Investigating the Impact of Climate Change on the Demand for Index Insurance

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1. Introduction

It is widely acknowledged that climate change presents a serious threat to agriculture in East Africa, especially among smallholder farmers with fewer means of adaptation. Rising temperatures, increased extreme weather events, and changing rainfall volatility all present difficult challenges to farmer livelihoods and increase the likelihood of systemic crop failure (Waithaka et al. 2013; Collier et al 2009). An increase in the frequency of droughts poses particularly devastating risks, as the majority of East Africans make their living through agricultural and pastoral work overwhelmingly dependent on rainfall (Katz and Brown, 1992; Burke et al. 2006; Lehner et al. 2006; Sheffield and Wood, 2008). East Africa has been singled out as a region where a change in rainfall patterns is expected and likely already occurring, although there is some debate as to the exact nature of the change and it will likely vary based on local topography (Funk et al 2005; Jury & Funk 2013; Doherty et al. 2010; Thornton et al. 2009). Systemic agriculture shocks result in widespread loss of income across a region and have been shown to lead to a greater decrease in consumption than idiosyncratic shocks such as an illness or injury, as shock coping mechanisms as informal sharing networks and the sale of assets at the local market become less viable (Carter et al. 2014). These dips in consumption are associated with decreases in childhood survival, body size and health, and educational attainment (Rose, 1999; Foster, 1995; Jacoby & Skoufias, 1997). An increase in drought frequency due to climate change could thus have drastic effects on human welfare in the region (Barratt & Santos 2014).

One tool proposed in the economics literature to help farmers and pastoralists alleviate systemic shock risk is index insurance. Index insurance is an insurance product that pays an indemnity based on an objective index such as rainfall at a local weather station or a measure of area yield captured by a satellite. Index insurance has been shown to have numerous theoretical benefits, including lower transaction costs and lower susceptibility to information problems such moral hazard and adverse selection when compared to traditional multi-peril crop insurance (Miranda & Farrin 2012; Barnett & Mahul 2007). Tests of its applicability in benefitting real-life farmers, however, have been met with mixed results (Giné and Yang 2009; Karlan et al. 2010; Karlan, Osei and Udry 2013). In general, it has been beneficial in reducing swings in consumption and increasing access to credit, but uptake rates without large subsidies have been low (Carter et al. 2014).

Index Insurance has been advanced as a method of mitigating the effects of climate change, but there is little research on the resiliency of index insurance programs themselves in the face of changing climate risk (Daron and Stainforth, 2014). On the insurers' side, there is a strong incentive to utilize climate models and be highly sensitive to the latest weather data when setting premiums to avoid losses (Daron 2012; Collier et al 2009). Demand for index insurance is also likely to respond to changing systemic risk. There is evidence, for example, that Kenyan pastoralists increase their demand for index insurance in response to early signals that a particular year is more likely to be a drought (Jensen et al. 2014). Without access to the same information and models of climate change as insurance companies however, it is unclear if the demand of farmers and pastoralists will increase at the same rate as insurers raise premiums. Thus, without large subsidies to keep premiums low, climate change could aggravate what up to present has been the Achilles' heel of index insurance implementation, low uptake rates. To address this question, we employ a methodology that is growing in usage and popularity in development economics, the framed field experiment (Fischer, 2014; Flatnes, 2014; Giné et al., 2010).

We posit that climate change may affect index insurance demand through multiple behavioral channels: ambiguity aversion, incomplete learning, and recency bias. There is a wide literature suggesting that people prefer risks with known probabilities over those with unknown probabilities (Ellsberg 1961; Hogarth & Kunreuther 1989; Gilboa and Schmeidler, 1993). By adding ambiguity and uncertainty around the true drought probability, climate change may affect farmers' insurance decisions even if the underlying probability of a drought remained unchanged.[1] The ambiguity and compound risk inherent in basis risk, which is the risk not covered by an index insurance policy, has been shown to decrease demand for index insurance (Bryan 2013; Elabed and Carter 2015). We hypothesize that ambiguity aversion will increase demand for insurance in the case of climate change, since the source of ambiguity is the likelihood of a drought rather than the design of the insurance product. We believe farmers, on average, will be willing to pay a positive premium to remove this source of ambiguity. This is consistent with past literature that finds ambiguity increases demand for complete insurance (Bryan 2013).

Better understanding how people use past data to learn about risks is another important area of economics research. Literature in this area has shown that while people do update their beliefs in response to data, this updating often systematically deviates from what we would expect if they followed Bayes' Rule (Holt & Smith 2009; Viscusi & Magat 1992).[2] In the context of development, researchers find a similar result, with farmers and pastoralists updating their beliefs and behavior in response to weather forecasts in ways systematically different than what Bayes' Rule suggests (Lybbert et al 2007; Jensen et al 2014). By simulating many years of climate data, this paper will study how differences between participants' beliefs about drought and the true probability affects index insurance demand. Here we hypothesize that participants will update their beliefs and increase their demand for insurance in response to an increase in the probability of drought. However, this increase in demand will be smaller

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[1] Farmers may become less certain of the probability of a drought for multiple reasons. Disruptions of usual seasonal patterns – such as rain in a traditionally dry season – may change farmers' confidence in their beliefs about drought in the growing season. Likewise, incomplete or conflicting weather and climate forecasts could increase ambiguity surrounding drought.

[2] Bayes' Rule has been the standard practice in economics of dealing with uncertainty (Gilboa et al 2008). Written mathematically $P(A|B) = P(B|A) * P(A)/P(B)$, the rule states that an agent's posterior belief about the probability of an event, given observed data, is proportional to the agent's prior belief about the event times the event's likelihood. While this literature finds that people do react to data, on average beliefs are updated asymmetrically or with other weighting inconsistent with Bayes' Rule.

than the increase in premium of an insurance company which follows Bayes' Rule in assessing the drought probability, leading to an overall decrease in insurance uptake.

