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Risk and ambiguity aversion behavior in index-based insurance uptake decisions: Experimental evidence from Ethiopia

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ABSTRACT

Index-based insurance (IBI) is an innovative pro-poor climate risk management strategy that suffers from low uptake. Evidence on the role of behavioral impediments in adoption of IBI is scant. We conducted lab-in-the-field experiments with 1139 smallholders out of whom 596 have adopted IBI in Ethiopia to elicit their risk and ambiguity aversion behavior, and examine whether risk and/or ambiguity aversion can explain actual IBI uptake decisions. Our study suggests that an increase in risk-aversion increases uptake, but an increase in ambiguity-aversion lowers uptake of IBI. We also find evidence that an increase in risk aversion speeds-up the uptake of IBI, while an increase in ambiguity aversion delays the adoption of IBI.

1. Introduction

Production risk is embedded in the day-to-day activities of smallholders. It is mainly driven by nature and seasonality-based variations. Insurance is the obvious risk management option to hedge household welfare from adverse risks. However, indemnity-based crop insurances that constitute the primary formal insurance markets are mostly unsuccessful in developing countries, due to information asymmetries and high transaction costs. Recent innovations in the form of index-based insurances (IBIs) aim to overcome moral hazard and asymmetric information problems by delinking payouts from individual behavior. Payouts will be made if an objectively determined index falls below a given threshold. The index can be constructed from the intensity of rainfall, images of vegetative cover on the earth's surface, often measured by satellite remote sensing, or area yield losses. Dependable indices of this type should closely correlate with individual yield losses, objectively quantifiable and publicly verifiable in order not to be manipulated by both the insurer and the insured (Barnett et al., 2008, Skees 2008, Zant 2008). An additional advantage is that the use of a single index for a group of farmers in an area for premium rating and determining payouts minimizes transaction and underwriting costs. Thus, IBI is a hedging instrument

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with immense potential to manage especially drought shocks induced by climate change (Barrett 2011; Barnett et al., 2008, Takahashi et al. 2016). However, the demand for IBI is sluggish and its uptake remains quite low in developing countries (Carter et al., 2014).

A main reason for the low uptake of IBI is basis risk. Basis risk refers to the imperfect correlation between computed indices and actual losses that can jeopardize actual uptake of IBI (Cummins et al., 2004; Jensen et al., 2014). In the presence of basis risk, a household exposed to production risk who contemplates to purchase IBI faces two hurdles of uncertainty. First, the household anticipates the likelihood of production risk. Second, the individual considers whether the IBI contract validly reflects the losses. While smallholders may be able to anticipate the probable failure of production based on their stochastic experience, they may not be able to comprehend whether the IBI contract accurately triggers payout once losses are incurred. This may imply that risk-averse individuals who are willing to buy IBI to hedge against production risk may withhold their IBI uptake decisions due to the ambiguity surrounding the validity of the insurance contract.

The aim of this study is to examine whether and how risk and ambiguity aversion behavior of smallholders influence their IBI adoption decisions. Our analysis begins with explaining why risk-exposed smallholders may remain behaviorally reluctant to hedge their production risks with IBI technologies. We argue that on top of being risk-averse, most smallholders are ambiguity-averse. As a result, they fear that if they buy any IBI, it may not payout when it is needed (and it may payout when it is not needed). This outcome is in line with the Ellsberg Paradox. Ellsberg (1961) indicated that most individuals prefer events with known probabilities (risk) over events with unknown probabilities (ambiguity). Individuals that exhibit such behavior are ambiguity-averse. Bryan (2010) further explained that ambiguity-averse individuals 'worry' that odds depend on their choice in such a way that their choices are always wrong.

