be called a high σ sample segment. For women, the low σ corresponds to a nontrivial density of extremely risk averse women (53 out of 519 have $\sigma \leq 0.1$), while for men the low σ segment is a larger group with less extreme risk aversion. Visualizing the estimated parameters in this fashion suggests that perhaps women as a whole are not inherently different from men in how they view or feel about risk, but rather there are some factors that increase the probability that some women will fall into an

[9] For comparison purposes, Tanaka et al. (2010) report average values of $(\sigma, \alpha) = (0.59, 0.74)$, while Liu (2013) reports average values of $(\sigma, \alpha) = (0.48, 0.69)$.

[10] Estimates of λ represent the lower bound of the intervals reported in Table 5 conditional upon each individual's estimated σ parameter.

extremely risk averse sub-group. Studying this phenomenon may be an avenue for future research.

We also calculate ambiguity averison coefficients (θ) based on equation 12. We compute these parameters under two alternative scenarios for subjective probabilities, one in which we naïvely assume that respondents subjectively assess the probability of a "winning" draw from a lottery at 0.5, and one in which we use responses given by the responents on their beliefs about the distribution of "winning" and "losing" chips. On average, men guessed that approximately 5 out of 10 chips were "winning", while women were less optimistic, guessing that only 4 of the 10 chips were "winning". The results are reported in Table 8. When we naïvely assume that respondents sujectively assess probabilities at 0.5, we find, on average, a very small degree of ambiguity aversion in both men and women (1.005 for men and 1.002 for women). When we use the subjective probabilities provided by respondents, we actually find on average a small degree of ambiguity seeking behavior, with ambiguity aversion coefficient estimates of (0.999 and 0.944 for men and women, respectively. In all, when we assume naïve subjective probabilities, we find that 27 percent of men and 26 percent of women were ambiguity averse, while 38 percent of men and 38 percent of women were ambiguity seeking. The remaining 34 percent of men and 36 percent of women were ambiguity neutral. When we use the subjective probabilities provided by respondents, we find that 43 percent of men and 16 percent of women were ambiguity averse, while 45 percent of men and 75 percent of women were ambiguity seeking. The remaining 12 percent of men and 9 percent of women were ambiguity neutral.

6 The Effects of Risk, Loss, and Ambiguity Aversion on Technology Adoption

To demonstrate the effects of risk aversion, loss aversion, and ambiguity aversion on the adoption of new agricultural technologies, we consider two empirical examples. In both cases, we are interested in exploring the effects of these parameters on adoption of new rice seeds. Since our sample consists of rice farming households, and since rice cultivation is largely still a manual operation in much of eastern India, new rice seeds seem a particularly relevant technology to consider given our context.

First, we consider the effects of σ, λ, and θ on experimentation with new seed varieties tried in the last 5 years; specifically, our dependent variable is the number of new varieties cultivated over that span. In addition to σ, λ and θ, we also include household income (logged), age, literacy, area of land owned, experience with rice cultivation, household size as additional explanatory variables, and district dummy variables. Summary statistics for these variables are reported in Table 9.

The results of OLS and Poisson regressions are reported in Table 10. From the OLS regression, we see that both λ and θ have statistically significant effects on trying new rice varieties. Specifically, more loss averse farmers are more likely to try more varieties, perhaps demonstrating a willingness to diversify and buffer against downside losses. More ambiguity averse households, on the other hand, are less likely to try new seeds, since the yield potential of new varieites is unknown to the farmer a priori. There does not appear to be a significant effect of risk aversion on trying new rice varieties, evidenced by the negligible coefficient for σ. The signs of the important effects persist when we consider the discrete, count nature of the data, though the estimated coefficient on θ is now insignificant at standard levels (the estimate is significant at just outside standard levels).