One form of belief weighting that has received particular attention in the insurance literature is recency bias. Recency bias, or the behavioral tendency to overweight the data received last, is a possible explanation for a persistent puzzle found in studies of index insurance demand: a large increase in demand in the period immediately following a payout. (Stein 2016; Platteau 2017). This increase has been found even when controlling for beliefs about the likelihood of receiving a payout in the future (Gallagher 2013). Predicting recency bias has been shown to be of potentially great importance in pricing index insurance contracts (Cai et al 2016). Since the framed field experiment examines index insurance demand over many periods, we hypothesize that willingness to pay for insurance will increase sharply in the period following a drought, and that the effect of that drought will steadily decrease as it recedes into the past.

This paper adds to the existing literature in three main ways. It is the first paper to our knowledge that directly studies the effect of climate change on index insurance demand. This allows us to draw broad conclusions on the viability of index insurance in the face of changing climate risk and assess the value of providing smallholder farmers with a forecast describing how climate change is expected to affect their area. Second, it is the first paper we know of that utilizes a framed field experiment to simulate the effects of climate change. Given the practical and moral impossibility of experimentally varying climate risk, we believe a framed field experiment is uniquely suited to address this question. Finally, it provides an experimental test of behavioral factors that have been of recent interest in the development literature in a new context.

The paper first describes the sample and procedures used in the framed field experiment. Second, it outlines a theoretical model meant to formalize farmer's willingness to pay for index insurance and capture the effects of the various behavioral factors described above. Third, it presents a reduced form analysis of the framed field experiment treatments. Finally, it concludes with a brief summary of the findings, policy recommendations, and possible directions for future research.

2. Experimental Sample

2.1. Sample Frame

The objective of a framed field experiment is to simulate a realistic scenario for participants that have real experiences with the circumstances being described. Therefore, the sample frame is constructed by reference to the central features of the research questions and game designs. The participants must be smallholder farmers with experience in cultivating crops in the presence of the risk of suffering a systemic shock, specifically drought. For this reason, the Dodoma region of Tanzania was selected as farmers there face a considerable risk of drought. We also decided that it was important that the farmers chosen had some exposure to financial products, given the limited amount time available to explain the workings of the insurance contract before each game session. The final sample population was identified through the cooperation of the Vision Fund Tanzania Dodoma branch who have agreed to participate in research activities and to assist in identifying farmer associations that may serve as partners in the research activity. We worked with most of the Vision Fund credit groups in the Dodoma Region.[3] This was beneficial in ensuring that the participants were engaged in farming and had experience with financial products (loans).

2.2 Sample Data Collection

Data collection began on September 8th in Mkoka village in Kongwa district. On September 12th, we moved to Ibugule in Bahi district and remained there for two days. Next, we collected data in Hombolo in Didoma Urban district for four days and then on September 20th moved to Gawaye for two days. On September 22nd, we collected data in Nolini in Kongwa district for two days. On September 26th, we returned to Mkoka for 3 days. On September 29th we moved to Makawa and remained there for two days. Our final week of data collection began in Mageseni for 2 days and then finished in Matongoro for 3. In addition to pre-testing, the full data collection process took 4 weeks and 2 days and 471 farmers were included in the sample from 43 farmer groups in 8 villages. While collecting data in Dodoma Urban and Bahi districts, the team stayed in Dodoma. While collecting data in Kongwa district we stayed in Kibaigwa. The villages that we visited as well as other notable stops can be found in Figure 1, a map of the study area. The location of the areas where the experiment was conducted are marked with blue flags in Figure 1.

[3] This sampling followed the same procedure as (Gallenstein et al, 2017), which also worked with Vision Fund Credit groups to study the effects of index insurance and joint-liability lending on agricultural risk-taking. To control for any possible effects of prior study participation on the results of this study, we collected data on which participants overlapped. Roughly 57% of the sample for this paper also participated in (Gallenstein et al 2017).

Figure 1: Map of Survey Area

2.3 Data:

Descriptive statistics of the 471 farmers in our sample are displayed below in Table 3. The sample is slightly majority female and from a variety of ages and backgrounds. Given the importance of risk aversion in determining the demand for insurance, we calculate risk aversion in two different ways. The CRRA coefficient displayed below was found using an unframed coin flip game where participants chose between a 50/50 lottery and a set of decreasing sure payments. This provided ranges for participants' CRRA coefficient, the center of which is used in the analysis. Later, we will also calculate individual risk aversion coefficients from our framed treatments. A larger number indicates higher risk aversion, meaning the agent would be willing to pay more to avoid risk. Since real-life insurance decisions also involve a tradeoff over time between paying a premium in the present and possibly receiving an indemnity in the future, we measured participants' discount rates. This was done using two survey questions and are likewise the center point of a possible range of values.[4] In this case, a larger number is associated with being more impatient.

[4] The survey questions asked participants to choose between two hypothetical payments at different times. For example: "Would you prefer to receive a payment of 10,000 TSH tomorrow or a payment of 14,000 TSH a month from now?"

Table 1: Descriptive Statistics

Variable	Mean	Minimum	Maximum
Age (in years)	38.575	16	80
Education (in years)	6.827	0	13
Female (female=1, male=0)	0.525	-	-
Household head (yes=1, no=0)	0.568	-	-
Household size (number of members)	5.370	1	20
Total land owned (in acres)	10.864	0	60
Community leader (yes=1, no=0)	0.336	-	-
Income from remittances (yes=1, no=0)	0.262	-	-
Income from selling (yes=1, no=0)	0.568	-	-
Income from wage labor (yes=1, no=0)	0.136	-	-
Unframed CRRA Coefficient	0.451	0	0.84
Discount Rate	0.708	0	1

Sample Size = 471 Participants

2.4 General Experimental Procedures

Experimental sessions were conducted with 8-16 participants and took roughly 4 hours to complete each session. After all participants arrived, an introduction of the research and the day's activities was given. Each participant could choose whether to participate in the survey and game or not and was given a written consent form to sign of which they received a copy.