Previous empirical studies on microinsurance were mostly undertaken within the expected utility (EU) framework. Under EU, a utility maximizing individual buys IBI at an actuarially fair price expecting that it provides a better coverage than remaining uninsured. Particularly, risk-averse households may prefer buying IBI since they derive higher utility from the payouts than the utility from stochastic production. But for a risk-neutral or risk-loving individual, purchasing IBI even at actuarially fair price might not be worthwhile. The reason is that unavoidable transaction costs associated with underwriting, filing a claim and collecting payouts can make the insurance premium to be higher than the certainty equivalent of losses of the buyer (De Bock and Ontiveros 2013). Hence, under EU, the demand for IBI is higher for a risk-averse individual than a risk-neutral or risk-loving one. However, in the presence of basis risk, a risk-averse individual can still have no or limited uptake of IBI due to ambiguity whether the contract accurately reflects the actual losses. The EU framework, thus, under-weighs the adverse effect of ambiguity aversion on IBI uptake, and systematically overstates the demand for IBI (Porth et al., 2015).

There are some earlier studies that have examined the relevance of risk and ambiguity aversion in explaining the low uptake of IBI. Elabed and Carter (2015) conducted a framed field experiment with cotton farmers in Mali to measure the effect of compound-risk and ambiguity aversion on household willingness to pay for microinsurance. Their findings indicate that individuals are willing to pay more for microinsurance contracts with reduced basis risk. Drawing on theoretical justifications, Clarke (2011) indicated that basis risk largely limits the theoretical rational demand for IBIs. However, both studies are based on hypothetical and theoretical cases. Evidence on the effects of ambiguity and risk-aversion on actual uptake of IBI is almost entirely absent. The main contribution of our study is that we assess the effects of risk and ambiguity aversion on actual uptake decisions of smallholders in Ethiopia who have repeated access to IBI.

The rest of the paper is organized as follows. Section 2 provides a model of IBI adoption under risk and ambiguity, and drives testable hypotheses based on the model. Section 3 describes our data sources. We use experimental and survey data collected in 2017, from insured and uninsured smallholders in Ethiopia. Section 4 explains the estimation procedures. Section 5 presents the main results. First, an increase in risk aversion speeds-up adoption of IBI. Second, ambiguity-averse smallholders have low uptake of IBI. Third, because learning diminishes ambiguity overtime, increased experience in adoption of IBI mitigates the effect of ambiguity aversion on IBI adoption. Section 6 concludes the paper.

2. Risk and ambiguity aversion in IBI adoption

Smallholders base IBI adoption decisions on their subjective expected utility (SEU). They make the decision to adopt IBI d through a subjective cost-benefit analysis. Let $x(d)$ represent the benefits from adopting IBI and $c_r(d)$ and $c_a(d)$ represent the costs associated with risk and ambiguity in making decision d, respectively. Since IBI uptake is binary, decision d is a discrete choice with $d = 1$, for households who decided to buy IBI and $d = 0$ for those who decided not to buy. Optimal choice of the household is maximized as:

$$\text{Choose}\, d^* = \begin{Bmatrix} 1 \\ 0 \end{Bmatrix} \text{when}\, x(1) - c_r(1) - c_a(1) \begin{Bmatrix} \geq \\ < \end{Bmatrix} x(0) - c_r(0) - c_a(0) \tag{1}$$

Eq. (1) shows that the decision to adopt IBI ($d = 1$) is preferred when the benefit from this decision $x(1)$ is higher, and when the costs of risk aversion $c_r(1)$ and ambiguity aversion $c_a(1)$ are lower. Eq. (1) is consistent with some empirical works. Highly profitable technologies entail higher adoption rates (Foster and Rosenzweig 2010). But new technologies can met low demand if smallholders perceive that these are risky (Feder et al., 1985; Foster and Rosenzweig 2010). Bryan (2010) shows that when there is imprecise knowledge, ambiguity reduces the adoption of insurance technologies. Barham et al. (2014) rather indicate that risk aversion has no effect while ambiguity aversion has a large positive effect on adoption of agricultural technologies. This unusual finding was argued to be due to the context of the study that US farmers can have a different risk and ambiguity attitude from smallholders in developing countries.

