Climate Change and Index Insurance Demand: Evidence from a Framed Field Experiment in Tanzania

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Abstract

Index insurance has been touted as part of an adaptation strategy to mitigate climate risks among smallholder farmers. However, in the face of increasing drought probabilities, demand for index insurance may decrease compared to a scenario with no climate change, if farmers learn slowly or place considerable weight on prior beliefs. Using data from a framed field experiment in Tanzania, we estimate a structural learning model based on a Bayesian change-point inference method and separately identify the effect of learning, expectations, recency bias, and ambiguity on insurance demand. Furthermore, by simulating the supply-side of the insurance market under a set of plausible assumptions, we show that climate change results in reduced uptake rates in most cases, although demand may increase if the severity of climate change is sufficiently low. Overall, our results provide an alternative explanation for the puzzle of low index insurance demand.

Keywords: Index Insurance; Climate Change; Learning; Ambiguity Aversion; Recency Bias; Framed Field Experiment

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1 Introduction

Weather risk poses numerous threats to farmers and pastoralists in developing countries, particularly smallholders who have limited ability to cope with systemic shocks. Such shocks may have dire consequences, including reduced childhood survival, body size, and educational attainment, the sale of productive assets, and poverty traps (Maccini and Yang 2009, Maluccio et al. 2009, Carter and Lybbert 2012, Barrett and Santos 2014). Formal index insurance programs, which pay an indemnity based on an objective index, have been proposed as a viable and cost-effective solution to systemic risk. However, while index insurance has been shown to reduce dips in consumption and the sale of productive assets, as well as to increase farmer investment and access to credit, (Kazianga and Udry 2006, Miranda and Farrin 2012, Janzen and Carter 2013, Karlan et al. 2014)[1], demand for such products has been surprisingly low (Giné et al. 2008, Giné and Yang 2009, Karlan et al. 2011, Cole et al. 2013). The literature has offered several explanations for the low uptake rates, including lack of trust, poor marketing, high prices, access to informal insurance mechanisms, and basis risk (Giné et al. 2008, Giné and Yang 2009, Cole et al. 2013, Clarke 2016).

This paper offers an alternative explanation to this puzzle. In the face of a changing climate, under which drought risk is increasing over time, farmers will face an uncertain distribution of losses and thus may be unable to evaluate the true benefits of insurance (Partridge and Wagner 2016, Daron and Stainforth 2014). If learning is slow or if they place considerable weight on prior beliefs, insurance demand will be lower under climate change relative to a world in which the distribution remains constant. In particular, we hypothesize that there are three factors that affect demand for index insurance in the face of climate change. First, as farmers observe weather shocks over time, they will learn about the new distribution and update their willingness to pay

[1] The impact of index insurance on demand for credit is less clear (Giné and Yang 2009). An important consideration discussed in Collier et al. 2009 and Isakson 2015 is that index insurance, particularly if heavily subsidized, may discourage more sustainable adaptation to climate change and incentivize smallholders to remain in untenable risk situations. Moreover, climate change may change which farmers stand to benefit from index insurance. In particular, as risk increases, farmers in low-risk areas may benefit and others will need other forms of adaptation. An open policy question is how to channel the increases in credit access and investment associated with index insurance toward more climate-sustainable outcomes. See Section 6 and Appendix B.2 for a discussion of this issue.

for insurance. Second, the mere expectation of climate change will impact demand, independent of whether climate change has occurred. Finally, the prospect of climate change introduces ambiguity, independent of expectations and actual changes in the underlying distribution.

Using data from a framed field experiment (Harrison and List 2004) in the drought-prone Dodoma Region of Tanzania, we estimate the insurance demand response to an unknown and changing drought risk. In particular, using both reduced-form regression analysis and a structural learning model that incorporates a Bayesian change-point inference method (Smith 1975), we separately identify the effects of learning, expectations, and ambiguity aversion on demand for index insurance. Our results indicate that while ambiguity aversion and expectations about climate change increase demand, farmers underestimate the true drought probability and place considerable weight on prior beliefs, resulting in a net decrease in overall demand for index insurance relative to a full-information world. The structural learning model also allows us to separately identify the effect of recency bias [2] from the effect of learning, and our results show that following a drought event, demand increases significantly beyond what can be explained by learning alone. This is consistent with several recent studies, which have found a large increase in insurance demand in the period immediately following a payout (Gallagher 2014, Cole et al. 2014, Stein 2016, Platteau et al. 2017, Cai et al. 2016).

In order to estimate the effect of climate change on insurance uptake rates, we simulate the supply-side response under three separate assumptions about how insurance companies update their premiums. In particular, we assume that the insurance company either has complete information about the true probability, learns using a naive Bayesian updating model, or uses a sophisticated Bayesian updating model in which it considers a distribution of climate change scenarios; moreover, we assume insurance companies offer insurance with an ambiguity load to account for climate change. Our simulation results show that under the sophisticated model, insurance uptake rates will always decrease relative to a full-information no-climate change scenario. Under the complete information

[2] Recency bias, also called attenuation bias, refers to individual's placing a higher weight on recent data when determining the expectations of the probability of future events.

or naive updating assumptions, uptake rates may increase if the change in the drought probability due to climate change is sufficiently low (by less than 10-15 percentage points), but decrease otherwise. Together, these results provide a plausible explanation for the low index insurance uptake rates in regions that have been subject to changes in the frequency of severe weather events.

Only a handful of papers have studied the effect of climate change on insurance demand, while none have identified the relative effect of different mechanisms. The closest work to ours is Botzen and Bergh (2012), who use a contingent valuation methodology to estimate demand for flood insurance in the Netherlands when flood probabilities increase due to climate change. Using prospect theory and a Bayesian learning model, they show that insurance demand increases less than proportionally to an increase in risk, suggesting that climate change could stifle demand. Moreover, Akter et al. (2017) shows that farmers who exhibited fatalistic views regarding the consequences of climate change were significantly less likely to purchase insurance. Furthermore, Brouwer and Schaafsma (2013) use a set of choice experiments to show that increases in both flood probability and severity increase the willingness to pay for insurance.

The process by which farmers learn about climate change has received considerable attention in the literature. In particular, there is evidence that people learn from new data in ways that are asymmetric or biased compared to a standard Bayesian updating model (Holt and Smith 2009, Gallagher 2014, Lybbert et al. 2007, Barham et al. 2015, Kala 2017, Taraz 2017). For example, Gallagher (2014) shows that a Bayesian learning model that discounts past information best explains U.S. flood insurance demand, while Holt and Smith (2009) find that people systematically deviate from Bayesian predictions when their priors are particularly high or low. Our results are consistent with these findings in that participants' slow response to probability changes is due to the considerable weight put on prior beliefs. Furthermore, Kelly et al. (2005) employ a Bayesian learning model to show that agricultural firms incur adjustment costs when learning about a changing distribution. While we do not model adjustment costs directly, we show that the utility loss due to learning results in sub-optimal demand for insurance when compared to the full-information scenario. To our knowledge, the first work that looks specifically at how learning about systemic risk affects index insurance demand is Jensen et al. (2018), who find evidence of spatial and intertemporal adverse selection in livestock index insurance in Kenya.

There is also a rich economics literature suggesting that people prefer risks with known probabilities over ambiguous risks with unknown probabilities (Ellsberg 1961, Gilboa and Schmeidler 1989, Klibanoff et al. 2005). By adding ambiguity to the true probability of a systemic shock, climate change may affect farmers' insurance decisions even if the underlying pure risk remains unchanged.[3] When the efficacy of a new technology or insurance product is ambiguous, ambiguity aversion has been shown to reduce demand for it (Carter et al. 2015, Bryan 2013). Conversely, when an insurance product fully covers an ambiguous risk, demand has been shown to increase (Alary et al. 2013, Bryan 2013). The results of this paper are consistent with this finding, as participants are willing to pay more for insurance when the risk it covers is ambiguous due to climate change. This effect is also consistent with results in the climate change adaptation literature more broadly, where the ambiguity inherent in climate change leads farmers to pay more for adaptation and exercise caution when choosing planting times (Alpizar et al. 2011, Kala 2017).

This paper contributes to the existing literature in three ways. First, it is the first paper to experimentally examine the effect of a change in climate risk on insurance demand. This allows us to draw conclusions about the economic viability of microinsurance programs in the face of changing climate risk and may provide a possible explanation for the low uptake rates found in most microinsurance pilot studies. Second, it is the first paper, to our knowledge, to apply a Bayesian change-point inference model to estimate farmers' beliefs about changing probability distributions. This analysis may be applied to other contexts where people learn about a changing risk. Finally, the results confirm the importance of two behavioral factors, ambiguity aversion and recency bias, in determining index insurance demand.

[3] Climate change may make farmers less certain of the weather risk they face for multiple reasons. Data that differs from smallholders' long-held beliefs about the likelihood of drought may call those beliefs into question. Disruptions of usual seasonal patterns – such as rain in the traditionally dry season – may also change farmers' confidence in their beliefs about drought in the growing season. Finally, incomplete or conflicting weather and climate forecasts may increase ambiguity.

The rest of the paper is structured as follows. Section 2 develops a theoretical model of the effect of climate change on index insurance demand incorporating Bayesian learning with a change-point in risk, as well as ambiguity aversion and recency bias parameters. Section 3 describes the framed field experiment and provides descriptive statistics for the data collected. Section 4 lays out the reduced-form and structural estimation strategy, and describes the estimation results. Section 5 outlines three potential insurance supply scenarios, and calculates how insurance premiums would be affected by climate change under each scenario. Section 6 describes our policy simulation, where we combine the structural model of insurance demand with the supply scenarios to draw conclusions on how climate change may affect insurance uptake rates. Section 7 concludes.

2 Theoretical Model

Consider an agent i with preferences that satisfy the axioms of Von Neumann-Morgenstern Expected Utility Theory so that they can be expressed as a utility function $u_i(c)$. Each season t, the agent receives non-farm income ω (from remittances, wage work, selling, etc.) and farm income that depends on the state of nature. There are two states of nature: good rains and drought. If rains are good, the agent receives y_h, while a drought yields an income of y_l, such that $y_h > y_l$. The subjective probability that the agent places on the likelihood of a drought in time period t, is p_{it}. There is no saving in this model, so the agent consumes her entire income. Without insurance, the agent's expected utility in period t can be written as:

$$Eu_{it}(.) = p_{it}u(\omega + y_l) + (1 - p_{it})u(\omega + y_h) \quad (1)$$

Now, assume that the agent has access to an insurance contract, which pays an indemnity I if the state of nature is a drought, and carries a premium π.

The agent's expected utility with insurance can be written:[4]

$$Eu^I_{it}(.) = p_{it}u(\omega + y_l + I - \pi) + (1 - p_{it})(\omega + y_h - \pi) \tag{2}$$

In order to maximize utility, agent i will purchase insurance in period t at a given premium π if and only if $Eu^I_{it}(.) \geq Eu_{it}(.)$. We assume the agent has a constant relative risk aversion utility function, with CRRA parameter γ. The agent's utility without insurance in round t is:

$$Eu_{it}(.) = p_{it}\frac{(\omega + y_l)^{(1-\gamma)}}{(1-\gamma)} + (1 - p_{it})\frac{(\omega + y_h)^{(1-\gamma)}}{(1-\gamma)} \tag{3}$$

Likewise, with insurance, the agent's utility in period t is:

$$Eu^I_{it}(.) = p_{it}\frac{(\omega + y_l + I - \pi_{it})^{(1-\gamma)}}{(1-\gamma)} + (1 - p_{it})\frac{(\omega + y_h - \pi_{it})^{(1-\gamma)}}{(1-\gamma)} \tag{4}$$

We model climate change as a change in the probability of a drought from a prior, known probability p_o to a new, unknown probability p_c, where $p_c \geq p_o$. This modeling assumption is consistent with abrupt climate change events resulting from climate tipping points (Alley et al. 2003, Lenton et al. 2012), which while an extreme climate scenario, is helpful for both analytical tractability and feasibility in our field experiment.[5] We build a learning model that takes as inputs past drought data, the agent's expectations about how the probability will change, and behavioral parameters for ambiguity aversion and recency bias. The model then outputs the agent's subjective drought probability p_{it}.

In the first round $t = 1$, the agent knows with certainty that $p_{i1} = p_o$. After round 1 and in each subsequent round, there is some chance that the probability will change from p_o to p_c. The probability can change at most once. There are thus two unknowns that an agent must learn about: whether or not the probability has changed and the new probability conditional on a change

[4]The framed field experiment, and thus this theoretical model, abstract away from basis risk, which is the residual risk not covered by the index, in order to improve participant comprehension and due to logistical constraints given the number of rounds played. We discuss the implications of this simplification in Section 6 below.

[5]Climate change involves many effects not modelled here such changes in temperatures and the likelihood of extreme weather events (IPCC 2015). We also acknowledge that in many contexts, climate change will be gradual and continuous; we discuss some implications of our modeling assumption in Section 6 and appendix B.4. In Appendix A, we discuss how climate change is likely currently affecting the probability of drought in Tanzania.

occurring. We model this learning process as a two-step Bayesian updating process with a change-point.[6] Each round, the agent updates her beliefs on both unknowns. Below, we first describe learning about the switch and then describe learning about the new probability.

Let agent i's prior belief about the likelihood that the probability switches each round have distribution H. We make the assumption that H is constant across rounds and has mean ϕ. This means that the agent, a priori, believes that the change is equally likely to occur at any round before receiving data, and ϕ represents the agent's expectations that climate change will occur. The agent will then use the data along with expectations to determine whether or not a switch has actually occurred. Now, let q_{it} be the agent's subjective belief in round t that the probability remains p_o, that is, that the change has not occurred in any of the previous t rounds, derived from applying Bayes' Rule.[7] The rule is used iteratively, so the posterior probability for each round multiplied by $(1-\phi)$ becomes the prior for the subsequent round. This multiplication by $(1-\phi)$ is due to the fact that between each data realization and the next draw, the agent believes there is a probability of ϕ of the switch occurring. The result is a recursive formula where the subjective probability each round is a sufficient statistic for the history up to that round. Thus,

$$q_{i1} = 1$$

$$q_{i2} = (1-\phi)$$

$$q_{it} = \begin{cases} \frac{(1-p_o)(1-\phi)q_{i,t-1}}{(1-p_o)(1-\phi)q_{i,t-1}+(1-\tilde{p}_{c,i,t-1}))(1-(1-\phi)q_{i,t-1})} & \text{if} \quad d_{t-1}=0 \\ \\ \frac{p_o(1-\phi)q_{t-1}}{p_o(1-\phi)q_{i,t-1}+\tilde{p}_{c,i,t-1}(1-(1-\phi)q_{i,t-1})} & \text{if} \quad d_{t-1}=1 \end{cases}$$

where $\tilde{p}_{c,it}$ is agent i's subjective belief about p_c in round t, and $d_t = 1$ if there was a drought in period t, and 0 otherwise. In this framework, the agent's

[6] Smith (1975) studies learning about the change-point of a distribution parameter in a sequence of random variables. This paper follows ibid. in assuming agents hold a prior distribution on the initial likelihood of a change and then calculate updated probabilities of the change by learning from observed data using a Bayesian model.