The experiments began with an introduction to the game procedures and game pieces. Players were allowed to familiarize themselves with the game materials and practice drawing colored balls from the bags. The games were designed to mimic real life scenarios regarding drought and insurance. The output yields and fixed incomes were calibrated as best as possible using input from focus groups conducted in advance of the experiment with leaders of the farmer associations.

After the general introduction by the facilitator, the participants were randomly separated into 3 groups and then dismissed to three stations located in the experiment area. Each station was manned by one enumerator. The station consisted of a table (a plastic Jambo Table), a privacy bucket for switching around the bags, a full set of drought bags, chairs for participants, games sheets for each participant, game decision cards, wooden privacy dividers to separate the participants, and a padfolio for each enumerator. The participants sat around three sides of a table with the enumerator at the remaining side administering the game.

During the explanation of the experiment, participants were told to imagine that they owned exactly one acre of land and all the required inputs (good soil, seeds, etc) to grow sunflower. The only risk they faced was rainfall: in a season of good rains they earned 200,000

Tanzanian Shilling (TSH)[5] from their land, in a drought, the crop completely failed and they earned no income from their field. Additionally, each participant was told that they had 150,000 TSH of income from another source (whether it be a family member, selling goods, working for a wage, etc).

The participants were then told that they had the ability to purchase weather-based index insurance in town, which costs a premium and fully reimburses the value of their lost crops in the event of a drought.[6] If there were good rains, however, then farmers would not receive an indemnity payment. Since the premium must be paid before the weather realization, farmers had the option of using some portion of the 150,000 TSH of nonfarm income to pay the premium. The final payouts in both weather outcomes are shown below in Table 1. Note that for simplicity, the insurance product does not include basis risk.

Table 2: Participant Payout Table

Weather Outcomes	Payout with Insurance	Payout without Insurance
Good Rains	350,000 – Premium (TSH)	350,000 (TSH)
Drought	350,000 – Premium (TSH)	150,000 (TSH)

We measured willingness to pay for each participant by asking a series of dichotomous choice questions as to whether the participant would like to buy insurance at the following premiums: 30,000 TSH, 60,000 TSH, 90,000 TSH, 120,000 TSH, and 150,000 TSH. The questions were framed in following way, based on a similar question used to measure willingness to pay in (Elabad and Carter 2015): "You have a friend who is going into town today and is willing to buy index 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 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. How much money would you like to give your friend?"

We began by asking if they would like to give their friend 90,000 TSH and then increased to the higher premiums if they said yes and decreased to lower premiums if they said no. We choose to start with the center value to minimize the effect of anchoring on the estimate. During the practice rounds we drew random premiums and demonstrated to participants how their willingness to pay determined their insurance decision and payout. At the end of the experiment we drew a random round and premium and made payouts per the insurance decision and weather outcome of that round.

5 As of March 2017, 1 US Dollar = 2200 TSH

6 In this experiment, we abstract away from other farming risks aside from drought and assume that the insurance contract accurately measures whether each farmer faces a drought. Thus, the insurance contract has no basis risk.

The decisions outlined above were made across five treatments in which the probability of a negative systemic shock and the participants' information about the shock were varied:

Treatment 1: Climate Change with No Information

Treatment 1 is meant to model climate change increasing the likelihood of a systemic shock in the absence of information about the timing and magnitude of the change. The participants were shown two identical-looking bags: The first bag was shown to have eight blue balls and two red balls, while the participants were told that the second bag has a total of ten balls, with between two and ten of them red and the rest blue. Before each draw, participants were asked to state their belief about the number of red balls in the bag and then make an insurance willingness to pay decision.[7] Each participant privately made and reported these decisions to the enumerator. Confidentiality was ensured by having the participants indicate their decisions by pointing to their decision on the decision board affixed to the privacy station. For the first draw, the first bag was used, and then between every draw the two bags were put into a privacy bucket and then the enumerator removed one unknown to the participant. The participants were told that the bag would switch once (from the first to the second bag) at some point over the experiment and then stay the same for the rest of the treatment. The treatment was played for twenty rounds. 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. The possible rounds when the bags switched were rounds 7, 11, and 15. The possible number of red balls in the second bag were 4 and 6.[8]

Treatment 2: Climate Change with Forecast

Treatment 2 followed the same procedure as Treatment 1, except participants were given a forecast which provided a short range around the timing and magnitude of the change in probability. For example, participants could have been told that at some round between 10 and 16, the number of red balls would increase to between 3 and 5. In the rounds before the start of the range, only the first bag was used. During the forecast range the enumerator used both bags and the privacy bucket as in treatment 1. At the end of the range, only the second bag was used.

Treatment 3: Climate Change with Full Information

Treatment 3 followed the same procedure as Treatment 1 and 2, except the timing of the switch and the number of red balls in the second bag were announced at the beginning of the

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[7] To maintain privacy, for the stated beliefs questions participants were asked to point at a diagram that showed different numbers of red balls rather than say the number out loud.

[8] We recognize that the probability of a drought increasing from 20% to 40% or 60% represents a drastic change that is outside of most climate change forecasts. This was chosen to increase the likelihood that participants perceived the increase given the limited number of rounds. Such a dramatic change is not entirely without precedent, however. While stressing it was an extremely rare case, (Collier et al 2009) shows that the observed risk of drought in the Sahel Region increased from 2% to 44% in the 1960s.

treatment. Before the switch only the first bag was used, and after the switch only the second bag was used. At no point were the participants unsure of the true drought probability.