Our second demonstration of the effects of risk aversion, loss aversion, and ambiguity aversion come from combining these data with a discrete choice experiment designed to study farmers' heterogeneous preferences for drought-tolerance characteristics in hypothetical seed options. Drought tolerance was presented in the choice experiment as a seires of yields under normal conditions, moderate stress conditions and severe stress conditions. Each seed alternative consisted of a yield distribution represented as a bundle of three levels, one corresponding to each of the aforementioned weather scenarios. The base level of this attribute roughly corresponds to the yield performance of Sabhagi dhan, a self-pollinating (inbred) drought tolerant rice variety approved for use in Jharkhand and Orissa, and soon to be tested in Bihar. Sabhagi dhan's yield distribution first-order stochastically dominates the yield distributions for most other inbred varieties, including IR 36 and IR 64, two common mega-varieties cultivated throughout much of eastern India. We incorporate a total of six yield attribute levels, three corresponding to inbred varieties that first-, second-, third-order stochastically dominate check varieites, and three corresponding to hybrid varieties also first-, second-, and third-order stochastically dominating the check varieties.[11] Other attributes included in the choice experiment include duration (short, less than 120 days; medium, 120-135 days; and long, more than 135 days), whether grain can be stored and re-used the following season as seed (binary), the seeding rate (amount of seed required per unit of land, also binary, with a high seeding rate–corresponding to 12–15 kg/ha–equal to 1, and low seeding rate–corresponding to 4-6 kg/ha–equal to 0), and price.

Choice sets were constructed by specifying a D-efficient design taking into consideration all main effects as well as potential interactions between the yield and seed rate attributes with the binary seed-type attributed. In each choice set, farmers were presented with three hypothetical seed alternatives, plus a fourth option in which they could choose to cultivate the variety they cultivated in the previous rice-growing season. Information on these "own varieties" were gathered during the household survey so that it could be used in the ultimate choice analysis.

Since farmers are heterogeneous, their preferences are expected to demonstrate a great deal of heterogeneity. One common way of modeling such heterogeneity is through a mixed (random parameters) logit (RPL). The RPL is a highly flexible model that can approximate any random unitlity model and relaxes assumptions on the independence of choice alternatives by allowing random teast variation within a sample according to specified distributions. Under this model, the deterministic component of utility is

$$v_{ijt} = x'_{ijt}\beta \tag{13}$$

where v_{ijt} is the utility associated with individual i choosing alternative j during choice task t, x_{ijt} is a vector of attributes for the j^{th} alternative. Following Train (2003), the probability that individual i chooses alternative j from the choice set $\mathcal{C}$ in choice task t is

$$P_{ijt} = \int \frac{\exp(v_{ijt})}{\sum_k \exp(v_{ikt})} f(\beta) d\beta \tag{14}$$

[11] Based on personal communication with rice breeders from the International Rice Research Institute (IRRI), it was determined that a realistic scenario for drought tolerant hybrid cultivars is that they could yield 15 percent higher than Sabhagi dhan during normal conditions, though this yield advantage would decrease to only 10 percent in moderate stress conditions and 5 percent in severe drought stress conditions (A. Kumar, peers. comm.).

where k defines the number of alternatives presented in each choice task. In order to allow P_{ijt} to depend on risk, loss, and ambiguity aversion, we modify equation (14) to allow for variables z_i (with corresponding alternative-specific parameter matrix γ_j) to condition this choice probability:

$$P_{ijt} = \int \frac{\exp\left(v_{ijt} + z_i'\gamma_j\right)}{\sum_k \exp\left(v_{ikt} + z_i'\gamma_k\right)} f(\beta) d\beta \tag{15}$$

Thus for a choice experiment in which respondents are presented with four alternatives per choice task (as in our case), we estimate four parameters for each column of z_i. In this specific context, $z_i = \left[\sigma_i, \lambda_i, \hat{\theta}_i\right]$, where we have converted our ambiguity aversion measure such that

$$\hat{\theta}_i = \begin{cases} 0 & \text{if} \ \ \theta_i \leq 1 \\ 1 & \text{if} \ \ \theta_i > 1 \end{cases}$$

Since we are only concerned with the effects of these three parameters on the choice probabilities for the four alternatives, we only report the relevant coefficient estimates. As reported in Table 11, σ, λ, and $\hat{\theta}$ are have statistically significant effects in conditioning the choice of "own seed" relative to the first alternative, but generally no significant effect on choosing either of the other two varying alternatives.[12] Thus, other things equal, the probabilities of choosing any of the first three alternatives are generally unaffected by risk aversion, loss aversion, or ambiguity aversion, but the choice to continue cultivating the variety cultivated last rice season is significantly affected by these parameters.[13] Not surprisingly, ambiguity averse individuals are significantly more likely to stick with what they know, even though the other three alternatives presented in the choice sets have stated yields under all three rainfall scenarios that stochastically dominate local check varieties to one degree or another. Also not surprising, we find that farmers with higher degree of loss aversion are less likely to prefer their own seed over drought tolerant varieties included in

[12] The positive and significant effect of loss aversion on the probability of selecting the second alternative (λ_2) is somewhat puzzling, as there is no systematic basis for which the second alternative presents a lower loss scenario. This may simply be an abberation or coincidental.