[7] Bayes' Rule states that the posterior beliefs are proportional to the prior beliefs times the likelihood. More formally, $P(B|A) = \frac{P(A|B)*P(B)}{P(A)}$. To solve for q_{it}, we substitute no change in the drought probability for B and the drought realization for A.

belief about the probability of a drought in period t (without yet introducing ambiguity aversion and recency bias) is the sum of the prior probability and the new probability weighted by the subjective belief over the switch:

$$\tilde{p}_{it} = q_{it} p_o + (1 - q_{it}) \tilde{p}_{c,it} \tag{5}$$

Next, we move to learning about the new probability p_c. The agent has initial prior beliefs about the new probability of a drought conditional on a change occurring, which have distribution G_1 and mean $\tilde{p}_{c,i1}$. We assume that the agent's initial beliefs about the new distribution follows $G_1 \sim Beta(\alpha, \beta)$, following the Degroot Beta-Bernoulli Bayesian Updating Model (DeGroot 1970, Camerer and Ho 1999, Gallagher 2014).[8] Here, we weight the information that goes into updating $\tilde{p}_{c,it}$ by the agent's belief that a switch has occurred $(1 - q_{it})$.[9] Then, at round t,

$$\tilde{p}_{c,it} = \frac{\alpha + D'}{\alpha + \beta + T'} \tag{6}$$

where: $D' = \sum_{j=1}^{t} d_j (1 - q_{ij})$, and $T' = \sum_{j=1}^{t} (1 - q_{ij})$.

Finally, we include ambiguity aversion and recency bias terms to find the behavioral effects-weighted subjective probability p_{it}. Following Gilboa and Schmeidler (1988), ambiguity aversion in this model is an over-weighting of bad states of the world compared with good states. In the context of climate change, ambiguity-averse smallholders would overweight the possibility of large increases in the probability of a drought. We model this by multiplying the Bayesian probability by an ambiguity aversion weighting parameter and an indicator function for when ambiguity in the drought probability is present, which occurs in all rounds except for round 1. We model recency bias as an attenuation effect where drought realizations focus the agent's attention on the risk and adds to its perceived severity. Thus we add the recency bias

[8] The formula for the mean of the Beta Distribution is $\tilde{p}_{c,i1} = \frac{\alpha}{\alpha+\beta}$. This serves as the agent's initial prior about the new probability $\tilde{p}_{c,i1}$, while the weight on the prior determines how quickly the agent's beliefs change given new data and is determined by the magnitude of the numbers in the fraction. For example, $\frac{1}{3}$ and $\frac{7}{21}$ have the same initial prior belief, but $\frac{7}{21}$ implies much more weight on the prior, so it would change less in response to new data.

[9] This is because if an agent believes the probability has not changed, little of the information received from the data will go into updating the conditional probability $\tilde{p}_{c,it}$. If, on the other hand, the agent is positive the change has occurred, then all of the information from the data will be used to update $\tilde{p}_{c,it}$.

parameters multiplied by indicator functions to the Bayesian probability. Following Cai et al. 2016, we consider the recency bias from the past two periods of data.[10] Here, the indicator function I_1 equals 1 if there was a drought the last period, while I_2 equals 1 if there was a drought two periods ago. The final subjective probability can then be written:

$$p_{it} = \tilde{p}_{it}(1 + \theta I_A) + \psi_1 I_1 + \psi_2 I_2 \tag{7}$$

Using the theoretical model to make predictions on how these behavioral channels will affect willingness to pay (WTP) for insurance is relatively straightforward. Given that $\frac{(\omega+y_l)^{(1-\gamma)}}{(1-\gamma)} < \frac{(\omega+y_l+I-\pi_{it})^{(1-\gamma)}}{(1-\gamma)} \leq \frac{(\omega+y_h-\pi_{it})^{(1-\gamma)}}{(1-\gamma)} < \frac{(\omega+y_h)^{(1-\gamma)}}{(1-\gamma)}$, from Equations 3 and 4 we see that $\frac{\partial WTP}{\partial p} > 0$ and $\frac{\partial WTP}{\partial \gamma} > 0$.[11] From Equations 5 and 6 we find that $\frac{\partial p}{\partial \phi} > 0$, $\frac{\partial p}{\partial \alpha} > 0$, and $\frac{\partial p}{\partial \beta} < 0$.[12] Finally, from Equation 7 we see that $\frac{\partial p}{\partial \theta} > 0$, $\frac{\partial p}{\partial \psi_1} > 0$, and $\frac{\partial p}{\partial \psi_2} > 0$. Thus, $\frac{\partial WTP}{\partial \phi} > 0$, $\frac{\partial WTP}{\partial \alpha} > 0$, $\frac{\partial WTP}{\partial \beta} < 0$, $\frac{\partial WTP}{\partial \theta} > 0$, $\frac{\partial WTP}{\partial \psi_1} > 0$, and $\frac{\partial WTP}{\partial \psi_2} > 0$. We summarize these predictions into the following four hypotheses which we will explore using reduced form and structural modeling in the subsequent sections.

1. *Ambiguity aversion will cause WTP for insurance to increase in the presence of ambiguous drought probabilities.*

2. *Recency bias will cause WTP for insurance to increase following drought realizations holding underlying probability of drought constant.*

3. *Learning about higher drought probabilities will increase WTP for insurance. If smallholders place a larger weight on their prior beliefs about drought probabilities, this adjustment will take longer.*

4. *An increase in expectations of an increase in drought probability will increase WTP for insurance.*

[10] We consider alternate specifications of how ambiguity aversion and recency bias impact willingness to pay for insurance and different numbers of recency bias lag terms in the structural model robustness checks in Appendix B.7.

[11] For risk aversion γ, given that basis risk is zero and the insurance is actuarially fair, consumption without insurance, c is a mean-preserving spread of consumption with insurance c_I. Thus, by Jensen's Inequality, increasing risk aversion leads to an increase in insurance demand.

[12] The effect of prior weight (the magnitudes of α and β holding constant their ratio) on insurance demand is more complicated. If the prior belief about the new probability is below the true new probability p_c, then more weight put on the prior will reduce the agent's belief about the true probability.

3 The Experiment and Data

In order to test the hypotheses described above, we collected data using a framed field experiment (FFE). We employed this method for multiple reasons. First, microinsurance programs in developing countries are relatively recent, and, given that learning about climate change takes many years, it would be difficult to estimate the effect of climate change on insurance demand using short panels without exogenous variation in climate change. Second, the FFE methodology is well suited to our research question as it allows us simulate and experimentally vary aspects of climate change in order to isolate behavioral parameters and learning.[13]

Our experiment measured willingness to pay (WTP) for insurance under treatments that experimentally varied participants' information about climate change. We use this data to assess how learning and behavioral factors affect WTP for insurance. Here, we describe the experimental procedures, the experimental treatments, and the data.

3.1 Experimental Procedures

We conducted 44 experimental sessions with a sample of 471 smallholder farmers in Tanzania in the fall of 2016. At the beginning of each session, oral and signed consent was collected from each participant and then participants were asked to sit at one of four tables on which we had privacy stations to ensure the participants' decisions remained confidential. When participants were seated, we provided them with a thorough introduction to the experiment by one of the enumerators.

During the introduction, participants were told to imagine they owned one acre of land and the required inputs to grow sunflower. If rains were good, they would achieve a normal yield and earn 200,000 Tanzanian Shilling (TSH), but in a drought, the crop completely failed, earning 0 TSH.[14] Rain outcomes were

[13]We acknowledge the ongoing debate in the economics literature regarding the external validity of such lab-in-the-field experiments (Lusk et al. 2006, Fréchette and Schotter 2015, Torres-Guevara and Schlüter 2016, Galizzi and Navarro-Martínez 2018) but note important contributions that find externally valid results using this methodology (Barr and Serneels 2009, Camerer 2011, Serra et al. 2011).

[14]Parameters were carefully set based on focus groups with smallholder farmer groups prior to the implementation of the experiment and resemble average yields for an acre of sunflower crop. 1 US Dollar = 2200 TSH in September 2016.

determined by drawing painted wooden balls from a cloth bag: A blue ball meant good rains and a red ball implied a drought. The rainfall realization was drawn for each table by one of the participants at the table; the tables were framed as villages that all experienced the same rainfall.[15] Additionally, participants were told that they had a guaranteed non-farm income of 150,000 TSH from another source (framed as wage labor). Participants were told that they had the ability to purchase weather-based index insurance in town, which would fully reimburse the value of their lost crops in the event of a drought. The premium had to be paid in advance of harvest, therefore farmers had the option of using part of their 150,000 TSH non-farm income to pay the premium. The final payoffs in both weather outcomes are below in Table 1.

Table 1: Participant Payoff Table

Weather Outcome	Payoff with Insurance	Payoff w/o Insurance
Good Rains	350,000 - π (TSH)	350,000 (TSH)
Drought	350,000 - π (TSH)	150,000 (TSH)

We measured WTP using a Becker-DeGroot-Marschak (BDM) mechanism following recent field experimental work on eliciting WTP estimates (Elabed and Carter 2015, Berry et al. 2018).[16] To simplify the process of submitting a WTP value, we asked each participant a series of dichotomous choice purchase decisions at offered premiums: 30,000 TSH, 60,000 TSH, 90,000 TSH, 120,000 TSH, and 150,000 TSH. To minimize anchoring, we started with 90,000 TSH and then moved to the next higher premium after a yes and the next lower after a no. Specifically, participants were told "Imagine you have a friend who is going into town today and is willing to buy insurance for you, but you don't know how much it will cost. You must choose how much money to give to your friend to buy insurance. If the premium equals or is less than

[15]Each table had one enumerator and up to four participants. We use table fixed effects in order to control for any unobserved differences caused by session(table)-specific rainfall shocks or other environmental factors (such as location, presentation of the material etc.). There should be no other implications of the participants' table on their decisions, and we allowed participants to self-select into table groups.

[16]The BDM mechanism is incentive compatible, i.e. a participant's dominant strategy is to provide their true WTP, if preferences follow expected utility theory (EUT). When preferences deviate from EUT, such as with reference dependent utility, BDM responses may deviate from true WTP (Horowitz 2006, Meza and Reyniers 2013, Bohm et al. 1997, Rutström 1998, Shogren et al. 2001). Based on Meza and Reyniers (2013), we anticipate that our WTP may overestimate true WTP if our participants express loss-aversion or disappointment aversion. In this regard, our simulation results can be considered an upper bound on demand for insurance.

what you give, your friend will buy it and bring back any change. If the premium is higher than what you give, your friend will not buy insurance for you and return your money. Are you willing to give your friend 90,000 TSH (and subsequent premiums)?" At the end of each session, enumerators drew one random round and one random premium and participants received cash payments corresponding to that round and premium; the payout assumed the participant purchased insurance if the randomly drawn premium was less than or equal to their stated WTP. In so doing, we adopted a random lottery incentive mechanism.[17] Incentive payments were issued at a rate of of 2% of the payoff from the corresponding to the randomly chosen round, rounded up to the nearest 500 TSH unit. The conversion rate was made clear to all participants verbally during the introduction and enumerators simulated it with participants during the practice rounds.[18]

3.2 Treatments

The basic decision framework discussed above was integrated into three treatments in which the probability of a negative systemic shock and the participants' information about the shock were varied. In each session, each participant played all three treatments and the order of the treatments was randomized to allow us to control for ordering bias.[19] The treatments are described in detail below.

Treatment 1 (Full Information, Control) serves as the control for our analysis, as participants are fully informed about the drought probability across all rounds, which eliminates ambiguity about climate change and the need for

[17] The random lottery incentive mechanism (RLIM) is a very common incentive mechanism in experiments with multiple lotteries and enjoys considerable support in the literature (Cubitt et al. 1998, Azrieli et al. 2018). However, we acknowledge a potential implicit inconsistency using this incentive mechanism to identify ambiguity aversion: The RLIM assumes rational agents (no ambiguity aversion) yet we use the RLIM to incentivize an experiment to identify ambiguity aversion Harrison and Swarthout 2014).

[18] We paid participants a portion of the game payouts to preserve the framing in the experiment; the parameters were framed in terms of realistic crop outcomes for cultivating an acre of sunflower. Full payouts equaling the game payouts would have been cost prohibitive to the project. While the complexity of the conversion from game payouts to cash payoff raises concerns that participants did not fully understand this conversion, in Appendix B.5 we present results and a discussion that support the incentive compatibility of our experiment.

[19] Randomly ordered treatments allow us to control for potential ordering effects bias. We explore this empirically in Appendix Table B.1 and show that treatment order has little effect on decisions in the experiment with the exception of the control game when played second; we believe this result is likely spurious.

learning. This treatment was played for twenty rounds, modeling 20 consecutive growing seasons. To implement this treatment, the participants were shown two identical-looking cloth bags. The first bag had eight blue balls and two red balls, implying a 20% drought probability, while the second bag had either six blue and four red balls and four blue or six red balls (implying either a 40% or 60% drought probability.[20] At a specified round, the enumerator changed which cloth bag was used to draw drought realizations, so that before the switch, only the first bag was used, and after the switch, only the second bag was used. The round when the actual switch of bags occurred and the number of red balls in the second bag were randomly chosen for each table in each session and known by participants in this treatment. The possible rounds when the bags could switch were rounds 7, 11, and 15. In addition to serving as the control for our information treatments, we utilize this treatment to isolate the effect of recency bias on WTP and test *Hypothesis 2*.

Treatment 2 (Climate Change Treatment) follows the same procedure as Treatment 1, except the participants were not informed about the distribution of colored balls in the second bag other than that there was a total of ten balls of which two or more were red, nor were they told the round when the switch would occur. For the first draw, the first bag was used. Between every subsequent draw, the two bags were put into a privacy bucket from which one was removed, thus concealing the timing of the switch. The participants were told that the bags would be changed exactly once during the treatment and then stay the same for the remainder of the rounds, although the drought probability could remain unchanged if the new bag also contained two red balls in it. The possible rounds when the switch occurred and the number of red balls in the second bag were randomized in the same way as the control treatment. By introducing a change of unknown timing and magnitude, we simulate a simplified depiction of climate change in that the risk of systemic shocks is increasing, yet information about this change is often unavailable, especially to low-income farmers. In our reduced form analysis, we compare

[20]Drought probabilities were constructed to be either 20%, 40%, or 60%. To check for manipulation, in appendix Table 10 we report the observed drought probability. We find some evidence that observed drought probabilities in the 20% scenarios fell statistically below 20%. To explore the implications of this, we re-estimate our structural model with a set of sessions where the observed drought probabilities were not statistically below 20%. We find our results are robust in Table 11.