Treatment 4: Ambiguity Treatment

Treatment 4 was meant to model a different possible consequence of climate change, an increase in ambiguity around the true drought probability (apart from a possible change in its central tendency). For this treatment, participants were shown three bags, the first with one red and nine blue balls, the second with 2 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 used each round can switch back and forth at any time or remain the same for the whole treatment. Before each draw, participants made willingness to pay for insurance decisions. Then, the enumerator placed the three bags into the privacy bucket and removed one to draw from. This treatment was played for five rounds. In order to compare the results of the ambiguity and full information treatment, the bag with two red balls was always chosen for the draws.

Treatment 5: Framed Learning Game

Treatment 5 was meant to isolate participants' learning processes. This game was modelled off the "drawing game" played in Barham et al (2015) and has similarities to the learning experiments played in Holt & Smith (2009) and Baillon et al (2013). Participants were shown one bag and told that there is a total of 10 either blue or red balls in the bag, and that the same bag was used for each draw. Since the bag does not change, we can observe how participants update their insurance decisions in response to new information. Before each draw, the participants were asked their beliefs as to the true number of drought balls in the bag and their willingness to pay for insurance was elicited. This treatment was played for 15 rounds. For this treatment, the bag always had five red balls.

Table 3: Treatment Characteristics

Treatment	Name	Switch from bag1 to bag2	Partial Information	Full Information
1	No Information	X		
2	Forecast	X	X	
3	Full Information	X		X
4	Ambiguity		X	
5	Learning Game			

3. Theoretical Model

To better understand the underlying effects described above, we now construct a theoretical model of purchasing index insurance in the face of changing climate risk. We begin with an agent that we assume follows Von Neumann Morgenstern expected utility theory and knows the probability of a negative systemic shock with certainty, and then relax these assumptions to include Bayesian learning in the case of unknown probability, ambiguity aversion, and recency bias.

3.1 Willingness to Pay for Index Insurance

An agent faces two possible rainfall realizations: a drought with probability p, and sufficient rain with a probability $1-p$. To start, we assume that the agent knows these probabilities with certainty. In the case of drought, the agent earns y_d, while in the case of rain she earns y_r, with $y_r > y_d$. The agent has nonfarm income ω, which the income can consume or use to purchase index insurance. Index insurance costs premium π, and in the case of a drought pays an indemnity equal to the losses resulting from the drought, $y_r - y_d$. We assume that the agent has a CRRA utility function, with:

$$u(c) = \frac{c^{1-\gamma}}{1-\gamma} \qquad (3.1)$$

where γ is the coefficient of relative risk aversion. Thus, the expected utility of agent i, in time t, without index insurance is:

$$u_{i,t}(\cdot) = p * \frac{(\omega + y_d)^{1-\gamma}}{1-\gamma} + (1-p) * \frac{(\omega + y_r)^{1-\gamma}}{1-\gamma} \qquad (3.2)$$

With index insurance, the agent receives the same income in cases of rain and drought, so her utility function can be simplified to:

$$u_{i,t}{}^{ii}(\cdot) = \frac{(\omega - \pi + y_r)^{1-\gamma}}{1-\gamma} \qquad (3.3)$$

Then, by equating $u_{i,t}(\cdot)$ and $u_{i,t}{}^{ii}(\cdot)$, we can solve for the premium the makes the agent indifferent between purchasing index insurance or not. This premium, π^*, is equivalent to the agent's maximum willingness to pay for index insurance. Rearranging, an agent's WTP is equal to:

$$\pi^* = \omega + y_r - \left(p * (\omega + y_d)^{1-\gamma} + (1-p) * (\omega + y_r)^{1-\gamma}\right)^{1/_{1-\gamma}} \qquad (3.4)$$

3.2 Learning about Drought Probabilities

Now we consider the case where an agent does not know the drought probability with certainty, but rather learns the true probability over time by observing data. We utilize a Degroot Beta-Bernoulli model to estimate how the agent updates her subjective probability of a drought (DeGroot 1970; Gallagher 2013). We assume that droughts are distributed Bernoulli with the probability of a drought in any given year equal to p. The number of droughts observed in previous periods is denoted d_t while t is the current period. The probability of a drought, p, is assumed to be distributed $Beta\sim(\alpha, \beta)$. The agent observes drought outcomes each year and updates her belief such that the conditional mean is equal to:

$$E[p|d_t, t] = \frac{d_t + \alpha}{t + \alpha + \beta} \qquad (3.5)$$

By inserting the equation above into the formula for WTP, we find an equation for a WTP as a function of past drought outcomes, agents' risk aversion coefficients, and α and β, Beta distribution parameters that jointly determine the agents' initial beliefs about drought and the weight that agents place on their initial beliefs. Utilizing data from treatment 5, we estimate averages values for γ, α, and β, using maximum likelihood estimation. The MLE estimates are displayed below in table 9.

Table 9: MLE Parameter Estimates

Variable	Parameter	(1) MLE
CRRA Coefficient	γ	0.370***
Alpha	α	3.014***
Beta	β	4.857***

*** Statistically significant at the 1% level.

The estimated CRRA coefficient is the average revealed risk aversion across individuals, so on average, in this treatment, our sample is mildly risk averse.[9] The ratio of $\alpha/(\alpha + \beta)$ determines the average initial drought beliefs across agents, in the case the average initial drought belief $\approx$ 38.3%. The magnitude of the coefficients determines the weight that they put on this initial belief relative to observed data.