[13] Note we cannot say anything about whether they would actually adopt the new seeds if they were available. That is, we lack a proper counterfactual to make such assertions. These new seeds may be prohibitively expensive, or farmers may not have adequate liquidity or access to credit, or there may be supply-side constraints. We are limited to making statements about farmers preference of the seed they are familiar with.

the other three choice alternatives. What is surprising, however, is that even after controlling for these other effects, more risk averse farmers (lower σ) are more likely to prefer their own seed. This suggests that risk averse farmers may be especially sensitive to extreme tail events and, even though the hypothetical seeds presented in the other three alternatives yield better than check varieties even under extreme drought stress conditions, risk averse farmers may perceive that the relative yield advantages of such varieties eventually deteriorate somewhere far out in the extreme tail of the rainfall distribution.

7 Conclusion

In this paper we have used a series of lottery-based field experiments to measure various behavioral parameters, including risk aversion, loss aversion, and ambiguity aversion. We reject expected utility theory as a sufficient heuristic for studying farmers' production decisions within our particular context, finding instead evidence in favor of cumulative prospect theory. Specifically, we find that risk aversion alone does not sufficiently describe individuals' behavior, but rather we also find that individuals have a tendency to weigh outcomes differently and demonstrate aversion to potential losses. Using gender disaggregated data, we have demonstrated that women are significantly more averse to both losses as well as risks. Additionally, we find evidence that some individuals exhibit a distaste for ambiguous situations, such as not knowing the probabilities of different events occurring. Other individuals seem to enjoy the ambiguity, valuing ambiguous gambles with known payouts more than unambiguous ones.

Coupling these estimated behavioral parameters with data from a discrete choice experiment over rice seeds, we find evidence that risk aversion, loss aversion, and ambiguity aversion significantly affect the probability of technology adoption. Ambiguity averse individuals are less likely to forego a familiar rice variety, while more loss averse individuals are more likely to switch to varieties offering yield advantages under drought stress conditions. We also find that more risk averse farmers are less likely to switch to new rice cultivars, even when the new cultivars outperform other popular varieties in normal conditions as well as in moderate and severe drought stress conditions. While this appears counterintuitive at first, we suggest this result may be capturing the sensitivity of risk averse individuals to perceived declines in the relative yield advantage of these hypothetical cultivars in the extreme tails of the rainfall distribution.

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Table 1: Payoff schedule for first experiment (in Indian rupees)

Round Number	Option (A)	Option (B) Chip 1	Option (B) Chips 2-10
1	10	26	5
2	10	28	5
3	10	32	5
4	10	36	5
5	10	41	5
6	10	47	5
7	10	56	5
8	10	63	5
9	10	72	5
10	10	85	5
11	10	104	5
12	10	133	5
13	10	181	5
14	10	280	5

Note: On average, men switched from Option A to Option B in round 6 , while women on average switched from Option A to Option B in 5.

Table 2: Payoff schedule for second experiment (in Indian rupees)

Round Number	Option (A)	Option (B) Chips 1-7	Option (B) Chips 8-10
1	40	56	5
2	40	57	5
3	40	60	5
4	40	62	5
5	40	65	5
6	40	69	5
7	40	73	5
8	40	77	5
9	40	82	5
10	40	87	5
11	40	95	5
12	40	105	5
13	40	119	5
14	40	137	5

Note: On average, men switched from Option A to Option B in round 5 , while women on average switched from Option A to Option B in 4.