Treatments 1 and 2 to isolate the effects of learning and test *Hypothesis 3*. We will not separately identify the impact of expectations per se, however, we will control for expectations by including a linear time trend in our regression models to account for increases in participants' expectation that a change will occur. We will use the coefficient on the time trend to test *Hypothesis 4*. Moreover, we will use the data generated from this experiment in our structural estimation to reinforce and deepen our analysis of our four hypotheses.

Treatment 3 (Ambiguity Treatment) was designed to model a different possible consequence of climate change, specifically an increase in ambiguity around the true drought probability, apart from a possible change in its central tendency. For this treatment, participants were shown the contents of three bags, the first with one red and nine blue balls, the second with two red and eight blue balls, and the third with three red and seven blue balls. The participants were told that each round, any of the three bags could be used and that the bag could switch back and forth at any time or remain the same for the whole treatment. Therefore, participants were unable to learn about the underlying probability through observations of the draws, so the probability was truly ambiguous. However, to ensure comparability with the control, enumerators only used the bag with a 20% probability of drought throughout all five rounds. Before each draw, participants made insurance decisions. Then, the enumerator placed the three bags into the privacy bucket and picked one bag from which a participant would make the draw. This treatment was played for only five rounds as the treatment was meant to measure the effect of ambiguity and not learning over many rounds. To isolate the ambiguity aversion affect on WTP and test *Hypothesis 1*, we compare the ambiguity aversion treatment to the first five rounds of the full information treatment (which are all before the switch at a 20% probability of drought), so the only difference is ambiguity and we can identify its effect.[21]

3.3 Data

The experiment was conducted in eight villages in the Dodoma Region of

[21] We assume that ambiguity is a single, constant, and individual characteristic that does not change across rounds and therefore five rounds of observations should be sufficient to identify this effect.

Tanzania, an area where farmers face a considerable risk of drought.[22] We chose this region in order to work with farmers familiar with drought and who may be potential clients for future drought insurance contracts. Additionally, as described in the Appendix, there is climate research suggesting that drought risk in the main March - May growing season experienced a sudden increase in the mid to late 1990s, which is consistent with the way we model climate change in the model and the experiment. To improve comprehension of the insurance product described in the experiment, we exclusively chose participants who were farmers and had experience with formal financial products. Therefore, we worked with the Vision Fund Tanzania (VFT) Dodoma branch to identify a sample population. The final sample included most of the Vision Fund credit groups in the Dodoma Region. Data collection took place from September 8th through October 7th, 2016.

Table 2: Sample Descriptive Statistics

Variable	N	Mean	Std. Dev.
Age (in years)	471	38.57	11.67
Education (in years)	471	6.88	2.54
Female (female=1, male=0)	471	0.53	0.50
Household Head (yes=1, no=0)	471	0.58	0.49
Household Size (# of members)	471	5.37	2.02
Total Land Owned (in acres)	451	9.42	6.57
Irrigation (yes=1, no=0)	471	0.23	0.42
Official Forecast (yes=1, no=0)	471	0.53	0.50
Irrigation	471	0.23	0.42
Drought Tolerant Crops (yes=1, no=0)	471	0.93	0.25
Intercropping (yes=1, no=0)	471	0.92	0.27
Agroforestry (yes=1, no=0)	471	0.48	0.50
Community Leader (yes=1, no=0)	471	0.34	0.47
Income: Remittances (yes=1, no=0)	471	0.27	0.44
Income: Selling (yes=1, no=0)	471	0.57	0.49
Income: Wage Labor (yes=1, no=0)	471	0.14	0.35
Risk Aversion (CRRA coefficient):	461	0.09	1.83
Ambiguity Aversion (ratio of known risk):	464	1.20	0.49

Descriptive statistics of the 471 farmers in the sample are in Table 2. We find that the population is roughly 39 years old on average with almost 7 years of schooling. Females represent over half of the sample, likely due to preferential

[22]The eight villages are Mkoka, Ibugule, Hombolo, Gawaye, Nolini, Makawa, Mageseni, and Matongoro, in the Kongwa, Bahi, and Dodoma Urban districts of the Dodoma Region.

targeting of VFT for female farmers. Over half the sample participants are household heads and the average family size is 5.37 members. The farmers on average have an average of 9.42 acres of land, which is skewed right by larger landholders (the median is 8 acres).[23] Roughly 23% of participants use some form of irrigation on any portion of their fields, and 53% have access to an official government forecast of the upcoming season's rains when making planting decisions. Only 27% have remittance income, 14% have income from wage labor, and 57% have income from selling processed food, merchandise, or charcoal. We solved for the individual CRRA risk aversion parameters by substituting in the average WTP of the pooled sample for rounds 16-20 for π in Equation 4 and setting it equal to Equation 3. We find an average risk aversion coefficient of 0.09, suggesting participants were not very risk averse.[24] We measured ambiguity aversion by taking the ratio of WTP for insurance in the ambiguity aversion treatment to the full information treatment in the first five rounds (before switch). We find that participants on average are willing to pay 20% more for insurance when the risk of drought is ambiguous.

4 Empirical Strategy and Results

We utilize the data generated from our framed field experiment to identify the behavioral effects that influence and mediate the impact of climate change on WTP for insurance. First, we provide some basic insights into the effect of climate change on WTP for insurance using a simple graphical representation of Treatments 1 and 2. Second, we present a series of reduced form regression results that tease out how behavioral biases and learning affect WTP for insurance. Third, we combine these insights by structurally estimating the parameters of our theoretical model. Finally, we discuss how these parameters will be used to simulate of insurance uptake rates in Section 5.

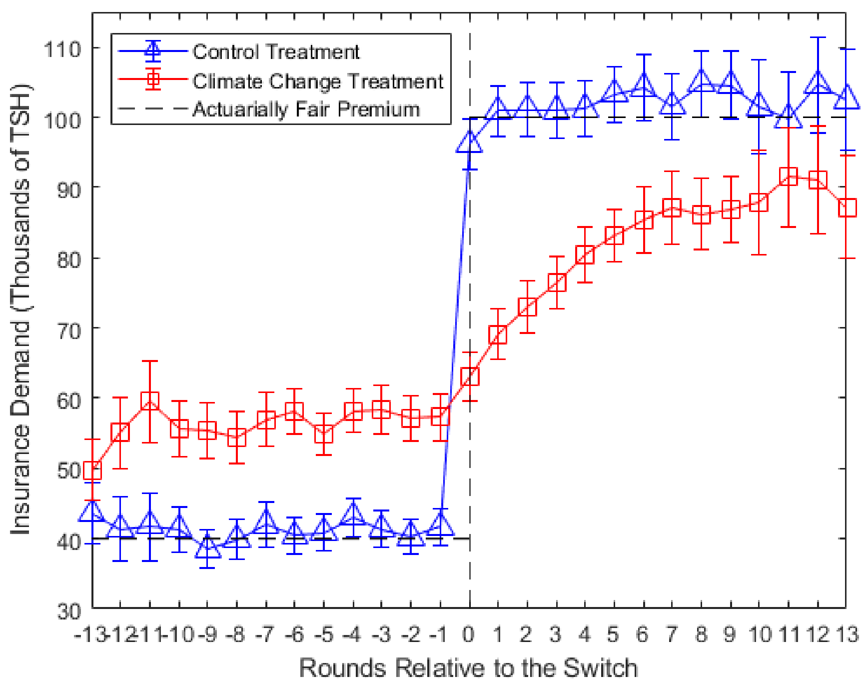
[23]Here,we remove outliers more than three standard deviations beyond the mean, which leaves out 20, 10, and 7 participants from total land owned, risk aversion, and ambiguity aversion, respectively. We run the reduced-form analysis and estimate the structural model parameters with and without the outliers and see no meaningful difference in the results, so in the analysis they are included.

[24]There are a number of possible explanations for this relatively low risk aversion coefficient. One possibility is that participants had a distaste for insurance given its framing as a rainfall insurance contract. It is also possible that the participants did not fully understand the change in probability or the repeated dichotomous choice elicitation method. We discuss these possibilities further in Appendix B.6

4.1 Graphical Analysis

We begin our analysis by graphically illustrating the impact of climate change on WTP for insurance. In Figure 1, we plot WTP for insurance for the climate change treatment and the full information treatment against rounds in the experiment. WTP is reported as the midpoint between the highest premium for which insurance was purchased and lowest premium for which it was not purchased.[25] Rounds are presented relative to the round in which the switch occurred.[26]

Figure 1: WTP by Treatment (with 95% Confidence Intervals)



In Figure 1, we can visualize the impact of climate change by comparing the climate change treatment (in red) to the WTP for the full information (control)

[25]For example, if the participant agreed to buy insurance at $\pi = 30$ but not at $\pi = 60$, then $WTP = 45$. If a participant rejected insurance at every premium, $WTP = 15$, the midpoint of 0 and 30. If the participant accepted every premium $WTP = 175$, the midpoint of 150 and the insurance indemnity, 200. We define WTP as such for the remainder of our analysis.

[26]Thus, there are more data points in the center of the graph than at the tails, which is why the tails have larger 95% confidence intervals. We omit data from round 1 since there is no ambiguity in the climate change treatment. In Figure B.5 in Appendix B.5, we show both treatments by round with no adjustment for the switch.

Treatment before and after the switch. In the climate change treatment before the switch, WTP for insurance increases relative to the roughly $41,000$ TSH in the Full Information treatment (when the drought probability if a known and constant 20%). After the switch, we see a slow increase in WTP that remains below the full information treatment even after 13 seasons.

More importantly, our experiments allow us to identify the causes of this impact and to differentiate them from the mere increase in drought probabilities implied by climate change. We find that before the switch, participants faced with an unknown climate increase their WTP for insurance; this may be due to ambiguity aversion and/or expectations that the climate may have already changed. After the climate changes, we observe a slow increase in WTP that likely reflects the learning process by which participants update their beliefs about a change in the observed rainfall distribution. Taken together, Figure 1 suggests that expectations of climate change and/or ambiguity aversion increase WTP for insurance but learning about actual climate changes reduces WTP as participants' do not quickly adjust to the new climate.[27] In the next two sections, we will use reduced form and structural modeling to precisely identify how learning, ambiguity aversion, expectations, and recency bias mediate the impact of climate change on WTP for insurance.

4.2 Reduced-form Results

We estimate a series or regression models that separately identify the effect of ambiguity aversion, recency bias, and learning on WTP for insurance. First, we conduct reduced-form tests of ambiguity aversion and recency bias. We then use these results in a separate reduced-form test to isolate the effects of participant learning and expectations.

4.2.1 Ambiguity Aversion

To measure the effect of ambiguity in the drought probability and test *Hypothesis 1*, we compare data from the five rounds of the ambiguity treatment to the first five rounds of the control treatment. The true probability in both

[27] It is difficult to tease out the effect of recency bias from this graphical analysis. However we will address this bias in our empirical analysis below.

treatments was the same ($p = 0.2$); the only difference being that under the ambiguity treatment, participants were not told the true probability but were instead told that it could be 0.1, 0.2, or 0.3. These results are shown in Table 3 and Figure B.4 in Appendix B.5.

Table 3: Effect of Ambiguity Aversion on WTP (Thousands of TSH)

Variable	(1)	(2)	(3)
Ambiguity Treatment	5.03***	5.03***	5.03***
	(0.87)	(1.06)	(1.06)
Age	-	0.36***	-
		(0.13)	
Education	-	-1.37***	-
		(0.41)	
Female	-	-0.69	-
		(2.99)	
Household Head	-	-1.40	-
		(2.78)	
Household Size	-	-0.85	-
		(0.51)	
Total Land Owned	-	0.20*	-
		(0.10)	
Irrigation	-	-7.22***	-
		(2.19)	
Official Forecast	-	-7.24***	-
		(2.21)	
Community Leader	-	-2.55	-
		(2.42)	
Income - Remittances	-	-3.46*	-
		(2.03)	
Income - Selling	-	-3.92**	-
		(1.93)	
Income - Wage Labor	-	-4.44	-
		(3.21)	
Constant	41.79***	50.80***	49.39***
	(0.62)	(6.53)	(0.84)
Round FE	NO	YES	YES
Participant FE	NO	NO	YES
R^2	0.01	0.09	0.01
N	4710	4710	4710

Standard errors in parenthesis, clustered at the table level (139 clusters). ***,**,* represent statistical significance at the 1%, 5%, and 10% level, respectively. The 4710 observations correspond to 471 individuals, who played 5 rounds each of the control and treatment.

In the first model, we include only the treatment variable. The second model includes individual covariates, shown above in Table 2, and round fixed effects, while the third model includes individual fixed effects, thus utilizing only within-participant variation.[28] Given that all participants took part in both the ambiguity treatment and the control, the effect of the treatment is very robust across specifications. The ambiguity aversion regression equation for WTP for index insurance in round t is:

$$WTP_{it} = \beta_0 + \beta_1 T + \beta' \mathbf{X} + \xi_t + \epsilon_{it} \tag{8}$$

where T is the ambiguity treatment, $\mathbf{X}$ are n various demographic controls, and ξ_t are round fixed effects. Note that in the third model, $\mathbf{X}$ are replaced by individual fixed effects.[29]

As shown in Table 3, we find that adding ambiguity to the true drought probability increases WTP for insurance by about 5,000 TSH, or 12% compared with the control, supporting *Hypothesis 1*. This confirms that ambiguity aversion is an important component of insurance demand in this context. It also confirms findings in Alary et al. (2013) and Bryan (2013) that ambiguity aversion leads to greater demand for full insurance that covers an ambiguous risk.[30]

4.2.2 Recency Bias

Next we identify the impact of recency bias on WTP for insurance. To isolate this effect and test *Hypothesis 2*, we use the full information treatment (control) WTP data, so there is no ambiguity and no learning; in this context past drought realizations should have no impact on WTP for insurance.[31]

[28]While individual covariates in Model 2 are not necessary due to our ability to use within- participant variation using the fixed effect model (Model 3), we include them here show how individual covariates relate to the WTP decision.

[29]We clustered the standard errors at the table level as participants at the same table all shared the same drought and rain data. The results were equally significant if we clustered at the individual, table, or session level.