[9] Given that the true drought probability used in treatment 5 is 50%, failing to account for participants' lower initial drought beliefs and learning processes leads to the conclusion that agents are risk-loving. The revealed average risk aversion here is slightly less than the average level found in the unframed coin flip game (=0.451).

3.3. Further Extensions

The model described above will be extended in multiple ways. First, we will account for recency bias by introducing a parameter to capture the increased weight placed on the newest data. Following (Camerer & Ho, 1999) and (Gallagher 2013) the equation (3.5) will be modified to:

$$E[p|d'_t, t'] = \frac{d'_t + \alpha}{t' + \alpha + \beta} \qquad (3.6)$$

, with $d'_t = \sum_{s=1}^{t} d_s * \delta^{t-s}$ and $t' = \sum_{s=1}^{t} \delta^{t-s}$. In the case, a value of $\delta < 1$indicates the presence of recency bias. An MLE estimation of this updated model is forthcoming, but a reduced form analysis of recency bias is discussed in the empirical analysis section below and shown in Table 8.

A second extension to the theoretical model will be to include the effect of ambiguity aversion on agents' willingness to pay for index insurance. Following (Elabed & Carter 2015), we will apply the smooth model of ambiguity aversion developed in (Klibanoff et al 2005) to data from the ambiguity treatment (treatment 4), where the agent is unsure of the true drought probability between three possibilities. Applying the smooth model of ambiguity aversion will modify equation 3.2 to

$$v_{i,t}(u_{i,t}(\cdot)) = v_{i,t}\left(\sum\nolimits_{1}^{3} q_i * \left[p_i * \frac{(\omega + y_d)^{1-\gamma}}{1-\gamma} + (1-p_i) * \frac{(\omega + y_r)^{1-\gamma}}{1-\gamma}\right]\right) \qquad (3.7)$$

with $v'_{i,t}(\cdot) > 0$ & $v''_{i,t}(\cdot) \leq 0$. By comparing the ambiguity and full information treatments we will solve for each participant's ambiguity parameter, which will characterize $v_{i,t}(\cdot)$. A structural estimation of this problem is still forthcoming, but a discussion and reduced form test for the presence of ambiguity aversion is shown below in Table 6.

Finally, we will also seek to structurally model participant's expectations of when climate change may occur in the future. We see in Figure 2 below that without information about when the likelihood of a drought will increase in the future, participants are willing to pay more for insurance before the change actually occurs. We will attempt to model the question of how agents form beliefs about when the change occurs as a Bayesian change-point inference problem (Smith 1975).

4. Empirical Analysis

4.1 Determinants of Index Insurance Demand

In addition to building a structural theoretical model, we also present reduced form analysis and graphical depictions of a series of questions related to climate change and index insurance demand. We begin by examining what covariates are correlated with index insurance demand. Here, age is positively correlated with insurance demand, which is different than much previous literature (Hill et al, 2013). One possible explanation for this is that in the absence of basis risk, the uncertainty in the experimental game comes not from the insurance product (as it often does in previous literature) but from the systemic shock itself. This is supported in our analysis of ambiguity, where age is positively correlated with ambiguity aversion. We also find that participants receiving remittances and that have higher discount factors are willing to pay less for insurance. While a higher risk aversion coefficient is associated with higher insurance demand, the effects is not statistically significant.

Table 4: Determinants of Index Insurance Demand (Average of Treatments 1,2, & 3)

Variable	(1) Average WTP
Age (in years)	0.301***
Education (in years)	-0.358
Female (female=1, male=0)	2.903
Household head (yes=1, no=0)	2.857
Household size (number of members)	-0.583
Total land owned (in acres)	-0.034
Community leader (yes=1, no=0)	-1.164
Income from remittances (yes=1, no=0)	-4.045**
Income from selling (yes=1, no=0)	-1.740
Income from wage labor (yes=1, no=0)	1.350
CRRA Coefficient	0.430
Discount Rate	-3.678**
Constant	67.057***

Sample Size = 471 Participants; Table fixed effects used

4.2 Climate Change on Index Insurance Demand

The first question we seek to answer is the effects do the overall process of climate change as defined in the experimental design affect willingness to pay for insurance? Our basic empirical model of our treatment effects is shown below:

$$WTP_{i,t,r} = \alpha + \beta_1 T_2 + \beta_2 T_3 + \beta_3 R_t + \beta_4 (T_2 * R_t) + \beta_5 (T_3 * R_t) + F_i + \varepsilon_{i,t,r}$$

Where: i, t, and r are individual, treatment, and round, respectively. $T_2$is the forecast treatment, $T_3$is the full information treatment, while the no information treatment serves as the baseline to avoid multicollinearity. R_t is the round number, which serves a linear time trend, and interaction effects between the treatments and the linear time trend are included, along with individual level fixed effects. Results are shown in Table 5 and Figure 2.[10]