We derive three hypotheses based on the model in Eq. (1). First, higher risk aversion levels increase uptake of IBIs. This is the case when the cost of risk under adoption is lower than the cost of risk if adoption of IBI is not undertaken. This means $c_r(1) < c_r(0)$ in Eq. (1). Risk-averse households can expect that the benefit (payout) from buying IBI can well-compensate the losses due to production risks. The cost of risk aversion associated with adoption is also expected to be lower than the cost associated with not to adopt. Second, increase in ambiguity aversion decreases uptake of IBI. Eq. (1) reflects this case when $c_a(1) > c_a(0)$. Ambiguity-averse households worry that if they decide to buy IBI, then their harvest can fail and the payout may not come forth. If this happens, out-of-pocket premium payment and the yield loss sums up to a higher cost, penalizing their wealth twice. Ambiguity-averse households thus can become reluctant to take-up IBI during the early adoption phase. Third, the effect of ambiguity aversion on IBI adoption diminishes overtime. Due to learning, experience in use of IBI and diffusion of information about IBI, smallholders can have a better understanding about IBI technology. This can help to reduce the effect of ambiguity on adoption decisions. The level of basis risk can also be minimized through improved IBI contract design overtime (Carter et al., 2014). Hence, the effect of ambiguity aversion on IBI adoption would likely be minimal overtime.

3. Data sources

3.1. Study area

We conducted this study in the Rift Valley zone of Ethiopia. The area is a semi-arid plain plateau with a low-land agro-ecology. It receives a very low level of annual average rainfall. The pattern and intensity of rainfall exhibits considerable spatial and temporal variation, with a bimodal type of distribution. Rainfall seasons are from May to August and during October and November. Moisture stress and drought frequently causes devastating crop failure, rampant livestock mortality and herd collapse (Biazin and Sterk 2013). Major droughts in the area include the 2015–16 drought which followed the historical trend of droughts during 1973–74, 1983–84, 1991–92, 1999–2000, 2005–06 and 2011–12 (Dercon 2004). Households in the area are smallholder subsistence farmers who mainly produce maize and wheat. They often face drought-induced income shocks that translate into erratic consumption patterns. Households employ various ex-post shock coping mechanisms including less meals per day, distress livestock sells, a reduction in investments in farm inputs like fertilizer and improved seed varieties, withdrawal of pupils from school for casual labor, renting land and family labor for local landlords and wage employment on floriculture farms held by foreign investors. Future drought shock predictions in Ethiopia are pessimistic, and the wide crop-livestock mixed farming system in arid and semi-arid areas like the Rift Valley zone were projected to transform into extensive systems to respond to the risks of climate change (Hulme et al., 2001; Meinke and Stone 2005; Thornton et al., 2010). Hence, innovative drought risk management mechanisms to transfer risks by means of IBI can be useful for smallholders in this area to complement on-farm (ex-ante and ex-post) adaptation strategies.

3.2. IBI adoption in the study area

Oromia Insurance Company (OIC) and Japan International Cooperation Agency (JICA) jointly launched IBI for crops in the study area in 2013, to improve the resilience of households in the face of climate change. The scheme is implemented in five districts: Boset, Bora, Ilfata, Adamitullu-Jido-Kombolcha and Arsi Negele. Major targeted stable food crops to be insured include maize, wheat, barley and teff. The IBI product sold in the study area is a vegetation index crop insurance (VICI). The product is marketed and sold twice per year in April and September, months preceding the two rainy seasons, to provide coverage against losses during the seedling and flowering stages of crop growth. VICI is designed based on the intensity of vegetation cover or greenery on the earth's surface. Greenery level is measured by a satellite indicator known as normalized differential vegetation index (NDVI). VICI design is based on NDVI data of 16 years, extracted at a geospatial resolution of 1 km × 1 km from the GeoNetCast System. NDVI reflects the already accumulated result of rain on crop growth. It is a primary measurement with no assumptions or calibrations. It is the proven standard index, in use by all early warning units globally. Actual decal NDVI data for a given period is calculated for a set of households grouped in similar agro-ecological zones known as crop production system (CPS) zones. In pricing the product, it is assumed that since uptake gradually increases, it is possible to pool more risks across areas with greater geo-spatial variations that can help to reduce transaction costs and to reduce the loading factor. OIC estimates nearly about one out of six households who purchased IBI may face losses, and hence, the premium amounts 15% of the sum insured. During each sales window, a household that decides to buy IBI pays a premium of ETB 100 (USD 27.5) per policy. Payout calculation procedures are based on every decal (10 days) NDVI data generated. In computing payouts, OIC uses a linearly proportional indemnification (LPI) approach. For instance, for a single insurance with premium of ETB 100, the maximum payout is 100/0.15 which is about ETB 667. Using the LPI approach, for instance, in areas where the index indicates a 50% loss, a partial payout of about ETB 333.5 is paid to the farmers. Institutional, technological and contractual innovations were also made to reduce basis risk. OIC annually undertakes a twin-tracking system about the IBI index. Based on this, payout on the basis of the satellite index ranges between 12% – 68% while payout as per the field assessment ranges between 10% – 70%. This indicates that there is a high correlation between the losses indicated by the index and the actual losses revealed at the ground.