Table 3: Switching points (point at which preferences switch from riskless option to risky option) and approximate values of parameters σ and α

Experiment 1

		α									
		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
	0.1	4	5	7	9	10	12	13	N	N	N
	0.2	3	5	6	7	9	11	12	13	14	N
	0.3	3	4	5	6	7	9	11	12	13	14
σ	0.4	2	3	4	5	7	8	10	11	12	13
	0.5	1	2	3	4	6	7	8	10	11	12
	0.6	1	1	3	4	5	6	7	9	10	11
	0.7	1	1	2	3	4	5	6	7	9	10
	0.8	1	1	1	3	3	5	6	7	8	9
	0.9	1	1	1	2	3	4	5	6	7	8
	1.0	1	1	1	1	2	3	4	5	6	7

Experiment 2

		α									
		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
	0.1	N	N	N	N	N	N	14	13	12	10
	0.2	N	N	N	N	14	13	12	11	10	9
	0.3	N	N	N	14	13	12	11	10	9	8
σ	0.4	N	N	14	13	12	11	10	9	8	6
	0.5	N	14	13	12	11	10	9	8	7	6
	0.6	14	13	12	11	10	9	8	7	6	5
	0.7	13	12	11	10	9	8	7	6	5	4
	0.8	13	12	11	9	8	7	6	5	4	3
	0.9	12	11	10	8	7	6	5	4	3	2
	1.0	11	10	9	7	6	5	4	3	2	1

Note: "N" indicates never switching from the riskless option to the risky prospect.

Table 4: Payoff schedule for third experiment (in Indian rupees)

Round	Option (A)		Option (B)	
Number	Chips 1-5	Chips 6-10	Chips 1-5	Chips 6-10
1	25	-4	30	-21
2	4	-4	30	-21
3	1	-4	30	-21
4	1	-8	30	-21
5	1	-8	30	-21
6	1	-8	30	-21
7	1	-8	30	-21

Note: On average, men switched from Option A to Option B in round 5 , while women on average switched from Option A to Option B in 5.

Table 5: Approximate ranges of loss aversion coefficient (λ) for different switching rounds under different values of risk aversion coefficient (σ)

Switching Round	σ = 0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
1	$\lambda < 0.13$	$\lambda < 0.14$	$\lambda \leq 0.16$	$\lambda \leq 0.17$	$\lambda \leq 0.19$	$\lambda \leq 0.21$	$\lambda \leq 0.23$	$\lambda \leq 0.25$	$\lambda \leq 0.27$	$\lambda \leq 0.30$
2	$0.13 < \lambda \leq 1.24$	$0.14 < \lambda \leq 1.27$	$0.16 < \lambda \leq 1.29$	$0.17 < \lambda \leq 1.32$	$0.19 < \lambda \leq 1.35$	$0.21 < \lambda \leq 1.38$	$0.23 < \lambda \leq 1.42$	$0.25 < \lambda \leq 1.45$	$0.27 < \lambda \leq 1.49$	$0.30 < \lambda \leq 1.53$
3	$1.24 < \lambda \leq 1.96$	$1.27 < \lambda \leq 1.88$	$1.29 < \lambda \leq 1.82$	$1.32 < \lambda \leq 1.77$	$1.35 < \lambda \leq 1.74$	$1.38 < \lambda \leq 1.71$	$1.42 < \lambda \leq 1.70$	$1.45 < \lambda \leq 1.70$	$1.49 < \lambda \leq 1.70$	$1.53 < \lambda \leq 1.71$
4	$1.96 < \lambda \leq 2.38$	$1.88 < \lambda \leq 2.32$	$1.82 < \lambda \leq 2.27$	$1.77 < \lambda \leq 2.25$	$1.74 < \lambda \leq 2.24$	$1.71 < \lambda \leq 2.25$	$1.70 < \lambda \leq 2.27$	$1.70 < \lambda \leq 2.31$	$1.70 < \lambda \leq 2.36$	$1.71 < \lambda \leq 2.42$
5	$2.38 < \lambda \leq 4.59$	$2.32 < \lambda \leq 4.33$	$2.27 < \lambda \leq 4.12$	$2.25 < \lambda \leq 3.95$	$2.24 < \lambda \leq 3.83$	$2.25 < \lambda \leq 3.73$	$2.27 < \lambda \leq 3.67$	$2.31 < \lambda \leq 3.63$	$2.36 < \lambda \leq 3.62$	$2.42 < \lambda \leq 3.63$
6	$4.59 < \lambda \leq 5.72$	$4.33 < \lambda \leq 5.43$	$4.12 < \lambda \leq 5.21$	$3.95 < \lambda \leq 5.03$	$3.83 < \lambda \leq 4.91$	$3.73 < \lambda \leq 4.82$	$3.67 < \lambda \leq 4.78$	$3.63 < \lambda \leq 4.77$	$3.62 < \lambda \leq 4.79$	$3.63 < \lambda \leq 4.84$
7	$5.72 < \lambda \leq 10.17$	$5.43 < \lambda \leq 9.78$	$5.21 < \lambda \leq 9.49$	$5.03 < \lambda \leq 9.29$	$4.91 < \lambda \leq 9.18$	$4.82 < \lambda \leq 9.14$	$4.78 < \lambda \leq 9.17$	$4.77 < \lambda \leq 9.27$	$4.79 < \lambda \leq 9.44$	$4.84 < \lambda \leq 9.67$