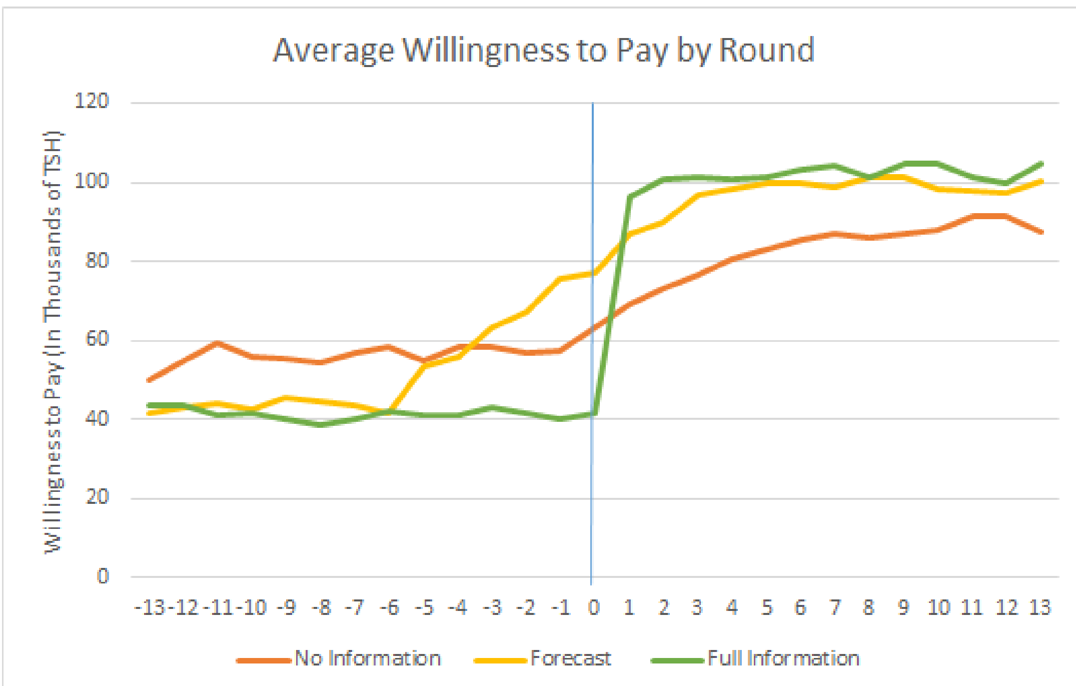
[10] Average willingness to pay is calculated by averaging across individuals and treatments by taking the midpoint of the two dichotomous choice bounds for each participant's response. For example, if the participant was willing to pay 30,000TSH but not 60,000TSH, the participant's average willingness to pay would be entered as 45,00TSH.

Table 5: Basic Treatment Regressions

Variable	(1) Average WTP
Forecast Treatment	-8.608***
Full Info Treatment	-17.953***
Round	2.018***
Forecast*Round	1.499***
Full Info*Round	2.133***
Constant	46.022***

Participant-level fixed effects are used and errors are clustered at the table level (139 clusters).

Figure 2: Willingness to Pay for Each Treatment by Round

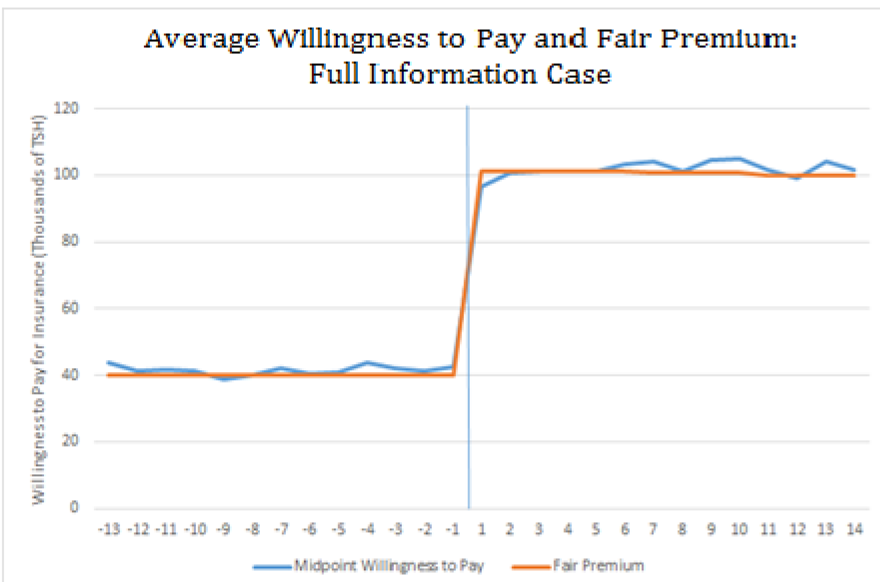


In the early rounds, we see that compared to the no information case, participants are willing to pay less for insurance than when they are given a forecast or full information. This indicates that participants form some expectation of climate change occurring without information. It appears that this expectation does not increase over time until after the switch in probability, when participants begin experiencing more droughts. We also see that providing a forecast or full information substantially decreases the time it takes participants to adjust their willingness to pay in response to the probability change. Importantly, the no information case remains below the other two treatments even 13 rounds after the switch.

4.3 Sustainability of Insurance Programs: Comparisons with Expected Fair Premiums

In order to determine how these changes in insurance demand will affect the sustainability of index insurance programs, we need to estimate how the premium will change as a result of the changing drought probability. Using a Bayesian updating rule, given the information for each treatment, we calculate actuarially fair insurance premiums. For this analysis, we abstract away from premium loading to cover ambiguity, capital, and administrative costs, only noting that including these loads would further increase the risk to sustainability of the insurance product. Figures 3, 4, and 5 assume that the insurance company will use a Bayesian updating formula, along with whatever information set is given to the participants regarding the possibility of changes to the drought probability.[11]

Figure 3



[11] Fair premiums were simulated using Bayes' Rule. In the case when agents were given a range of possible probabilities, the simulation uses the midpoint.