3.3. Sampling and survey procedures

We used a multi-stage random sampling technique with probability proportional to size to identify our final units of observation. More concretely, we first selected three districts (Bora, Adamitullu-Jido-Kombolcha and Arsi Negele) out of the five districts covered by the IBI project. Next, we identified a random sample of kebeles covered by IBI in these three districts. Thirdly, we referred the roaster of each kebele consisting of list of smallholders. In addition, from OIC, we also collected the list of adopters, and the years in which each household was engaged in adoption over the period 2013–2017. Based on the list of adopter and non-adopter households, we randomly selected a total of 1139 households for the survey. From these, 596 households were adopters of IBI while the remaining 543 were non-adopters. We conducted a household survey in 2017. The survey was administered in each kebele about one month prior to the execution of the experiments. We collected data on a wide range of topics including household and village characteristics as well as IBI adoption history. There are two IBI adoption cycles per year that provide coverage for the seedling and flowering stages of crop growth, respectively. We categorized households who adopted IBI during the first 3 adoption cycles as early adopters, and those who joined the adoption process during the last 3 cycles as late adopters. Similarly, we considered households who dropped the adoption for at least 3 cycles as dropouts, and those who did not dropout for more than 3 cycles as persistent adopters. Accordingly, from the total adopters, 187 households were late adopters, 260 households were dropouts and 149 households were persistent adopters.

3.4. Experiments

We conducted incentivized lab-in-the-field experiments to separately elicit risk and ambiguity aversion attitudes of the smallholders. All households who participated in the survey were invited for the experiment. We used multiple price list (MPL) protocols to elicit risk and ambiguity aversion. The experiment sessions were undertaken at the Farmers' Training Centre (FTC) in each kebele. In each session, respondents were introduced with the purpose of the experiments. We explained the opportunities for respondents to keep their winnings from the experimental games and to receive payments for show-up. Enumerators explained at the outset that payoffs for the experiments were part of a research grant from a project, and that individuals running the experiment received no personal gains from the experiments or the payoffs made to participants. Such explanation was meant to minimize the extent to which participants might assume that the experimenters would benefit if respondents earned less. The ambiguity experiment involves choosing from a risky option with 50−50 probability, and an ambiguous option with unknown probability. Our procedures are similar to the procedures followed in previous studies (Holt and Laury 2002; Ross et al., 2010; Barham et al., 2014). The risk experiment involves choosing from a safe option (100% sure) and a risky option with 50−50 probability. With slight modification, this design is similar to the protocols used in many studies (Binswanger 1980; Holt and Laury 2002; Brick et al., 2012).

All respondents started with playing the ambiguity game before the risk game to avoid anchoring effects.[1] The ambiguity game consists of 11 decisions (see the details in Appendix A). There were two bags to play the ambiguity game: bag I for the risky option and bag II for the ambiguous option. Each bag contains 10 pens, some of which were blue and some of which were red. The win or loss in the ambiguity game depends on whether the respondent draws a blue or red pen. For each of the 11 decisions, drawing a blue pen resulted in a gain of ETB 20, while drawing a red pen awards nothing. Respondents had to make their decisions without any prior information about the number of blue and red pens in the ambiguity bag. Respondents were confronted with varying enumerators. Moreover, the proportion of blue and red pens in Bag II differed for each participant. After all respondents made the 11 decisions, they were asked to draw one card from another bag containing 11 cards, serially numbered 1 to 11, in order to determine the payout for the ambiguity game. The payoff was determined as follows. For instance, consider a respondent who draws card No. 7 in the ambiguity game. Then, we refer the color of the pen that this respondent has drawn in decision 7. If s(he) has drawn the blue pen, we pay the respondent Birr 20. But if s(he) has chosen the red pen, we pay him/her nothing.