Table 6: Payoff schedule for fourth and fifth experiment (in Indian rupees)

Round Number	Option (A)	Option (B) Chips 1-5	Option (B) Chips 6-10
1	20	40	20
2	20	40	16
3	20	40	13
4	20	40	10
5	20	40	8
6	20	40	7
7	20	40	6
8	20	40	5
9	20	40	4
10	20	40	2
11	20	40	0

Note: In experiment 4, subjects are not told what the underlying probability of a "winning" draw in the lottery from Option B. In experiment 5, subjects are given information that chips 1-5 are "winning chips", while chips 6-10 are "losing" chips. On average, men switch from Option B to Option A in round 5 in experiment 4, while women on average switch from Option B to Option A in round 5. In experiment 5, men on average switch from Option B to Option A in round 5, while women on average switch from Option B to Option A in round 5.

Table 7: Estimates of prospect theory parameters over male and female sub-samples

Parameter	Males	Females	t-Statistic	
σ	0.58	0.52	3.24	***
α	0.73	0.73	0.01	
λ	4.99	5.97	-3.80	***

Note: * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level. Note $\sigma = 1 - \rho$, where ρ is the coefficient of risk aversion. Increasing σ on $(0, 1)$ implies less curvature in the prospect value function, consistent with a lower degree of risk aversion.

Table 8: Estimates of ambiguity aversion parameters over male and female sub-samples

Parameter	Males	Females	t-Statistic
θ_{naive}	1.01	1.00	0.68
$\theta_{\text{subjective}}$	1.00	1.00	-0.37

Note: * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level.

Table 9: Summary statistics of variables included in empirical analysis of effects of risk, loss, and ambiguity aversion on technology adoption

	Mean	Std. Deviation	Minimum	Maximum
Number of new varieties (last 5 years)	1.211	1.141	0.000	7.000
σ	0.589	0.263	0.020	1.000
λ	5.127	3.415	0.112	10.568
θ	1.007	0.076	0.602	1.802
ln(Income)	10.900	0.891	8.517	14.914
Experience cultivating rice	54.818	42.354	1.000	99.000
Area of land owned	1.974	3.524	0.000	37.500
Household size	6.380	2.910	2.000	23.000
Age	49.562	12.802	17.000	81.000
Bhojpur (=1)	0.409	0.492	0.000	1.000
Nawada (=1)	0.230	0.422	0.000	1.000
Madhubani (=1)	0.361	0.481	0.000	1.000

Table 10: OLS and Poisson Regression Estimates: Effects of risk, loss, and ambiguity aversion on experimentation with new rice varieties

	OLS			Poisson		
	Estimate	Std. Error		Estimate	Std. Error	
Intercept	1.826	1.179		0.604	1.048	
σ	0.089	0.237		0.088	0.193	
λ	0.071	0.025	***	0.056	0.021	***
θ	-1.480	0.813	*	-1.189	0.764	
ln(Income)	0.082	0.072		0.066	0.062	
Experience cultivating rice	-0.000	0.002		-0.000	0.001	
Area of land owned	0.006	0.018		0.005	0.016	
Household size	0.008	0.022		0.008	0.018	
Age	-0.003	0.005		-0.003	0.004	
Bhojpur (=1)	-0.455	0.181	**	-0.331	0.155	**
Nawada (=1)	-0.616	0.207	***	-0.525	0.193	***
N	313			313		
Adjusted R^2	0.136					
Pearson's χ^2				387.176		

Note: * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level.