[30]While not the focus of this paper, the effects of the various controls on insurance demand here have interesting interpretations. Some of the statistically significant effects are intuitive for insurance demand, such as the negative effect of potential substitutes including irrigation, an official drought forecast, or other non-farm income. The positive effect of age and negative effect of education, however, contradict previous literature that suggests index insurance demand is driven by similar factors as other new technologies, with education increasing WTP and age reducing it (Hill et al. 2013, Gallenstein et al. 2019). This apparent contradiction may be resolved by the fact that in previous studies, the success of the insurance product in covering losses was ambiguous, while in this case, the ambiguity is inherent in the drought risk covered by the insurance.

[31]If participants do not understand the incentive mechanism, there could be concerns that participants believe they are accumulating rewards across rounds and thus our recency bias results could be confounded

Table 4: Reduced Form Recency Bias Test (Thousands of TSH)

Variable	(1) WTP	(2) WTP	(3) WTP	(4) WTP
Drought Probability	18.10***	17.98***	18.27***	18.56***
	(0.90)	(1.14)	(1.38)	(0.78)
Drought (-1)	10.44***	11.08***	10.85***	10.21***
	(1.46)	(1.53)	(1.35)	(1.00)
Drought (-2)	4.77***	5.26***	5.13***	4.53***
	(1.10)	(1.17)	(1.03)	(0.87)
Drought (-3)	3.90***	4.54***	3.67***	3.43***
	(1.10)	(1.25)	(1.25)	(0.97)
Drought (-4)	4.90***	4.62***	4.19***	4.17***
	(1.08)	(1.23)	(1.28)	(0.95)
Drought (-5)	2.54**	2.45**	1.85	2.09
	(1.04)	(1.22)	(1.14)	(0.96)
Drought (-6)	-	1.79	1.38	1.66
		(1.26)	(1.66)	(1.06)
Drought (-7)	-	0.88	1.21	1.62
		(1.25)	(1.53)	(1.08)
Drought (-8)	-	1.24	1.18	1.49
		(1.25)	(1.51)	(1.13)
Drought (-9)	-	0.033	1.15	1.54
		(1.31)	(1.37)	(0.97)
Round (Linear Trend)	-	-	-0.18	-0.24
			(0.38)	(0.24)
Constant	0.082	-1.16	0.93	0.58
	(3.26)	(4.47)	(5.15)	(3.47)
Individual Fixed Effects	NO	NO	NO	YES
Table Fixed Effects	NO	NO	YES	NO
R^2	0.49	0.43	0.43	0.43
N	7065	5181	5181	5181

Standard errors in parentheses, clustered at the table level (139 clusters). ***,**,* represent statistical significance at the 1%, 5%, and 10% level, respectively.

We use the following regression model to investigate the impact of recency bias on WTP for index insurance in round t is:

$$WTP_{it} = \alpha + \beta_1 p_{T,it} + \sum_{j=1}^{9} \beta_{j+1} d_{-j} + \xi_k + \epsilon_{it} \tag{9}$$

where $p_{T,it}$ is the true probability of drought faced by participant i in round t,

by a wealth effect. To ameliorate these concerns we also ran an additional model in which we regressed WTP on droughts lagged from round -5 to -10 only. If recency bias drives the effects of past rounds, then only recent droughts will affect WTP. If wealth affects drive the impacts of past rounds, then any lagged period of drought will affect WTP. We find that lagged rounds -5 through -10 show no significant correlation with WTP, thus demonstrating evidence against wealth effects. These results are available upon request.

d_{-j} is the drought realization from j periods in the past, and ξ_k are table fixed effects. We use table fixed effects to identify effects using within table variation; tables shared the same rainfall shock and thus this fixed effect removes any differences across participants with respect to the rainfall realizations to which they were exposed. To establish robustness, we control for 5 and 9 lagged rounds and and show that the results are unchanged by adding individual fixed effects. We also control for a linear time trend to test if participants' reaction to droughts varied based on how long they participated in the treatment. Using Equation 9, significant coefficients on past drought realizations indicates recency bias.

We present results for recency bias in Table 4. In Models 1 through 4, we find significant positive impact of past droughts on WTP for insurance, indicating recency bias and supporting *Hypothesis 2*. Moreover, we find our results to be robust across specifications. We find that recency bias diminishes by more than half after the first round, and becomes statistically insignificant after five rounds.

4.2.3 Learning

Finally, we move to a reduced-form test of learning. To identify the effect of learning on WTP for insurance, we seek to observe how participants' WTP responds to past drought realization in the climate change treatment. To isolate the effect of learning, we must control for risk aversion, ambiguity aversion, expectations, and most importantly, recency bias. To control for risk aversion we include individual level CRRA parameters estimated using WTP responses from the last five rounds of the full information treatment.[32] To control for ambiguity aversion, we include a dummy variable indicating the presence of ambiguity, which is present in each round after round 1 (in round 1 the drought probability is known at 20%). We include a linear time trend to account for participants' expectations that the switch has occurred and use this estimated coefficient to explore *Hypothesis 4*. Finally, to control for recency bias, we "de-recency-bias" the data by subtracting the recent drought coefficients found in

[32]We derive our individual risk aversion measures, γ_i, by substituting in the average WTP for each participant in rounds 1-5 for π in Equation 4 and setting it equal to Equation 3.

Table 4 from the individual WTP estimate for each corresponding round.[33] In the reduced form, we cannot estimate the specific learning parameters, however any impact of past droughts will lend support to *Hypothesis 3*.[34] Thus, we estimate the following model to investigate learning and WTP for insurance:

$$WTP_{it} = \alpha + \beta_1 p_{T,t} + \beta_2 R_t + \beta_3 \gamma_i + \beta_4 \theta_t + \sum_{j=1}^{9} (\beta_{5,j} - \hat{\beta}_{C,-j}) d_{-j} + \xi_k + \epsilon_{it} \quad (10)$$

where $p_{T,t}$ is the true probability of a drought in time period t, $\hat{\beta}_{C,-j}$ is the effect of a drought j periods ago in the control treatment in Table 4, R_t is the linear time trend, γ_i is individual-level risk aversion, θ_t is presence of ambiguity in round t, and ξ_k are table fixed effects.[35]

The results in Table 5 show that past drought realizations increase WTP, which provides evidence of learning about drought probabilities which supports *Hypothesis 3*. We also find that the magnitude of the impact of the true drought probability, which is unknown to the participants, is substantially smaller than when participants know the probability (as in the recency bias analysis in Table 4 above). This supports the idea that participants do not know the underlying probability but instead are learning from the data they observe. After recency bias is removed, the effect of a past drought still appears to decrease slightly over time, but the effect is no longer clear and consistent as in Table 4. In Model 2, we find that the results are robust to using individual-level fixed effects, while in Model 3 we find that risk aversion is positively correlated with WTP for insurance. We also find that there is an increase in

[33] We assume that participants' recency bias is uniform across the learning treatment and the full information treatment. Assuming uniform recency bias is consistent with our theoretical model and is an intuitive approach to modeling and controlling for recency bias in this analysis. However, we acknowledge that this assumption may not hold and we are not able to tease out how recency bias may differ in an environment with ambiguity using our data. For additional exploration of how optimal learning relates to ambiguity and/or recency bias under different circumstances see Epstein and Schneider (2007) and Kala (2017).

[34] We must adjust our standard errors to account for our dependent variable being a function of estimated coefficients from the recency bias estimation model. We use bootstrapping (clustered at the table for models 3 and 4) in which each bootstrapped sample is used to estimate our recency bias model, calculate the de-recency biased WTP, and then estimate the learning model.

[35] In model 3, we impute missing values for past droughts to ensure that we can include all rounds, including round 1, which enables us to capture and control for the presence of ambiguity. We imputed values of 0.2 for past rounds as this was the drought probability for the initial rounds of the climate change treatment before the switch. Although this imputation could introduce some bias, by comparing models 1 and 2 (without imputation) with model 3, we find that the impact of past droughts is not statistically different.

Table 5: Reduced Form Learning Test (Thousands of TSH - Adjusted for recency bias)

Variable	(1) WTP	(2) WTP	(3) WTP	(4) WTP
Drought Probability	2.19***	2.49***	1.53***	1.88***
	(0.56)	(0.46)	(0.60)	(0.53)
Drought (-1)	7.83***	8.11***	7.40***	6.62***
	(1.46)	(1.37)	(1.48)	(1.28)
Drought (-2)	5.04***	5.28***	4.53***	4.13***
	(1.29)	(1.29)	(1.28)	(1.28)
Drought (-3)	5.99***	5.87***	5.33***	5.06***
	(1.42)	(1.40)	(1.42)	(1.30)
Drought (-4)	5.29***	4.97***	4.49***	3.40***
	(1.52)	(1.44)	(1.51)	(1.21)
Drought (-5)	7.89***	7.23***	7.08***	5.28***
	(1.45)	(1.40)	(1.43)	(1.29)
Drought (-6)	4.21***	3.64***	3.36***	2.60*
	(1.64)	(1.42)	(1.69)	(1.48)
Drought (-7)	5.29***	4.68***	4.46***	4.61***
	(1.53)	(1.41)	(1.57)	(1.43)
Drought (-8)	5.90***	5.61***	5.20***	5.85***
	(1.61)	(1.47)	(1.65)	(1.53)
Drought (-9)	1.23	0.17	-0.05	0.22
	(1.61)	(1.44)	(1.60)	(1.56)
Round (Linear Time Trend)	-	-	0.465**	0.456***
			(0.23)	(0.16)
Estimated CRRA Coef.	-	-	4.23***	3.62***
			(0.83)	(0.71)
Ambiguity Present	-	-	-	14.44***
				(1.62)
Constant	41.38***	41.12***	39.23***	25.19***
	(3.07)	(2.60)	(3.54)	(2.29)
Individual Fixed Effects	NO	YES	NO	NO
Table Fixed Effects	YES	NO	YES	YES
R^2	0.10	0.11	0.14	0.14
N	5181	5181	5181	9420

Bootstrapped standard errors to control for using estimated coefficients in the calculation of the dependent variable. ***,**,* represent statistical significance at the 1%, 5%, and 10% level, respectively.

demand for insurance over rounds suggesting expectations about an impending change in climate increases WTP, supporting *Hypothesis 4*. Lastly, in Model 3, we find that the presence of ambiguity is positively correlated with WTP.

4.3 Structural Estimation

To simultaneously estimate the parameters that are driving the impact of climate change, we now turn to a structural estimation of our theoretical model. Using this method will allow us to deepen our analysis and simulate insurance uptake rates in the subsequent section.

We adapt our theoretical model into a random utility framework by adding a random error term to the utility functions, Equations 3 and 4. The error terms have mean 0 and are weighted by the agent's belief about the drought probability, p.[36] Let ϵ_{it} be the difference between the error terms of the two utility functions divided by the normalized probability weight such that $\epsilon_{it} = \epsilon_{it}^{I} - \epsilon_{it}^{NI}$. Subtracting the two utility functions and then rearranging, let:

$$\Omega(\pi_t) = p_{it}u(\omega+y_l+I-\pi_t)+(1-p_{it})u(\omega+y_h-\pi_t)-p_{it}u(\omega+y_l)-(1-p_{it})u(\omega+y_h) \tag{11}$$

Here, $\Omega(\pi_t)$ represents the average utility gained (or lost if negative) from buying insurance at a given insurance premium π_t. Given that the error term has mean 0, if $\Omega(\pi_t) > 0$, then the probability of the agent buying insurance is greater than 50%. Given the variance of the error term, the agent will actually purchase insurance in period t if and only if $\epsilon_t \geq \Omega(\pi_t)$. Thus, the probability of the agent purchasing insurance is:

$$Pr(Insurance|\pi_t) = Pr(\epsilon_t \geq \Omega(\pi_t)) \tag{12}$$

More generally, for a set of increasing premiums $\pi_{j\epsilon(1,k)}$, the probability the agent purchases insurance at a premium π_j, but not at premium π_{j+1}, is: $Pr(\Omega(\pi_{j+1}) > \epsilon > \Omega(\pi_j))$. Likewise, the probability of agent i not purchasing insurance at π_1 is: $Pr(\epsilon < \Omega(\pi_1))$ or purchasing insurance at the maximum premium, π_k, is: $Pr(\epsilon > \Omega(\pi_k))$. We then assume ϵ has a cumulative distribution, F, which has a known mean 0 and standard deviation σ.

Similarly, we can create ranges for the realizations of ϵ_{it} where the agent buys insurance at each of the lower bounds but not at the corresponding upper

[36] Each ϵ is weighted by the agent's belief about the drought probability, in this case normalized as $\frac{p}{p_o}$, so that its variance scales up with the increase in probability. Otherwise, uptake would be biased toward 50% for low probability risks and away from 50% for high probability risks. Intuitively, this means that variations in the agent's preference for insurance depend on the size of the risk the insurance covers.

bound. Note that each lower bound from the experiment $[0, 30, 60, 90, 120, 150]$ has a corresponding upper bound that is 30 greater, except for 150, which has an upper-bound of the insurance indemnity $I = 200$.

Next, we maximize the log-likelihood function, $\ln \mathcal{L}(\sigma, \phi, \alpha, \beta, \theta, \psi_1, \psi_2 | \mathbf{X})$, where $\mathbf{X}$ are all of the observed data in the climate change treatment.[37] To estimate this model, we assume $F \sim N(0, \sigma)$. Maximizing the log-likelihood yields the parameter estimates displayed in Table 6:

Table 6: MLE Structural Estimation Parameters

Variable	Parameter	(1) MLE
Variance of the Utility Error	σ	12.07***
		(0.14)
Expectation	ϕ	0.026***
		(0.005)
Learning Parameter 1	α	16.08**
		(7.89)
Learning Parameter 2	β	29.32**
		(12.74)
Ambiguity Aversion Weight	θ	0.26***
		(0.018)
Recency Bias (1 round)	ψ_1	0.036***
		(0.005)
Recency Bias (2 rounds)	ψ_2	0.012**
		(0.005)

Standard errors (in parentheses) calculated using the inverse of the square root of the diagonal elements of the Fisher Information Matrix. ***,**,* represent statistical significance at the 1%, 5%, and 10% level, respectively. Implied switch probability proxies for expectations in the structural estimation.

These structural estimates have several important economic implications. The variance of the error term, $\sigma = 12.07$, implies that at the initial probability of $p_o = 0.2$, a 95% confidence interval around the average WTP for insurance will have a range of $47,067$ TSH, reflecting considerable heterogeneity in WTP for insurance. The prior probability of a switch, $\phi = 0.026$, implies that on average, participants believe there is about a 1 in 40 chance that the switch will occur in any given round. This implies a 0.615 belief, a priori, that the switch would not occur at any time over the twenty rounds.[38] This level of climate

[37]The structural estimation requires inputting a value for risk aversion γ, which consistent with our discussion in the descriptive statistics section, we use the CRRA coefficient associated with the average willingness to pay in rounds 16-20, $\gamma = 0.132$.