Figure 4

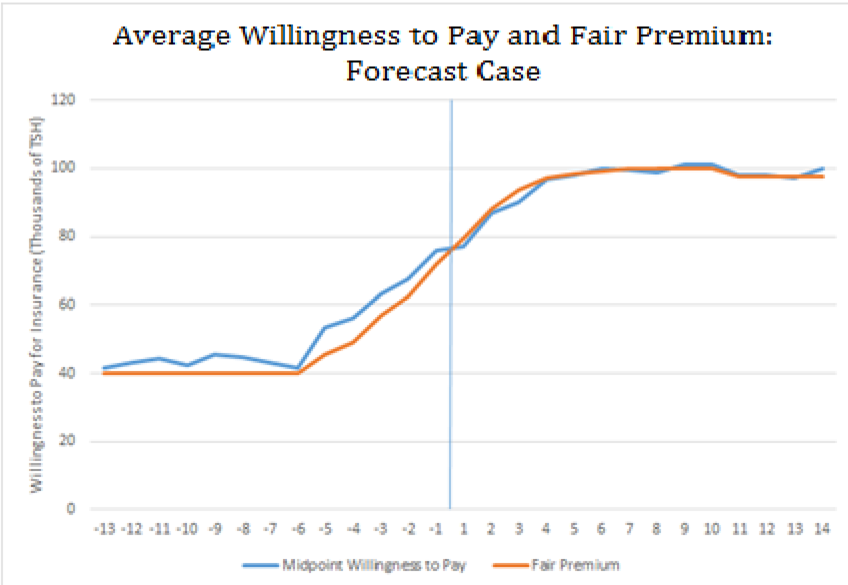
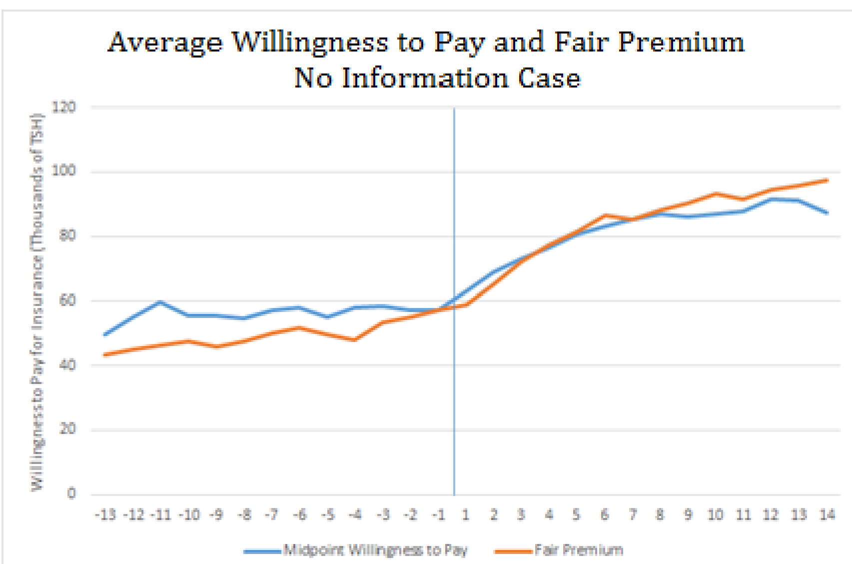


Figure 5



We see that in Figures 3 & 4, average willingness to pay tends to track expected fair premium quite closely. In Figure 5, however, we see that in the change in probability leads to a decrease in the demand for index insurance relative to the Bayesian actuarially fair premium in the no information case. This suggests (although does not prove) that while insurance uptake is likely to remain relatively constant when farmers are full informed about changes in weather risk, if farmers are not informed climate change could result in a serious decrease in insurance uptake.

4.4 The Effect of Ambiguity Aversion in Rainfall Probabilities

Next we turn to examining the individual behavioral effects that play a role in determining the effect of climate change on index insurance demand, beginning with ambiguity aversion. In order to isolate the effect of ambiguity aversion, we utilize data from the ambiguity game and the first five rounds of the full information treatment (control) to measure ambiguity aversion as a treatment effect with the following empirical model:

$$WTP_{i,t,r} = \alpha + \beta_1 T + \beta_2 D_{-1} + \beta_3 D_{-2} + F_i + \varepsilon_{i,t,r}$$

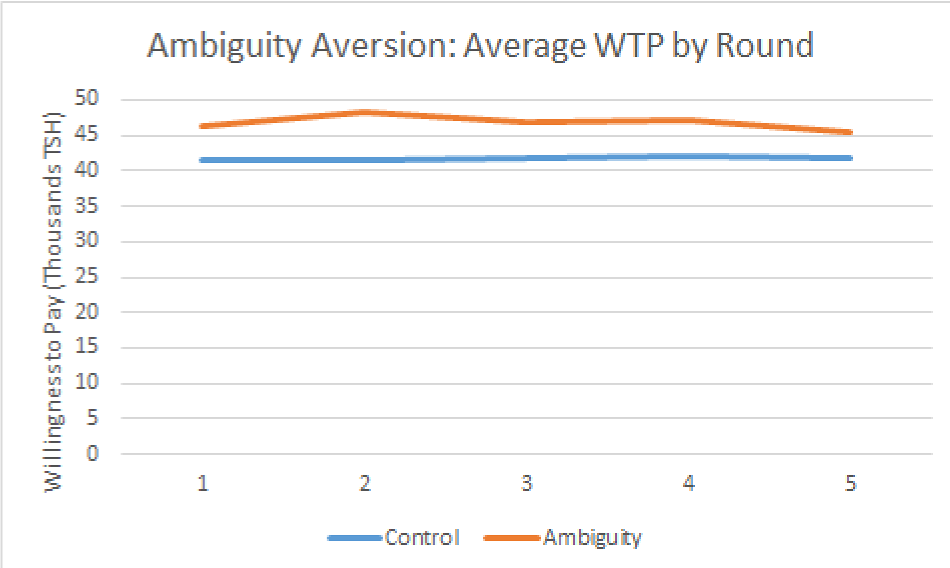
where: i, t, and r are individual, treatment, and round, respectively. T is the ambiguity treatment, D_{-1} and D_{-2} are two rounds of lagged drought outcomes (1 for drought, 0 for good rains), and F_i are individual level fixed effects. The results of analysis are shown below in Table 6 and Figure 8:

Table 6: Effect of Ambiguity Aversion on WTP in Ambiguity Game vs. Control

Variable	(1) WTP	(2) WTP
Ambiguity Treatment	5.032***	4.700***
Drought (-1)	-	6.471***
Drought (-2)	-	2.919**
Constant	41.786***	40.401***

Participant-level fixed effects are used and errors are clustered at the table level (139 clusters).