Table 11: Random Parameters Logit Estimates: Effects of risk, loss, and ambiguity aversion on choice probabilities of hypothetical alternatives and continued cultivation of familiar seed

	Estimate	Std. Error	
σ_2	-0.142	0.158	
σ_3	-0.073	0.144	
σ_4	-0.837	0.185	***
λ_2	0.040	0.017	**
λ_3	0.007	0.016	
λ_4	-0.198	0.023	***
$\hat{\theta}_2$	-0.009	0.147	
$\hat{\theta}_3$	-0.104	0.138	
$\hat{\theta}_4$	0.556	0.164	***

Note: * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level. Estimates of choice experiment attribute main effects and their distributions have been suppressed. These estimates are based on random parameters logit estimation of choice responses from 348 individuals, each of whom responded to 9 choice sets consisting of four alternatives, the fourth alternative being to use the variety cultivated during the previous *kharif* (monsoon) season. Subscripts refer to the alternative number, with the first alternative being the reference to which estimates are being compared.

Figure 1: Prospect theory value function with risk aversion and loss aversion

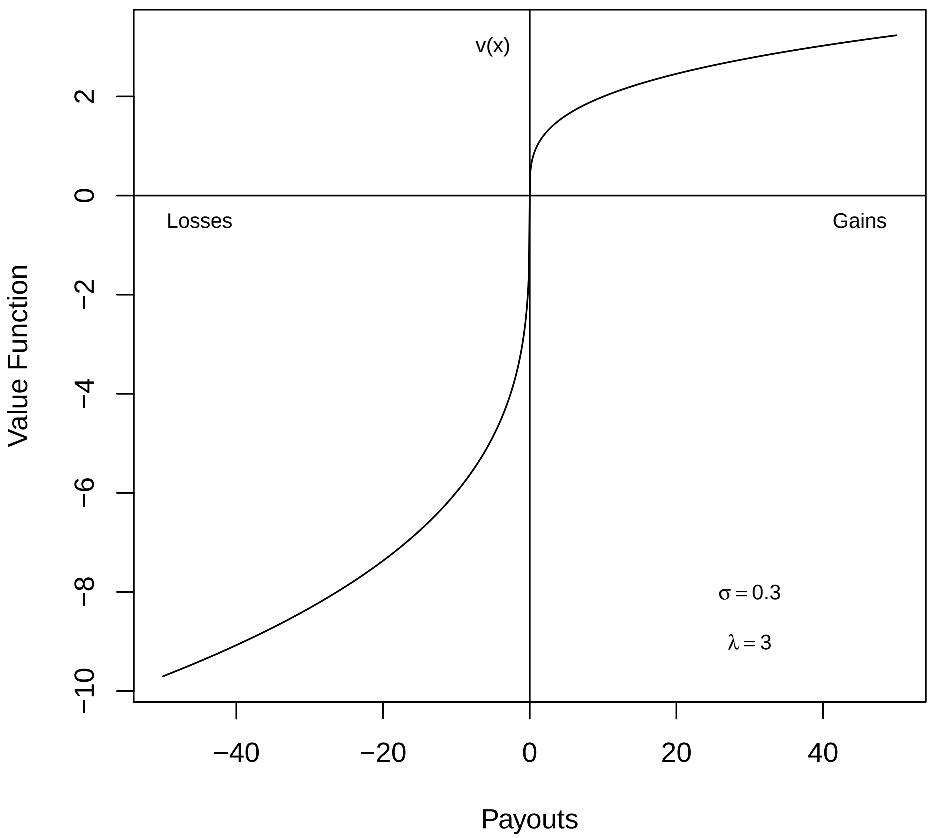
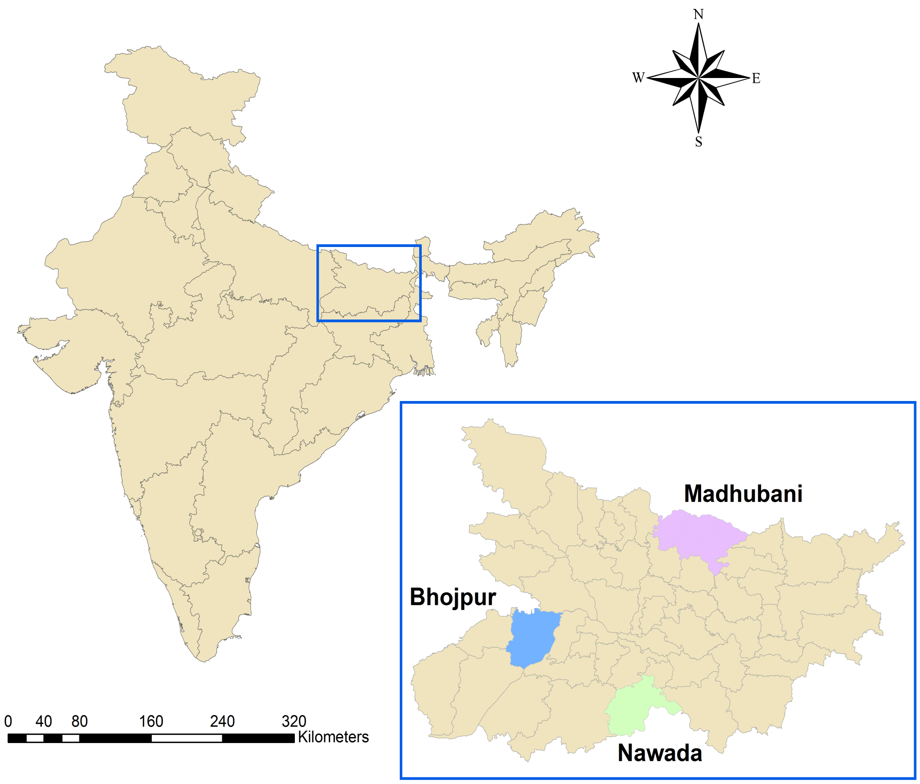