[38]This is calculated by solving $(1 - \phi)^{20}$. Recall from the Treatments section that the participants were

change expectations is lower than the 0.05 we would expect if participants treated each round as equally likely for the switch to occur. All else equal, this reduces insurance demand under climate change consistent with *Hypothesis 4*. The learning parameters α and β suggest that on average, participants have a prior belief about the mean of the new distribution of $\tilde{p}_{i1} = 0.354$. The magnitudes of α and β imply that if the participant is certain the change has occurred, observing one drought would increase the agent's Bayesian drought belief by about 0.6 percentage points, to 0.36. Compared with having a smaller weight on their initial prior, agents with these parameters will on average learn slower, consistent with *Hypothesis 3*.[39]

The behavioral effects that were confirmed in the reduced-form analysis also play an important role in determining WTP for insurance under climate change. The coefficient on the ambiguity aversion parameter is statistically significant and considerably larger than the reduced form estimate (26% compared to 14%), lending additional support to *Hypothesis 1*. This large ambiguity aversion is an important counterweight to the relatively slow learning process described above. While on average, participants take many rounds to learn about the new probability, they are willing to pay 26% more for insurance each round in which they are unsure about the level of risk. The one-round recency bias parameter is statistically significant and implies a 7,200 TSH increase in WTP following a drought beyond what can be explained by learning, and this is somewhat smaller than the reduced-form estimate of 10,440 TSH. The two-round recency bias term is statistically insignificant and far below the reduced-form estimate (2,400 TSH compared to 4,770 TSH). Together these results lend additional support to *Hypothesis 2*.

Our reduced form and structural estimation strategies provide evidence for each of our four hypotheses. Specifically, we find that the impact of climate change on WTP for insurance is mediated by farmers' learning about the new rainfall probability under climate change, expectations about coming changes to the rainfall probability, recency bias, and ambiguity aversion. In the next

told that the cloth bags would switch once during the treatment, although there was a chance the probability of a drought would remain constant if the second bag also contained exactly two red balls.

[39]In our simulation section we estimate "optimal" learning parameters that ex ante minimize error in the farmers beliefs relative to the true probability, which imply a much smaller probability weight.

section, we use the parameters estimated from our structural model to simulate insurance uptake decisions for farmers.

5 Insurance Uptake Simulation

The estimated parameters from the structural model allow us to simulate the demand response to a change in risk caused by climate change. In order to estimate the effect of climate change on insurance uptake rates, however, we also require assumptions about the supply-side response to the changing risk.

5.1 Insurance Company Supply Scenarios

In this section, we consider three potential insurance company scenarios: 1) The insurance company has complete information about the change; 2) the insurance company naively learns about the change using a simple Bayesian model; and 3) the insurance company considers a distribution of possible climate change scenarios and then optimizes learning and adds an ambiguity load to the premium in order to maximize expected profits. In all scenarios, we assume that the insurance company makes zero profit in expectation, conditional on its beliefs about the underlying probability.[40] The expected profit function for each insurance company scenario is given by Equation 13:

$$P_I = v_t {\pi^k}_t - v_t p_t I \tag{13}$$

where π_t^k is the insurance premium for insurance company of type $k \in f, n, s$ in time period t, v_t is insurance uptake in time period t, I is the insurance payout, and p_t is the true drought probability in time period t.[41]

Under the first scenario, the insurance company (f) knows exactly when the climate switch occurs and the new drought probability. This scenario serves as a benchmark for comparison to other scenarios and might approximate to

[40] There are two potential reasons for the assumption of a zero-profit insurance company: A non-profit insurance company that seeks to maximize farmer welfare subject to remaining financially sustainable, or a profit-maximizing insurance company in a competitive market where free entry drives profits to zero.

[41] We model the insurance company without a fixed operating cost for simplicity. We discuss the implications of adding a fixed cost in the appendix and visualize it in Figure B.3.

a world in which insurance companies have access to sophisticated climate change models. The premium under this scenario, ${\pi^f}_t$, is thus ${\pi^f}_t = p_t I$.

In the second insurance company scenario, the "naive updating" scenario, the insurance company (n) learns from past data using a simple Bayesian updating model with no ambiguity load. Following Degroot (1970), the insurance company updates its belief about droughts by assuming a Beta distribution. In this case, we assume its original belief about the probability is $p_o = 0.2$, so we fix α and β such that $\frac{\alpha}{\alpha+\beta} = 0.2$. We simplify the model to one parameter, λ, which reflects the weight the insurance company places on the original prior. The smaller the value of λ, the more sensitive the insurance company's risk estimate is to new information. Thus, the insurance company's belief about drought in period t is equal to:

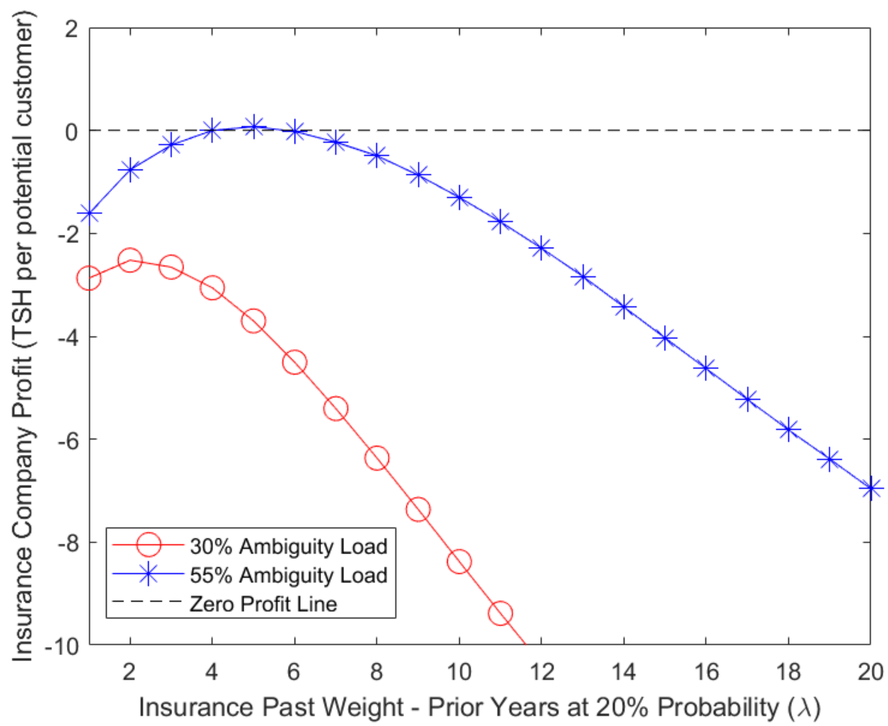
$$\tilde{p}_t = \frac{0.2\lambda + D}{\lambda + t} \tag{14}$$

where: $D = \sum_{j=1}^{t} d_j$. In this scenario, we set $\lambda = 1$, as the naive insurance company learns mainly from the data it observes. We assume the insurance is priced at the actuarially fair rate, given the insurance company's perception of risk, so the premium is ${\pi^n}_t = \tilde{p}_t I$. If $p_t > \tilde{p}_t$, which would occur if the insurance company learns over time that the drought probability has increased, the expected profit will be negative as the probability of a loss is greater than the probability used to determine the premium. Conversely, if $p_t < \tilde{p}_t$, then expected profit would be positive.

In the third supply scenario, the "sophisticated updating" scenario, the insurance company will charge an ambiguity load to avoid the losses that could occur under niave updating. The insurance premium in this case is equal to ${\pi^s}_t = \tilde{p}_t(1+\xi)I$, where ξ is the ambiguity load. The size of the ambiguity load is based on the insurance company's perception of the size of the potential change in risk it faces.

In this case, the insurance company assumes a uniform distribution over the same possible changes in drought probability that participants were informed of at the start of the climate change treatment. It then chooses λ optimally to maximize profit, at the lowest possible ambiguity load such that this maximum is equal to zero.[42] Figure 2 displays expected insurance company profits in the sophisticated supply scenario by learning parameter λ, for two different ambiguity loads: $\xi = 0.3$ and $\xi = 0.55$.

Figure 2: Insurance Company Profit by Ambiguity Load



The profits are averaged over the first ten years after the switch in drought risk has occurred. Figure 2 demonstrates that $\xi = 0.3$ is not sufficient for the insurance company to remain zero-profit in expectation. The optimal learning parameter in this case is roughly $\lambda = 2.3$, where the insurance company is losing over 2 (TSH) per potential customer. At $\xi = 0.55$, however, the insurance company is able to break even in expectation with optimal learning parameter $\lambda = 5.2$.[43]

[42]The insurance company could earn zero profit in expectation at higher ambiguity loads by setting λ sub-optimally. We assume the insurance company will set λ optimally because: 1) If the insurance company is a non-profit, this level will have the highest social benefit while ensuring the non-profit remains financially viable, or 2) If the insurance company is profit-maximizing in a competitive market, on average it faces losses by setting λ sub-optimally and will exit the market.

[43]The parameter λ is equivalent to how many years of previous data at an average drought probability of $p_o = 0.2$ the insurance company is weighing at the time of the change in probability. A smaller λ (less

5.2 Simulated Insurance Uptake Rates

Using the structural demand model and the supply scenarios described in the previous sections, we can now address the question of how climate change affects insurance uptake rates. Recall from the structural demand model that an agent purchases insurance in period t if and only if the random error term ϵ_t (the utility difference with and without insurance) is greater than $\Omega(\pi_t)$. Now, we substitute in the set of insurance premiums from the three supply scenarios into $\Omega(\pi_t)$ to determine the average uptake rates. We then simulate 30,000 agent-insurance company pairs for each supply scenario and potential increase in the true drought probability from 0 to 50%.

Figure 3: Insurance Uptake by Supply Scenario

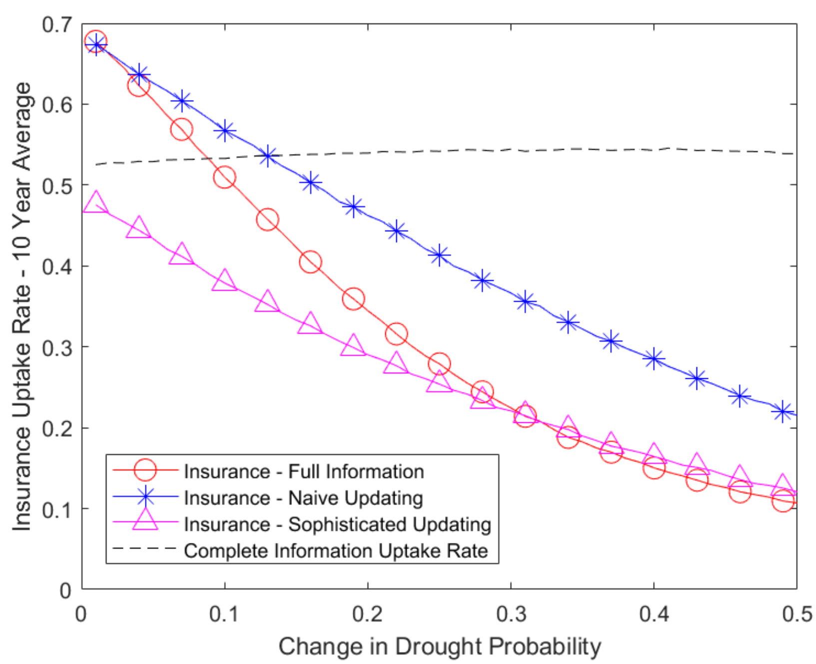


Figure 3 shows the average, post-switch, uptake rates plotted against change in drought probabilities for each scenario. The black dashed line indicates the uptake rate when both the insurance company and the participants know the

weight on the prior) leads to large fluctuations in premiums and profits in the first few rounds but allows the company learn the new probability more quickly. On average, the larger the ambiguity load, the larger the optimal λ, as the insurance company loses less by underestimating the risk due to slower learning and thus seeks to increase profit in the first few rounds by reducing premium fluctuations.

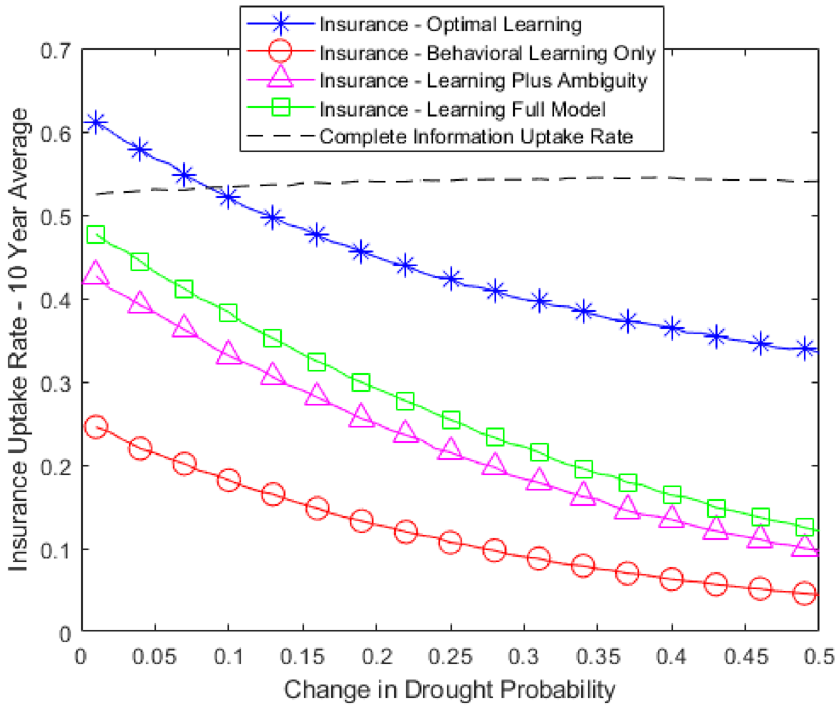
true drought probability with certainty (complete information). Note that this line is above 50% since agents are risk averse on average and insurance completely eliminates risk in the experiment.[44] Here we observe how the insurance company's learning process and pricing affect insurance uptake rates relative to the complete information case. When the insurance company has full information or naively updates, insurance uptake increases when the change in drought probability is small. This is due to farmers' increased WTP for insurance from ambiguity aversion and expectations with no corresponding increase in premiums, leading to increased demand. Thus, mild but uncertain climate change could lead to a net increase in insurance uptake. However, in the case of a sophisticated insurance company that considers a wide range of climate change outcomes, the effect on uptake is always negative. This is a result of the insurance company factoring in a wide range of possible drought probabilities and therefore charging an ambiguity load; the negative effect of the ambiguity load outweighs the positive effect of consumers' expectations and ambiguity aversion on insurance demand. Moreover, we observe that if the true risk of drought increases due to climate change, uptake declines as a function of the magnitude of the increase in drought risk in all three scenarios. Figure 3 suggests that climate change will reduce insurance uptake rates under each insurance company model for moderate to severe climate change.