Second, respondents played the risk game. The risk game also consists of 11 decisions. Each decision was a choice between two lotteries: Lottery A with a sure payoff and lottery B, a risky payoff with 50−50 probability. The risky option of the risk game was played by flipping a coin by the respondents (see Appendix B). Similar to the ambiguity game, after respondents made the 11 decisions, they were asked to draw one card from a bag containing 11 cards, serially numbered 1 to 11. The card number drawn was considered for the final payment of the respondent for the risk game. That means, corresponding to the card number that each respondent draws, we see their choice. If the respondent has chosen the safe option, we pay the respondent the amount of the safe option. But if the respondent has opted for the risky option, we let the respondent toss a coin, and consider her/his payment based on the flip of the coin.

The average payoff per participant including the ETB 15 payment for show-up was about ETB 38.5. This payment was well above the opportunity cost for labor in the area. For example, one full day's agricultural wage like daily wage from works on floriculture farm (a known daily work in the area) was approximately ETB 50. All the 1139 households have taken part in the experiments. A total of 13 enumerators and one coordinator have worked for about 30 days to conduct the

[1] As the probabilities for the risk game are much more explicitly known than the probabilities in the ambiguity game, respondents may fix their choices to a given row in the risk game and then choose the same row in the ambiguity game, if they are allowed to play the risk game before the ambiguity game.

Table 1A
Risk aversion (η).

(1) Task	(2) Safe option	(3) Risky option	(4) EV^{safe}	(5) EV^{risky}	(6) CRRA ranges	(7) η	(8) %	(9) Risk aversion class*
1	ETB 18	0.5 of ETB 20; 0.5 of ETB 0	ETB 18	ETB 10	$-1.73< \eta < -1.49$	−1.73	0.01	Extremely risk-loving
2	ETB 16	0.5 of ETB 20; 0.5 of ETB 0	ETB 16	ETB 10	$-1.49< \eta < -0.95$	−1.49	0.04	Highly risk-loving
3	ETB 14	0.5 of ETB 20; 0.5 of ETB 0	ETB 14	ETB 10	$-0.95< \eta < -0.42$	−0.95	0.15	Risk-loving
4	ETB 12	0.5 of ETB 20; 0.5 of ETB 0	ETB 12	ETB 10	$-0.42 < \eta < 0.00$	−0.42	0.16	Moderately risk-loving
5	ETB 10	0.5 of ETB 20; 0.5 of ETB 0	ETB 10	ETB 10	$0.00 < \eta < 0.11$	0.00	0.12	Risk-neutral
6	ETB 8	0.5 of ETB 20; 0.5 of ETB 0	ETB 8	ETB 10	$0.11 < \eta < 0.41$	0.11	0.10	Slightly risk-averse
7	ETB 6	0.5 of ETB 20; 0.5 of ETB 0	ETB 6	ETB 10	$0.41 < \eta < 0.68$	0.41	0.09	Moderately risk-averse
8	ETB 4	0.5 of ETB 20; 0.5 of ETB 0	ETB 4	ETB 10	$0.68 < \eta < 0.97$	0.68	0.08	Risk-averse
9	ETB 2	0.5 of ETB 20; 0.5 of ETB 0	ETB 2	ETB 10	$0.97 < \eta < 1.37$	0.97	0.15	Highly risk-averse
10	ETB 1	0.5 of ETB 20; 0.5 of ETB 0	ETB 1	ETB 10	$1.37 < \eta < 3.76$	1.37	0.07	Very high risk-averse
11	ETB 0	0.5 of ETB 20; 0.5 of ETB 0	ETB 0	ETB 10	$3.76 < \eta < \infty$	3.76	0.03	Extremely risk-averse