Figure 2: Location of sample districts in Bihar, India



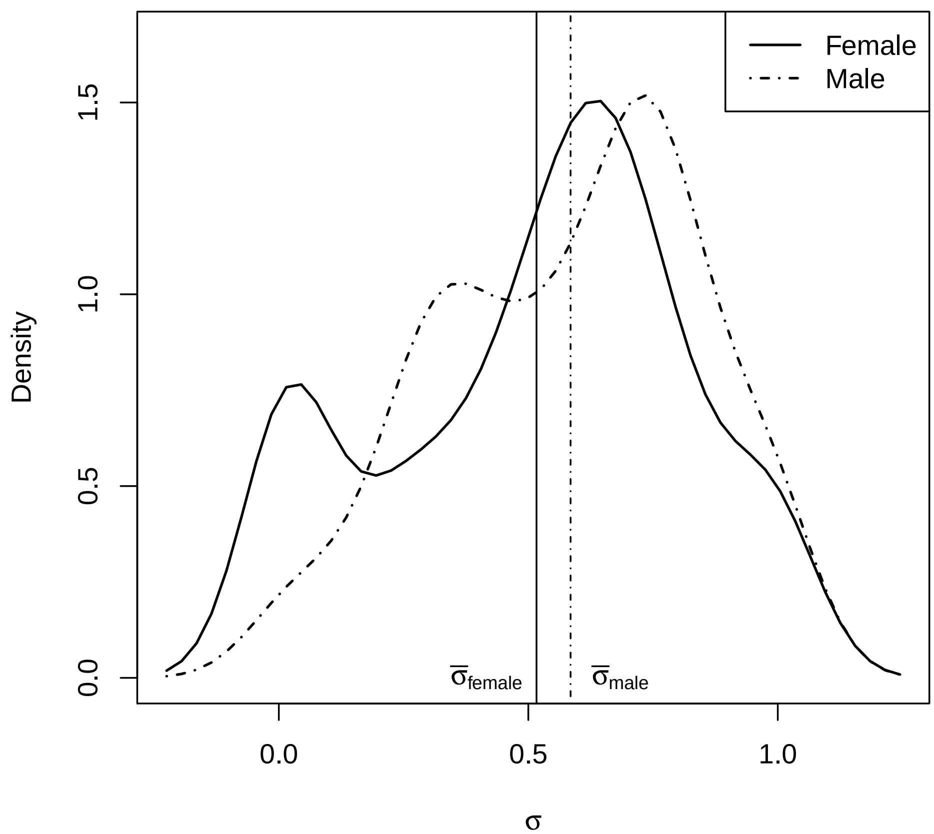


Figure 3: Empirical distribution of σ over male and female samples
Note: $\overline{\sigma}_{\text{male}}$ and $\overline{\sigma}_{\text{female}}$ indicate sample means for male and female samples, respectively.