Figure 8



We see that ambiguity leads participants on average to purchase more insurance (an increase of about 12%). This effect is consistent with previous literature given that the insurance removes the sources of the ambiguity in payouts (Elabed & Carter 2015, Bryan 2013). Figure 8 demonstrates that the effect is relatively consistent across rounds. We see some evidence of recency bias as past droughts have a large effect on willingness to pay, but including drought history has very little effect on the ambiguity treatment estimator.

While on average ambiguity surrounding the drought probability increases willingness to pay for insurance, we now analyze which factors make a particular participant to be ambiguity averse. We define a participant as ambiguity averse if she is on average willing to pay more for insurance in the ambiguity treatment than in the control treatment (48.8% of our sample). Table 7 displays the results of regressing an ambiguity aversion indicator on a variety of covariates. We see that older participants are more likely to be ambiguity averse, while self-described community leaders and participants who are less risk averse, more patient, or participated in the earlier framed field experiment (Gallenstein et al 2017) are less likely to be ambiguity averse.

Table 7: Determinants of Ambiguity Aversion

Variable	(1) Ambiguity Aversion
Age (in years)	0.009***
Education (in years)	-0.006
Female (female=1, male=0)	-0.005
Household head (yes=1, no=0)	-0.064
Household size (number of members)	-0.009
Total land owned (in acres)	0.002
Community leader (yes=1, no=0)	-0.095**
Income from remittances (yes=1, no=0)	0.058
Income from selling (yes=1, no=0)	0.059*
Income from wage labor (yes=1, no=0)	0.070
Participated in first study (yes=1, no=0)[12]	-0.172***
CRRA Coefficient	-0.148***
Discount Rate	-0.070*
Constant	0.450**

Sample Size = 471 Participants; Table fixed effects used

4.5 Recency Bias and Learning

Finally, we look specifically at recency bias across the other four treatments. The regressions demonstrate the effects of previous drought realizations on insurance demand by treatment. The positive and significant effects of previous droughts on insurance demand in the full information treatment suggest that recency bias is an important factor, while the larger coefficients found in the learning and no information games suggest that learning also plays an important role. The pattern of willingness to pay increasing significantly after a payout and then having the effect decline to zero over several periods is consistent with what is found in other studies looking at insurance demand over time (Gallagher 2013; Cai et al 2016).

[12] Participated in the pre-testing or data collection of (Gallenstein et al 2017).

Table 8: Effect of Past Droughts on Average Willingness to Pay by Treatment (Thousands TSH)

Variable	(1) No Information	(2) Forecast	(3) Full Information	(4) Learning Game
Climate Change – Low	7.378***	8.160**	36.191***	-
Climate Change – High	6.740***	15.596***	74.490***	-
Forecast Range	-	20.172***	-	-
Round	0.368	1.019***	-0.219	1.035***
Drought (-1)	17.731***	8.991***	10.200***	13.317***
Drought (-2)	9.103***	7.210***	4.520***	10.446***
Drought (-3)	8.561***	5.630***	3.412***	6.702***
Drought (-4)	8.183***	3.935***	4.142***	5.324***
Drought (-5)	8.344***	0.914	2.065*	4.474***
Drought (-6)	4.214***	0.115	1.635	3.584***
Drought (-7)	5.197***	1.711	1.598	3.761***
Drought (-8)	6.060***	-0.216	1.465	3.642***
Drought (-9)	0.712	-0.492	1.502	2.086*
Constant	42.182***	36.489 ***	37.681***	53.502***

Participant-level fixed effects are used and errors are clustered at the table level (139 clusters).

5 Conclusions

Climate Change has the potential to increase the likelihood of systemic shocks faced by farmers through multiple channels. Index insurance has been proposed as part of the solution to this increased risk, but little research has examined whether index insurance programs themselves are vulnerable to changes in risk associated with climate change. Using a framed field experiment in the Dodoma Region of Tanzania, we find that farmers take many rounds to respond to data and update their willingness to pay for insurance in response to a change in the systemic shock probability in the absence of ex ante information about the timing and magnitude of the change. We show by estimating actuarially fair premiums that the sustainability of index insurance programs could be imperiled due to lower uptake rates. Finally, we show that portions of our sample exhibit ambiguity aversion, recency bias, and incomplete learning, and that these behavioral factors play important roles in determining smallholder farmers' responses.

There are a number of possible policy recommendations stemming from this research. The delayed and incomplete response to the probability change in the no information treatment suggests that index insurance programs may face especially low uptake in areas where climate change is increasing the effect of systemic shocks. Conversely, the faster adaptation in the forecast and full information treatments suggest to providing smallholder farmers with information about possible changes in climate patterns may counteract this effect by helping them avoid underestimating the true risk. Likewise, 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 the insurance product to individual farmers.

There are also multiple possible directions for future research. While basis risk was omitted from this experiment in order to make playing many rounds per treatment more manageable, we believe it would be interesting to investigate how basis risk and changes in the systemic shock probability interact. In this experiment willingness to pay was measured without changing the insurance premium across rounds. We believe an interesting unresolved question is to what extent smallholder farmers attribute changes in premiums as a signal of a change in the underlying risk versus the insurance company attempting to increase profits. A final important question considered in (Collier et al 2009) but not addressed here is how index insurance fits with other climate risk mitigation strategies such as irrigation, changes in crop choice and farming practices, and migration.

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