* Note: The classifications in Table 1A are based on the terminologies used in Holt and Laury (2002: p 1649). The CRRA values at each switch off points were estimated entirely assuming the CRRA utility function $U(x) = x^{1-\eta}/(1-\eta)$, for $\eta \neq 1$, and $U(x) = logx$ for $\eta = 1$. For instance, for a respondent that switches at the 5th row, we compute the CRRA by equalizing the expected utility of the risky lottery with the expected utility of the safe lottery (i.e., $EU_R^5 = EU_S^5$), where $EU_R^5 = [(0.5 * 20) + (0.5 * 0) = 10]$, and $EU_S^4 = E(10) = 10$. Then, substituting, $U(x) = 10$, and $x = 10$, and solving for the equation, $U(x) = x^{1-\eta}/(1-\eta)$, provides, $\eta = 0$.

Table 1B
Ambiguity aversion (τ).

(1) Task	(2) Risky option	(3) Ambiguous option	(4) EV^{risky}	(5) $EV^{ambiguous}$	(6) CRAA ranges	(7) τ	(8) %	(9) Ambiguity aversion class*
1	1.0 of ETB 20; 0.0 of ETB 0	?(20), ?(0)	ETB 20	[?(20)]	$-\infty< \tau < -2.57$	−3.50	0.00	Extremely ambiguity-loving
2	0.9 of ETB 20; 0.1 of ETB 0	?(20), ?(0)	ETB 18	[?(20)]	$-2.57 < \tau < -1.93$	−2.57	0.03	Highly ambiguity-loving
3	0.8 of ETB 20; 0.2 of ETB 0	?(20), ?(0)	ETB 16	[?(20)]	$-1.93 < \tau < -0.31$	−1.93	0.22	Ambiguity-loving
4	0.7 of ETB 20; 0.3 of ETB 0	?(20), ?(0)	ETB 14	[?(20)]	$-0.31 < \tau < 0.00$	−0.31	0.18	Moderately ambiguity-loving
5	0.6 of ETB 20; 0.4 of ETB 0	?(20), ?(0)	ETB 12	[?(20)]	$0.00 < \tau < 0.07$	0.00	0.15	Ambiguity-neutral
6	0.5 of ETB 20; 0.5 of ETB 0	?(20), ?(0)	ETB 10	[?(20)]	$0.07 < \tau < 0.18$	0.07	0.05	Slightly ambiguity-averse
7	0.4 of ETB 20; 0.6 of ETB 0	?(20), ?(0)	ETB 8	[?(20)]	$0.18 < \tau < 0.27$	0.18	0.04	Moderately ambiguity-averse
8	0.3 of ETB 20; 0.7 of ETB 0	?(20), ?(0)	ETB 6	[?(20)]	$0.27 < \tau < 0.69$	0.27	0.07	Ambiguity-averse
9	0.2 of ETB 20; 0.8 of ETB 0	?(20), ?(0)	ETB 4	[?(20)]	$0.69 < \tau < 1.17$	0.69	0.16	Highly ambiguity-averse
10	0.1 of ETB 20; 0.9 of ETB 0	?(20), ?(0)	ETB 2	[?(20)]	$1.17 < \tau < 2.53$	1.17	0.09	Very high ambiguity-averse
11	0.0 of ETB 20; 1.0 of ETB 0	?(20), ?(0)	ETB 0	[?(20)]	$2.53 < \tau < \infty$	2.53	0.01	Extremely ambiguity-averse

* Note: For the ambiguous option, with uninformative prior, the probability distribution of the payoff is unknown. This is indicated with the question in pair as ?(20), and ?(0) under column 3 and with [?(20)] under column 5. In each row, we calculate the expected value of the risky option. Though we cannot calculate the expected value of the ambiguous option, we can, however, construct ranges for the possible CRAA values as given in column 6. The CRAA values at each switch off points were estimated entirely assuming the CRRA utility function $V(x) = 1 - e^{-\tau x}/1 - e^{-\tau}$, for $\tau > 0$ and $V(x) = x$ for $\tau = 0$.Based on the minimum value of the CRAA ranges, we can determine the τ values corresponding to each row as given under Column (7) of Table 1B.

experiments. Enumerators informed the participants that discussing with each other about the choices in the experiment is not allowed. Each participant is asked to carefully think over and decide their choices. The two experiments together have approximately taken about 2½ h per respondent. Our experiments were scheduled after typical morning farm activities.