To assess the role of learning and behavioral biases on uptake rates, we simulate uptake for a sophisticated insurance company while suppressing the behavioral biases. In Figure 4, we visualize uptake rates under the following four scenarios: (1) Optimal learning and no biases: in this scenario we assume farmers have learning parameters that allow their drought probability beliefs to most closely match the true probability. (2) Observed (behavioral) learning: in this scenario, we add in the learning parameters and expectation we estimated in our structural model (in Table 6) but no biases. (3) Learning plus ambiguity aversion: in this scenario we add in ambiguity aversion. (4) Learning full model: finally, we add in recency bias, this scenario is identical to Figure 3.[45]

[44]The complete information uptake line varies only slightly with the size of the change in drought probability. The increase in the drought probability has no effect on the decision to purchase insurance on the margin, but it does increase the variance in utility between the two choices.

[45]The parameters for each scenario are as follows: (1) $\alpha = 2.11$, $\beta = 1.05$, $\phi = 0.065$, $\theta = 0$ and $\psi_1 = \psi_2 = 0$. (2) $\alpha = 16.015$, $\beta = 29.193$, $\phi = 0.026$, $\theta = 0$ and $\psi_1 = \psi_2 = 0$. (3) $\alpha = 16.015$, $\beta = 29.193$,

Figure 4: Insurance Uptake by Behavioral Factors



In Figure 4, we disentangle these characteristics assuming the sophisticated insurance company. We find that insurance uptake rates are highest when we assume farmers' learning parameters allow them to most closely track climate change (optimal learning). However, when farmers learn according to their estimated learning parameters, insurance uptake rates drop precipitously; uptake drops roughly 40 percentage points. Adding in ambiguity aversion and recency bias, we find that both increase uptake. These results demonstrate that "slow learning" relative to the optimal learning process, along with the insurance ambiguity load, drive low uptake rates as we noted in Figure 3.[46] This

$\phi = 0.026$, $\theta = 0.255$ and $\psi_1 = \psi_2 = 0$. (4) $\alpha = 16.015$, $\beta = 29.193$, $\phi = 0.026$, $\theta = 0.255$, $\psi_1 = 0.036$, and $\psi_2 = 0.012$. Parameters for the optimal learning were estimated by assuming a uniform distribution over all possible switch points and changes in probability, and then solving for the parameters that minimized the squared difference between the agent's beliefs and the true probability.

[46] The impact of climate change on insurance uptake illustrated here stem both from demand factors and supply factors. In the appendix section B.4, we attempt to isolate demand factors by reproducing Figure 4 while holding the insurance company's optimal learning and ambiguity load fixed across each type of costumer. We find that both demand and supply factors play key roles in what we observe in Figure 4, and demand factors drive the majority of the effect for moderate and severe climate change. See appendix B.4 for further discussion.

observation is consistent with participants' learning parameters listed in Table 6, which imply participants have a relatively low expectation of the switch occurring and put a heavy weight on their prior. The insurance company, in each scenario, learns about the change in risk faster than the consumers and update premiums accordingly. The combined effect can lead to a substantial decrease in uptake rates compared with the case when all parties know the true risk. As we see in Figure 4, slow learning is partially offset by ambiguity aversion and recency bias.

Taken together, these results suggest that when farmers expect and learn about climate change, their demand for insurance products may be lower than in a full-information world, in which both farmers and the insurance company know the true distribution of droughts. This result implies that climate change may represent a threat to the financial sustainability of these programs in the future. Moreover, slow learning about climate change and insurance ambiguity loads may provide additional explanations for the low uptake rates that have been observed in index insurance programs.

6 Limitations and Structured Speculation

The primary contribution of our work is to identify the channels through which climate change affects insurance demand. Our lab-in-the-field experiment allows us to isolate the effects of ambiguity aversion, learning, expectations, and recency bias on demand for insurance when climate change is modeled as a discrete increase in the drought probability. While our experiment was designed to capture a plausible climate change scenario without compromising comprehension, our results should also be interpreted with caution. Here, we summarize and address some limitations of our work and provide recommendations for future research.

First, while modeling climate change as a discrete increase in the drought probability helped keep the experiment feasible and easy to understand for the participants, this simplification arguably limits the generalizability of our results. Specifically, our results are consistent with climate systems reaching a tipping point resulting in abrupt climatic change, which has been documented in some instances (Lenton 2011; Alley et al. 2003).[47] However, climate change could also manifest itself as a gradual change in environmental conditions affecting both the probability and the severity of adverse events.

In light of this, we argue that our results have a more general interpretation. While the relative magnitude of our coefficients likely depends heavily on the climate change definition, our evidence shows that farmers respond to ambiguity and systematic changes in the underlying drought probability. In particular, we demonstrate that when drought events become more frequent, farmers respond by updating their beliefs about the underlying probability. We also show that ambiguity increases the WTP for insurance. Hence, we can interpret our results as evidence that farmers respond to ambiguity and a changing distribution, although the magnitudes of our coefficient are context-specific.

To understand how our results may change under gradual climate change, we repeat our insurance uptake simulation assuming a continuous, rather than a discrete change in the drought probability and a simplified learning process with no discrete change point (Appendix B.1). We find qualitatively similar results as those shown in Figure 3: for a sophisticated insurance company, climate change leads to significantly lower uptake rates. However, we acknowledge that we cannot fully address this concern using our data, as our model parameters are estimated conditional on the experimental design.[48] If the drought probability is continuously changing, farmers cannot learn about a new fixed probability but rather must learn about a potentially non-linear trend. In this case, ambiguity would play a larger role and learning a smaller role relative to our results, and the net effect on insurance demand would depend on the relative magnitude of each effect. In the extreme, but unrealistic scenario that the drought probability changes unpredictably each period, there will be no learning, and ambiguity averse farmers would likely increase their insurance demand, as predicted by our results.

Furthermore, in addition to affecting the frequency of drought, climate

[47] In appendix A.1 we demonstrate some evidence for an abrupt change in drought probability in Tanzania in the 1990's.

[48] For the simplified learning model, we use the same ambiguity and recency bias parameters that we estimate from the climate change treatment data, but use data without a switch to estimate the learning weight - see Appendix B.1 for details.

change likely also affects the severity of drought events. Rather than modeling climate change as an increase in the drought probability, a more realistic approach would be to conceptualize climate change as a modification of the entire yield distribution over time. This would obviously be difficult to implement in a framed field experiment; however, we could speculate as to how this scenario would affect our results. In particular, if the entire yield distribution changes, learning would likely become more difficult, and ambiguity would likely increase. Also, we hypothesize that the possibility of more extreme events could increase the response to recent events (recency bias), as these events become more salient.

Second, our experiment assumes that farmers do not have access to climate change forecasts, while in reality, farmers likely can obtain partial information about climate change. Such forecasts, assuming they are correct, would likely speed up learning and reduce ambiguity. Moreover, they would likely help farmers form realistic expectations as to whether climate change has happened or may happen in the future.

Third, our experimental design does not consider alternative adaptation strategies that may affect insurance demand in the face of climate change. Such strategies may include the use of climate smart agriculture (intercropping, agroforestry, conservation agriculture, etc.), adoption of irrigation and financial instruments (savings and credit), diversification of income, and migration. While the purpose of our study is to isolate the channels through which climate change affects insurance demand, not modeling other adaptation strategies may limit the external validity of our results.

However, even if farmers are faced with other adaptation options, our results may still have a more general interpretation. While the hypothetical product offered to participants in our experiment was framed as index insurance, it functions similarly to other risk management tools in that it constitutes a trade-off between a reduction in risk and a higher expected income. If we re-conceptualize index insurance in this way, our results could be interpreted as demand for a more general risk management tool that comprises all available risk adaptation strategies. For example, in the face of climate change, ambiguity-averse farmers would have a higher demand for risk management in general. Moreover, if farmers are slow to learn about climate change, they may not invest in risk-mitigating technologies.

Although the experimental design limits our ability to study how farmers would behave in a world with multiple adaptation options, we speculate that many of these strategies will act as substitutes for insurance, which would reduce overall insurance demand in the face of climate change, as farmers switch to other, and potentially cheaper risk mitigation strategies. However, certain adaptation strategies may also act as complements to insurance. For example, index insurance is often bundled with other innovations, such as advanced seeds, credit and savings programs, and risk mitigation technologies, such as irrigation.[49] In this case, climate change may increase insurance demand.

Furthermore, to better understand which adaptation strategies act as substitutes and which act as complements to insurance, we regress stated interest in insurance (based on a survey question) on several other adaptation mechanisms, as reported by farmers in the survey, controlling for the other demographic variables listed in the descriptive statistics table. The results are reported in Table 8 in Appendix B.2. We find that the use of irrigation is positively correlated with stated insurance interest while engagement in agroforestry and wage income are negatively correlated. While we admit that these results may be driven by omitted variables (e.g. farmers with more resources invest in both irrigation and index insurance), these results provide some suggestive evidence that farmers face a variety of adaptation options, which may either be substitutes or complements to insurance.

Despite these limitations, our research nonetheless allows us to identify how different behavioral mechanisms may affect insurance demand under a plausible climate change scenario. Our work should therefore be seen as a complement to existing work on climate change adaptation in smallholder agriculture. In light of this, we recommend several avenues for future research. First, there is a need for further theoretical and experimental analysis of optimal climate change adaptation strategies. Second, future research should explore the implications of allowing for different manifestations of climate change, such as

[49] See for example the R4 Rural Resilience Initiative by the World Food Program, the seed replanting guarantee offered by ACRE Africa, or the Feed the Future Innovation Lab on Market Risk and Resilience Drought Tolerant Maize and Index Insurance project.

assuming a gradual increase in drought probabilities rather than a discrete jump. Third, we recommend using field experiments to investigate the impact of climate change on insurance demand by bundling insurance with climate risk education and climate prediction information.

7 Conclusions

By increasing the likelihood of systemic shocks, climate change poses a grave threat to smallholder farmers and pastoralists in the developing world. Index insurance has been proposed as part of the solution to this increased risk, but most economic models of index insurance assume weather risk is constant over time and known by purchasers and insurers. There exists little research examining whether index insurance programs themselves are vulnerable to changes in risk associated with climate change. Using data from a framed field experiment, we estimate a Bayesian structural learning model and separately identify the effect of learning, ambiguity, recency bias, and expectations on insurance demand. While we show that ambiguity aversion, recency bias, and expectations result in higher demand, we find that farmers underestimate the drought probability and place considerable weight on prior beliefs, resulting in slow learning. Furthermore, given plausible assumptions about how insurance companies set premiums when modeling the supply-side of the market, we show that uptake rates decrease relative to a scenario with no climate change, except in cases where climate change is sufficiently mild.

Our results suggest that climate change could imperil the economic sustainability of index insurance programs in the future. Climate change both increases insurance costs by necessitating an ambiguity load, and lowers demand if there is an asymmetry between the learning processes of insurers and smallholders. It may offer an additional partial explanation for low uptake rates of insurance in certain areas.[50] Thus, climate change may not only harm rural households through increased weather risks but reduce the feasibility of an important risk management tool for those risks.

[50]For a detailed analysis of where climate change is most likely affecting current weather patterns, see IPCC (2015).

Policymakers and development practitioners may use several tools to address the impact of climate change on insurance demand. The low uptake rates stem largely from slow learning about changes in drought probabilities. This implies that providing smallholder farmers with information or forecasts about possible changes in climate patterns may help them avoid underestimating the true risk. Moreover, marketing index insurance products to meso-level institutions such as banks, seed companies, and farmer cooperatives, which have better access to climate forecasts and better means of interpreting them may be more effective than marketing index insurance to individual farmers.

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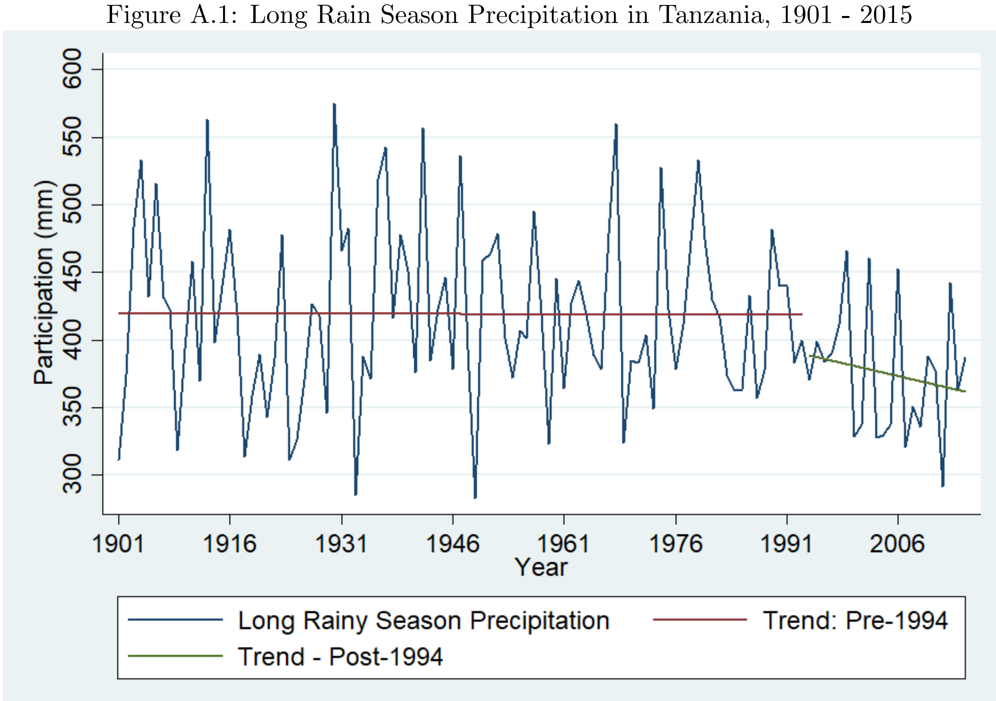
Appendix A Shift in Long Rain Season Precipitation in Tanzania, 1901 - 2015

Figure A.1 below displays long rain season (March - May) precipitation levels from 1901 to 2015, averaged across Tanzania. The data are available from the World Bank Climate Change Knowledge Portal here: `http://sdwebx.worldbank.org/climateportal/index.cfm?page=country_historical_climate&ThisCCode=TZA`.