4. Estimation strategy

4.1. Measuring risk and ambiguity aversion parameters

Constant relative risk aversion (CRRA) and constant relative ambiguity aversion (CRAA) values were determined based on individual responses in the experiments. The outcome of the experiments in terms of the measures of CRRA and CRAA values are presented in Tables 1A and 1B, respectively. We determined the CRRA values following the procedures in previous studies (Barham et al., 2014; Ross et al., 2010). Accordingly, we assume that household risk preferences entirely exhibit a constant relative risk aversion with a utility function over payoff given by $U(x) = x^{1-\eta}/(1-\eta)$, where $U(x)$ is the expected utility of payoffs under the safe option, x is the payoff under the risky option, and η is the CRRA (Pratt 1964). Thus, the CRRA ranges presented under column 6 in Table 1A were determined using this function. Then, the CRRA for each respondent is determined based on the row in the risk experiment at which a respondent switches for the first time from the safe option to the risky option. Specifically, we set the CRRA values for each respondent at the minimum value of the range since this reflects the minimum risk aversion level of the respondent. For instance, in Table 1A, consider a respondent who chooses the safe option in the first 7 decisions, and switched-off to the risky option on the 8th decision. Since the minimum value of the CRRA range determined using the above function corresponding to the 8th decision is 0.68, we assigned the value $\eta = 0.68$ for all respondents in this category. Our data shows that the proportion of respondents falling in this category is 16%. Similar procedures were undertaken to determine the CRRA values for each respondent. Table 1A shows that cumulatively about 53% of the respondents were risk-averse or risk-neutral with $\eta \geq 0$.

Table 2
Summary statistics of IBI adopter and non-adopter households.

Variables	(1) Full sample	(2) Adopters Late	Dropout	Persistent	(3) Non-adopters	(4) Mean difference	(5) T-value
Ambiguity aversion	−0.29 (1.11)	−0.24 (1.07)	−0.40 (1.13)	−0.41 (1.16)	−0.22 (1.09)	0.13 (0.07)	2.04**
Risk aversion	0.16 (1.01)	0.41 (1.04)	0.07 (1.01)	0.27 (1.07)	0.08 (0.98)	−0.15 (0.06)	−2.52**
Time preference	0.26 (0.21)	0.25 (0.19)	0.28 (0.25)	0.20 (0.18)	0.26 (0.21)	0.01 (0.01)	1.05
Age	40.56 (12.36)	41.61 (11.41)	41.36 (11.76)	40.56 (10.25)	39.81 (13.42)	−1.43 (0.73)	−1.96
Gender	0.84 (0.37)	0.89 (0.32)	0.83 (0.37)	0.86 (0.35)	0.82 (0.38)	−0.03 (0.02)	−1.58
Education	2.39 (1.15)	2.51 (1.07)	2.45 (1.15)	2.62 (1.15)	2.25 (1.16)	−0.26 (0.07)	−3.80***
Family size	7.00 (2.80)	7.98 (3.25)	7.22 (2.55)	7.46 (3.06)	6.43 (2.54)	−1.09 (0.16)	−6.67***
Dependency ratio	0.50 (0.20)	0.52 (0.19)	0.49 (0.21)	0.48 (0.19)	0.50 (0.21)	0.00 (0.01)	0.14
Land size in *qarxi*	8.83 (8.65)	9.93 (10.52)	9.64 (8.53)	9.91 (13.04)	7.78 (5.99)	−2.02 (0.51)	−3.96
Livestock size (TLU)	9.61 (8.00)	10.31 (8.27)	10.52 (8.24)	10.91 (10.52)	8.57 (6.79)	−1.98 (0.47)	−4.19
Distance from market	1.72 (1.03)	1.63 (1.07)	1.87 (1.12)	1.87 (1.10)	1.64 (0.95)	−0.15 (0.06)	−2.52**
Extension contact	0.94 (0.24)	0.93 (0.26)	0.95 (0.21)	0.99 (0.08)	0.92 (0.27)	−0.04 (0.01)	−2.50**
Crop production zone (CPZ)	0.71 (0.45)	0.51 (0.50)	0.81 (0.39)	1.00 (0.00)	0.65 (0.48)	−0.12 (0.03)	−4.37***
Observations	1139	187	260	149	543	1139	