Figure A.1: Long Rain Season Precipitation in Tanzania, 1901 - 2015



The two trend lines are drawn to illustrate the potential shift in East African rainfall patterns that occurred in the mid to late 1990s (Funk et al. 2008 Williams and Funk 2011, Lyon and DeWitt 2012, Lyon et al. 2014, Yang et al. 2014). While this effect has been tied to the rapid warming of the western Indian Ocean, there is some debate within the literature as to whether this shift is primarily due anthropogenic factors or natural long-run climate variation. The decrease in average rainfall has been observed only for the long rain (and main planting) season, there no corresponding decreasing trend in the short rain season (October - December) precipitation. These effects appear to vary greatly based on local topography, and there is some uncertainty as to how climate change will affect rainfall in East Africa over the long-run (Hession and Moore 2011, Doherty et al. 2010, Thornton et al. 2009).

Appendix B Robustness Checks

In this appendix section, we present a series of robustness check for our structural and simulation models. We seek to establish robustness of our model to alternative specifications of climate change, insurance company cost structure, potential biases in the experimental design, and structural modelling assumptions.

B.1 Gradual Climate Change Scenario

We explore the impact of gradual and continuous climate change on insurance demand using an alternative simulation model. We adjust the simulation model from section 5 in two critical ways. First, we assume the probability of drought changes in small fixed intervals in each round (the total change divided by 10, ex. if the total change is 50%, there will be a 5% change in drought each round) rather than a discrete change. Second, we assume that both the insurance company and smallholders update using a standard Bayesian learning model without a switch point using 20% as the initial prior. These adjustments allow us to mimic a gradual but continuous change in drought probability. In order to simulate insurance uptake in this scenario, we need to estimate a single Bayesian learning parameter that measures how much weight participants place on the initial prior. To estimate, we utilize data from an additional experimental game that we excluded from the discussion in the main text, which we called the learning game. The learning game followed the same structure as the other treatments yet with an alternative rainfall probability structure. In the learning game, there is no probability switch but rather that is a fixed but unknown probability of a drought set at 50%. This game was played for 15 rounds.

In the learning game, participants are able to learn about the drought probability without a switch and therefore their learning process is best modeled using a standard baysian updating model rather than with a switch point. The learning equation here is essentially the same as the insurance company's learning equation from the supply simulations above in Equation 14, except τ is taken from the learning game while λ was chosen by the insurance company. We assume τ is an ingrained behavioral parameter, whereas λ can be interpreted as how many years of past data do insurance companies choose to factor in when deciding the premium, or a trade-off between stability and sensitivity to the new trend. Thus the farmer's simplified learning formula is:

$$\tilde{p}_t = \frac{0.2\tau + D}{\tau + t} \tag{15}$$

Using this simplified learning model and data from the learning game, we estimate a basic structural model and present these results in Table 7. The $\rho_o = 0.38$ implies that farmers, on average, began this game with a initial prior of 38% and updated upward (at a rate determined by drought data and the prior weight τ) toward the true probability of 50%. We are not able to separately estimate ambiguity aversion here since there is ambiguity in every round of the learning game.

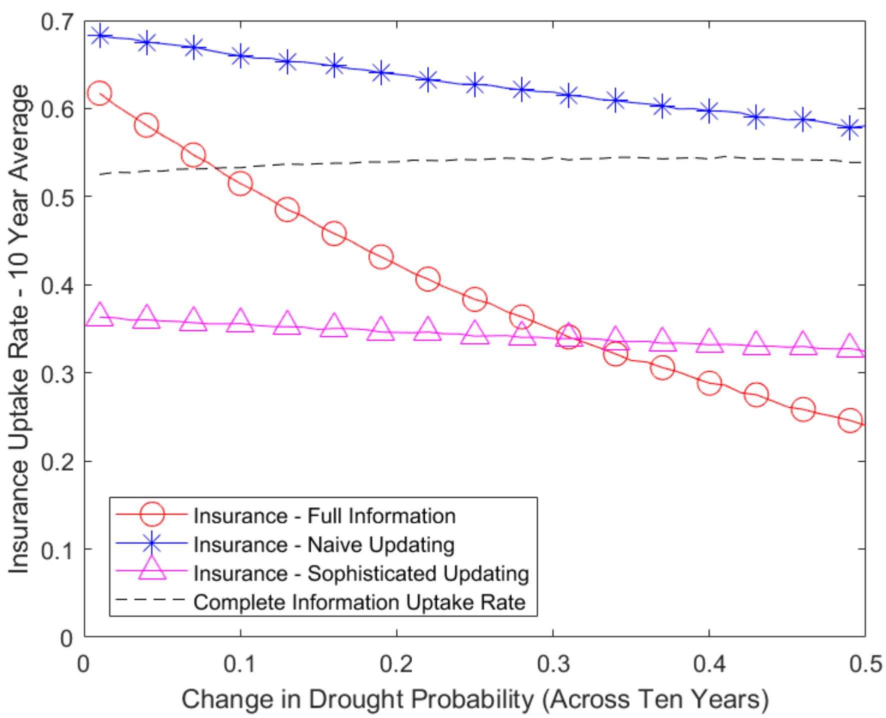
Table 7: Learning Game Structural Estimation Parameters

Variable	Parameter	(1) MLE
Variance of the Utility Error	σ	17.47***
		(0.66)
Implied Initial Probability	ρ_o	0.36***
		(0.013)
Learning Weight	τ	14.06***
		(1.04)
Recency Bias (1 round)	ψ_1	0.012**
		(0.005)
Recency Bias (2 rounds)	ψ_2	0.003
		(0.005)

Standard errors (in parentheses) calculated using the inverse of the square root of the diagonal elements of the Fisher Information Matrix. ***,**,* represent statistical significance at the 1%, 5%, and 10% level, respectively.

Using the learning weight parameter from this basic structural model, we then repeat our insurance uptake simulation assuming an insurance company and consumers that learning using a standard Bayesian updating model and a continuously changing drought probability. We report our simulation results in Figure B.1, which should be compared to Figure 3 in the main text. We find that insurance uptake decreases under the sophisticated insurance company across drought change probabilities as in Figure 3. These results demonstrated that our main results are robust to gradual and continuous model of climate change.

Figure B.1: Insurance Uptake in Gradual Climate Change Scenario



B.2 Index Insurance and Other Climate Adaptations

In Table 8, we find that stated interest in insurance is positively correlated with use of irrigation but negatively correlated with agroforestry and wage income. We may expect insurance and other mitigation tools to be substitutes which we find evidence for in the cases of agroforestry and wage income. However, the positive correlation with irrigation (and to a lesser degree, drought tolerant crops and intercropping) could stem from highly risk exposed or risk averse farmers demanding multiple risk management tools.

Table 8: Index Insurance and Other Adaptations

Variable	(1) Stated Insurance Interest
Official Forecast (yes=1, no=0)	-0.01
	(0.05)
Irrigation (yes=1, no=0)	0.12***
	(0.05)
Drought Tolerant Crops (yes=1, no=0)	0.10
	(0.09)
Intercropping (yes=1, no=0)	0.07
	(0.08)
Agroforestry (yes=1, no=0)	-0.11**
	(0.05)
Remittances (yes=1, no=0)	0.02
	(0.05)
Sales Income (yes=1, no=0)	0.01
	(0.05)
Wage Income (yes=1, no=0)	-0.16**
	(0.06)
Constant	0.47**
	(0.18)
R^2	0.07
N	471

The demographic variables displayed in the descriptive statistics are included as control variables. The dependent variable is a binary variable of stated interest in index insurance, which is 1 for "high interest" and 0 for less than "high interest." Roughly two thirds of our sample chose "high interest." Standard errors in parenthesis, ***,**,* represent statistical significance at the 1%, 5%, and 10% level, respectively.

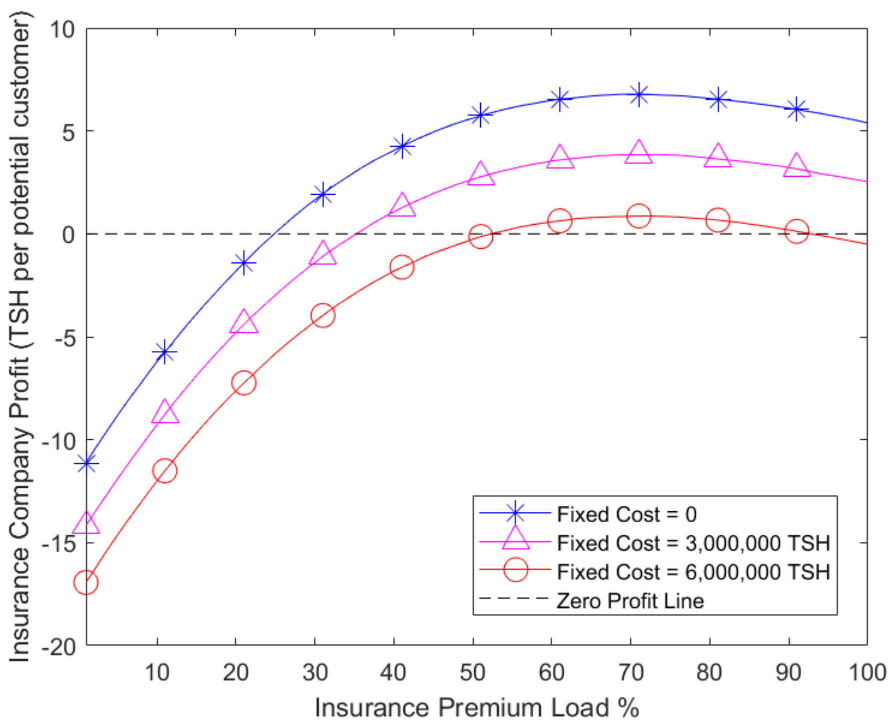
B.3 Fixed Costs

In Figure B.2 we present the insurance company's profits by insurance premium with three levels of fixed costs: 0 TSH, 3 million TSH, 6 million TSH (we assume a target population of 1000). We assume the sophisticated insurance company with the following profit function:

$$P_I = v_t {\pi^z}_t - v_t p_t I - K \tag{16}$$

where K is a fixed cost. We find that fixed costs affect the insurance company's profits but not their optimal load. The effect of the fixed cost on profits will influence how large of a population the insurance company will market to and whether the insurance company will enter the market, but will not affect the percentage of the population that will take up the insurance. Therefore, for simplicity of presentation, we exclude fixed costs from the model.

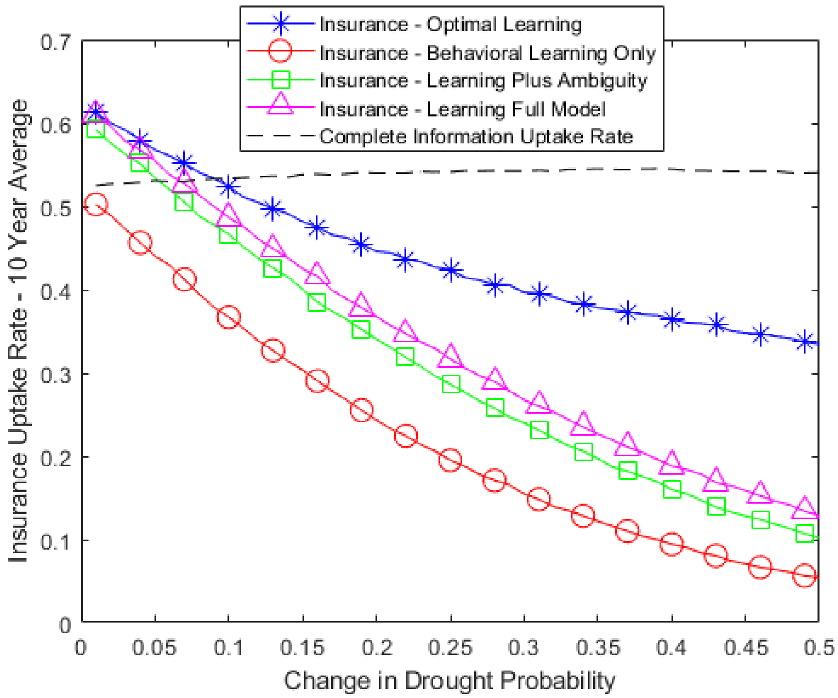
Figure B.2: Insurance Company Profit by Fixed Cost Level



B.4 Isolated Demand Effects on Uptake

In Figure B.3 we illustrate the portions of the total effect that can be attributed exclusively to demand effects. In this figure, we hold the insurance company's ambiguity load and learning parameter fixed at their zero-profit levels for the farmer optimal learning case, so the optimal learning uptake rate is the same as in Figure 4. For other cases, the insurance company will suffer a loss in expectation of between 4,000 and 5,000 TSH depending on the case. Compared with Figure 4, insurance uptake rates increase or fall far less for small changes in the drought probability.

Figure B.3: Insurance Uptake Holding Supply Factors Constant



This difference is driven by the fact that the insurance company reacts to slower learning on the part of farmers by increasing its ambiguity load and slowing its own information updating to avoid losses. With the insurance ambiguity load fixed at a lower level, farmers' ambiguity aversion accounts for the increase in demand above the complete information uptake rate. This implies that the insurance company updating its ambiguity load in order to remain zero profit in expectation is the main factor driving the reduction in uptake rates for small drought probability changes. For larger changes however, the decreases in uptake rates are quite similar to those in Figure 4. This is because this effect is primarily driven by the difference in the rate of learning between the insurance company and farmers. Holding the insurance company learning parameter constant increases this difference, which roughly balances out the higher ambiguity load in these cases. Thus, the decline in insurance uptake appears to be mainly driven by the supply response (partially balanced out by farmers' ambiguity aversion) when the change in probability is small, and by differences in learning when the change in probability is larger.

B.5 Experiment Robustness Checks

Our experimental games were played in a random order to allow us to control for ordering bias. To demonstrate the impact of order on our results we regressed WTP on the order in which the game was played for each game. The only significant result we found is a small, negative effect of the full information treatment played in the third round, which is likely spurious. Therefore we found no compelling evidence that our results were affected by ordering bias.

Table 9: Test for Experiment Order Effects

Order/Treatment	Climate Change	Full Information	Ambiguity
First	0.46	1.31	0.09
	(1.06)	(1.06)	(1.05)
Second	0.54	0.59	0.14
	(1.05)	(1.05)	(1.04)
Third	-1.17	-2.44**	0.43
	(1.03)	(1.03)	(1.02)
Fourth	-0.50	0.43	-0.02
	(1.05)	(0.005)	(1.04)
Constant	69.25***	71.84***	44.90***
	(9.86)	(9.89)	(9.79)
R^2	0.008	0.029	0.001
N	471	471	471

Standard errors in parenthesis. ***,**,* represent tatistical significance at the 1%, 5%, and 10% level, respectively.

Our experimental games were designed to include drought probabilities of 20%, 40%, 50%, and 60%. To check for signs of manipulation, we report the observed drought probabilities. We find that in fact there is some evidence for manipulation for the 20% probabilities scenarios as the observed probabilities drop significantly below 20%, displayed below in Table 10.

After thorough reviewing this issue, we found no clear explanation for this phenomenon. We found no variation in this phenomenon across rounds, refuting the concern that this occurred as as result of farmers learning how to

Table 10: Experiment Drought Probability Check

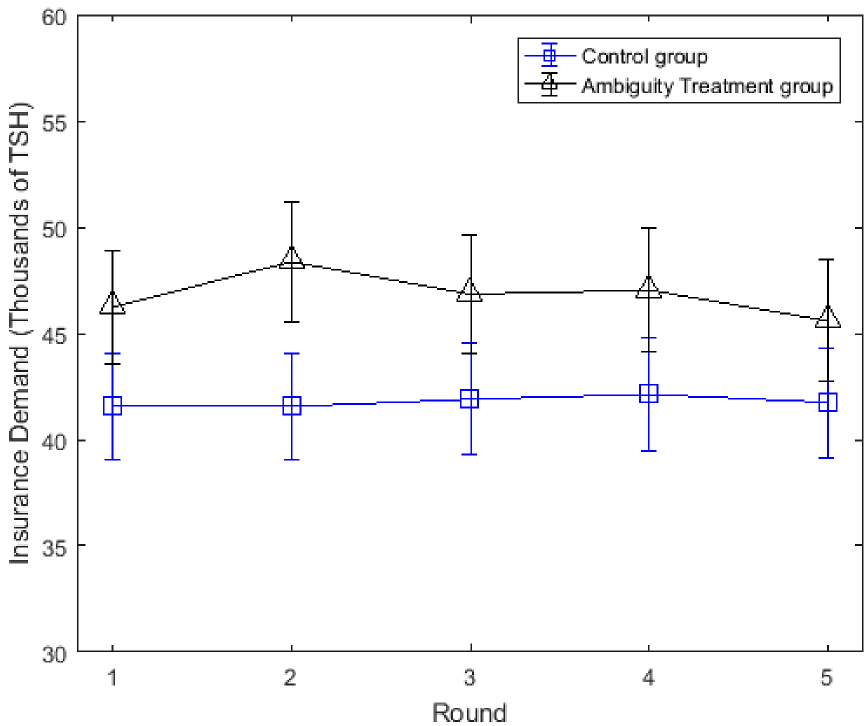
Probability	Climate Δ	Full Info	Ambiguity	Learning
20%	15.33***	15.00***	13.23***	-
40%	40.06	38.27	-	-
50%	-	-	-	49.38
60%	56.89*	56.05**	-	-

Standard errors in parenthesis. ***,**,* represent tatistical significance at the 1%, 5%, and 10% level, respectively, for difference the chosen probabilities.

detect drought balls and then avoiding them in the experiment. Moreover, we were present throughout the entire experimental implementation and were able to ensure no tampering with the experimental materials and that farmers were not able to see into the bags used to generate the probabilities. In the next section we confirm our results are robust to this potential problem. We re-estimate our structural model dropping the sessions with lowest drought probabilities until the observed probabilities were not statistically significantly below 20%: 12 sessions out of a total of 44. We find no significant differences in the coefficient estimates. Results are presented in Model 5 in Table 11.

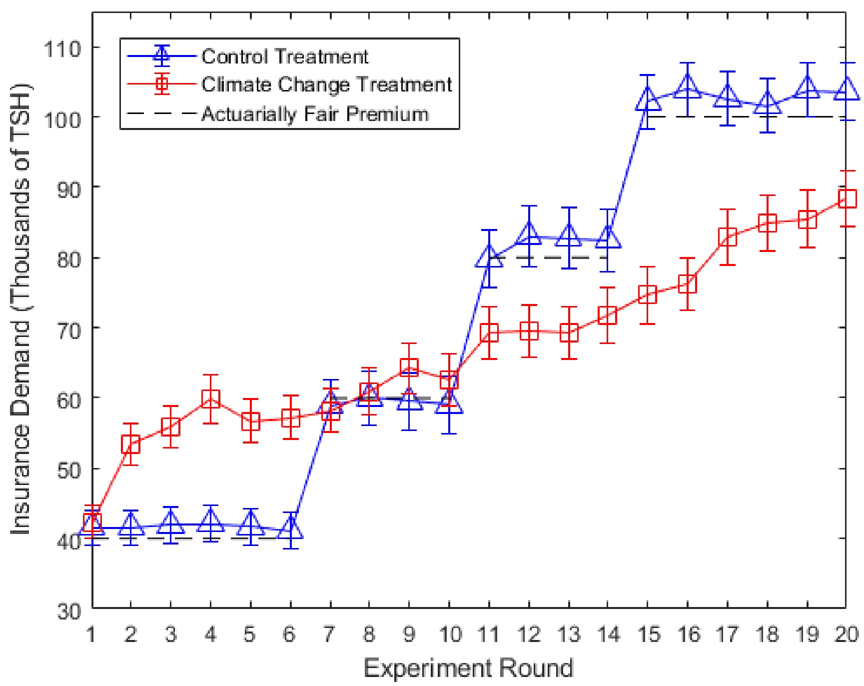
We also include here a graph of the results of the ambiguity regression in Table 2 broken down by round. We see in Figure B.4 that the difference between the ambiguity and control treatments is relatively constant and statistically significant across rounds (at the 5% or greater for rounds 1-4 and at the 10% level for round 5). We also reran the ambiguity regression dropping data from the sessions with the lowest drought realizations until the ambiguity and control drought realization were not significantly different from 20% and the effect of ambiguity aversion increased slightly, results available upon request.

Figure B.4: Ambiguity Treatment (with 95% Confidence Intervals)



Finally we include a graph of WTP by treatment by round, instead of round relative to switch as above in Figure 1. Here we can clearly see the three potential switch points at rounds 7, 11, and 15, where we observe large increases in average willingness to pay in the control treatment (when participants are immediately aware of the rise in probability). We also see that the two treatments are basically identical in round 1, where participants know the true probability with certainty in both treatments. Between rounds 1 and 2 we see an extra large jump in the climate change treatment, which we attribute mostly to ambiguity aversion.

Figure B.5: WTP for Insurance by Treatment by Round



B.6 Robustness Checks for Data Integrity

To confirm that our structural model is robust to a number of alternative specifications and potential challenges to the internal validity of our experiment, we conducted a series of eight robustness checks and present them below.

The first potential challenge to the internal validity of our experiment is that the complexity of how our experimental outcome (income from crop sales in the experiment) maps to actual incentive payouts raises the concern that participants did not understand the incentive mechanism, leading to potential strategic behavior in the game.[51] To address this concern we present three robustness checks for our structural model. First, we re-estimated our model using the incentive payment cash equivalent for each WTP rather than the revealed WTP. Similar results with this adjustment should indicate that participants behaved "as if" they understood the incentive mechanism. Second,

[51]One may also be concerned that poor comprehension could lead to wealth effects. We also performed reduced form analyses that suggest there are not wealth effects. These are available upon request.

we re-estimated our model on the sample of participants that correctly answered at least 3 of 4 comprehension questions. Third, we re-estimate our model excluding those with the lowest education as an additional means of addressing the concern of poor understanding of the experiment and to mitigate concerns related to strategic behavior driving our results. We present these results in Table 11 in models 2, 3, and 4. In each model we find very similar results for expectations (ϕ), learning (α and β), ambiguity (θ), and recency bias (ψ_1 and ψ_2) parameters. These results suggest that behavior in the experiment are "as if" the participants were making decisions over their real incentive payments and that poor measured comprehension and low education do not bias our results in an appreciable way.

Table 11: Structural Parameters fo Data Integrity Robustness Checks

Parameter		(1) Baseline Table 6	(2) Incentives	(3) Comprehension	(4) High Edu	(5) Manipulation	(6) Outliers
Error Variance	σ	12.07***	13467.19***	6.44***	13.55***	13.23***	15.84***
		(0.14)	(155.58)	(0.091)	(0.17)	(0.17)	(0.19)
Expectation	ϕ	0.026***	0.025***	0.030***	0.031***	0.032***	0.032***
		(0.005)	(0.005)	(0.005)	(0.007)	(0.008)	(0.006)
Learning	α	16.08**	12.13***	14.04**	13.99**	12.09***	20.80*
		(7.89)	(5.17)	(6.64)	(6.61)	(4.80)	(11.63)
Learning	β	29.32**	21.18**	23.17**	25.71**	24.24***	39.65**
		(12.74)	(7.78)	(9.73)	(10.73)	(8.04)	(20.06)
Ambiguity	θ	0.26***	0.20***	0.15***	0.23***	0.26***	0.26***
		(0.018)	(0.017)	(0.021)	(0.021)	(0.022)	(0.020)
Recency Bias 1	ψ_1	0.036***	0.036***	0.033***	0.037***	0.035***	0.037***
		(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)
Recency Bias 2	ψ_2	0.012**	0.010**	0.016***	0.010**	0.011***	0.013***
		(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
N		471	471	321	410	359	438

Standard errors (in parentheses) calculated using the inverse of the square root of the diagonal elements of the Fisher Information Matrix. ***,**,* represent statistical significance at the 1%, 5%, and 10% level, respectively. Implied switch probability proxies for expectations in the structural estimation.

The second potential challenge to internal validity is the presence of statistically significant deviations from the drought probabilities as described above. We present results of the restricted sample in Table 11 in Model 5 and find almost identical results compared with using the full sample, ameliorating concerns that our results are biased due to manipulation with our experiment.

We conducted one additional robustness check. First, we re-estimated the model while dropping outliers with respect to risk aversion, ambiguity aversion, and land holdings (in each case dropping individuals with observations beyond 3 standard deviations from the mean). We report this result in Table 11 in Model 6 and find no statistically significant difference in the coefficient estimates while dropping outliers.

B.7 Robustness Checks for Structural Model Specification

We also performed two robustness checks regarding the specification of the structural model. Specifically, we altered how recency bias and ambiguity aversion are incorporated into the model. First, we re-estimated the structural model by varying the number of recency bias terms to ensure our model was not overly sensitive to the number of recency bias lags. This would alter Equation 7 to be: $p_{it} = \tilde{p}_{it}(1 + \theta I_A) + \psi_1 I_1 + \psi_2 I_2 + \psi_3 I_3 + \psi_4 I_4 + \psi_5 I_5 + \psi_6 I_6$, for the case of six lags. We find overall similar results, which we display in Table 12. As the number of recency bias terms increases, the expectations parameter and the initial prior weight decrease, which have opposite effects on the speed in which agents learn. In Figure B.6 we show that there is very little overall effect of including additional recency bias terms on insurance uptake rates, so for simplicity we choose to keep two lags in our base model.[52]

In our final robustness check, we estimate our structural model with the ambiguity aversion and recency bias terms added in the agent's utility function instead of weighting the agent's drought beliefs. In this case, the ambiguity aversion and recency bias terms would be removed from Equation 7, and instead Equation 4 would be rewritten: $Eu_{it}^{I}(.) = p_{it}\frac{(\omega+y_l+I-\pi_{it}+\theta I_A+\psi_1 I_1+\psi_2 I_2)^{(1-\gamma)}}{(1-\gamma)} + (1-p_{it})\frac{(\omega+y_h-\pi_{it}+\theta I_A+\psi_1 I_1+\psi_2 I_2)^{(1-\gamma)}}{(1-\gamma)}$. Here we find large parameter changes, which we report in Table 13. It's important to note that the new ambiguity aversion and recency bias are in different units compared with Table 6 (Thousands of TSH instead of % chance of drought), which account for some of the difference. The changes in the learning parameters work in opposite directions:

[52] There is also some concern that adding more recency bias terms could wash out the effect of learning that we are trying to isolate. In the extreme case, including recency bias terms for every lagged drought would be the same as estimating an entirely non-parametric learning model.

Table 12: Structural Model Parameters for Varying Recency Bias Terms

Parameter		(1) Baseline Table 6	(2) Recency Bias (4)	(3) Recency Bias (6)
Error Variance	σ	12.07***	12.05***	12.04***
		(0.14)	(0.14)	(0.14)
Expectation	ϕ	0.026***	0.021***	0.015*
		(0.005)	(0.006)	(0.008)
Learning	α	16.08**	11.83*	7.13
		(7.89)	(6.40)	(4.93)
Learning	β	29.32**	24.69**	16.97*
		(12.74)	(11.10)	(8.87)
Ambiguity	θ	0.26***	0.26***	0.27***
		(0.018)	(0.018)	(0.017)
Recency Bias 1	ψ_1	0.036***	0.046***	0.054***
		(0.005)	(0.005)	(0.005)
Recency Bias 2	ψ_2	0.012**	0.019***	0.027***
		(0.005)	(0.005)	(0.005)
Recency Bias 3	ψ_3	-	0.020***	0.026***
			(0.005)	(0.005)
Recency Bias 4	ψ_4	-	0.017***	0.022***
			(0.005)	(0.005)
Recency Bias 5	ψ_5	-	-	0.019***
				(0.006)
Recency Bias 6	ψ_6	-	-	0.009
				(0.006)
N		471	471	471

Standard errors (in parentheses) calculated using the inverse of the square root of the diagonal elements of the Fisher Information Matrix. ***,**,* represent statistical significance at the 1%, 5%, and 10% level, respectively. Implied switch probability proxies for expectations in the structural estimation. Model 1 represents results from main text table 6. Model 2 re-estimates the model with additional lagged recency bias terms. Model 3 re-estimates the model with ambiguity aversion incorporated into the utility function.

The agents' implied expectations (ϕ) are much greater, but their initial prior ($\frac{\alpha}{\alpha+\beta}$) is smaller (29.15% compared with 35.42%). As in the case of adding more recency bias terms, this robustness check also produces strikingly similar insurance uptake predictions, as shown in Figure B.6.

Table 13: Robustness Check: Alternate Structural Model Parameters

Variable	Parameter	(1) MLE
Variance of the Utility Error	σ	14.86***
		(0.31)
Expectation	ϕ	0.082***
		(0.018)
Learning Parameter 1	α	7.59**
		(1.00)
Learning Parameter 2	β	18.45***
		(2.26)
Ambiguity Aversion Weight	θ	5.21***
		(0.99)
Recency Bias (1 round)	ψ_1	15.68***
		(1.10)
Recency Bias (2 rounds)	ψ_2	8.89***
		(1.15)

Standard errors (in parentheses) calculated using the inverse of the square root of the diagonal elements of the Fisher Information Matrix. ***,**,* represent statistical significance at the 1%, 5%, and 10% level, respectively. Implied switch probability proxies for expectations in the structural estimation.

Figure B.6: Robustness Check: Insurance Uptake across Structural Models