***p<0.01, **p<0.05, *p<0.1. Standard deviations are in parentheses. Note that T-values compare differences between adopters and non-adopters.

Similarly, in determining the CRAA values for each respondent, we assume that abiguity preferences of the households exhibit a constant relative ambiguity aversion with a utility function over payoff given by $V(x) = 1 - e^{-\tau x}/1 - e^{-\tau}$, for $\tau > 0$ and $V(x) = x$ for $\tau = 0$, whereas $V(x)$ represents the expected utility of payoffs under the risky option and τ estimates the coefficient of ambiguity aversion (Klibanoff et al., 2005). As we have 11 decisions involving choices between risky and ambiguous options in the experiment (see Table 1B), we consider the switch-off points to determine the minimum CRAA value for each respondent (Barham et al., 2014; Ross et al., 2010). The switch-off point is the row at which the respondent prefers the ambiguous option over the risky option for the first time. For instance, consider a respondent who persistently chooses the risky option for the first 3 decisions, and switch-off to the ambiguous option at the 4th decision row in Table 1B. The CRAA for this respondent is $\tau = -0.31$, and the respondent is considered as ambiguity-loving. Table 1B presents the minimum CRAA (τ) and the percentage of the respondents is this category is 18%. While there is no definitive way to estimate the minimum coefficient of relative ambiguity aversion for those who always chose the ambiguous option (since the minimum could be negative infinity), this behaviour remains rational.

It simply implies extreme ambiguity lovingness. Thus, we assign these smallholders with CRAA of −3.50. Table 1B shows the proportion of respondents in each ambiguty aversion class. It shows that in sum, about 57% of the respondents were ambiguity-averse or ambiguity-neutral with $\tau \geq 0$.

The risk and ambiguity aversion values determined in this study are consistent with the estimates in various studies in developing countries. The share of ambiguity-averse individuals ranges between 42 to 61 percent (Akay et al., 2012). In our sample, 57% of the respondents are ambiguity-averse or ambiguity-neutral while the remaining 43% were ambiguity-loving. Camerer and Weber (1992) report that 50% of their sample were ambiguity-averse.

4.2. Summarizing the data

Table 2 presents summary statistics separately for the entire sample, categories of adopters (late adopters, dropouts and persistent adopters) as well as non-adopters. Column 1 of Table 2 shows that, the mean CRAA for the entire sample is −0.29. The mean CRAA values are −0.35 and −0.22 for adopters and non-adopters, respectively. Similarly, the corresponding mean CRAA values are −0.24, −0.40 and −0.41 for late adopters, dropouts and persistent adopters, respectively. Column 5 in Table 2 presents the p-values of the *t*-test for the difference-in-means between adopters and non-adopters of IBI. The two groups have statistically significant differences in their ambiguity aversion behaviour. Adopters are less ambiguity-averse than non-adopters. But in terms of their risk behaviour, adopters are more risk-averse than non-adopters. Table 2 also shows that the average coefficient of relative risk aversion is 0.16 for the entire sample; while the corresponding CRRA values are 0.23 and 0.08 for the sample of adopters and non-adopters, respectively. Similarly, the average coefficients of relative risk aversion among late adopters, dropouts and persistent adopters are 0.41, 0.07 and 0.27, respectively. The estimated coefficients of risk aversion parameter in this study are relatively lower than the value indicated in previous studies. This may be attributed to the experimental design.[2] Compared to non-adopters, IBI-adopters are more educated and have larger

[2] Literature identifies two main causes for this: the order effect and the comparative ignorance. Fox and Tversky (1995) found some evidence of ambiguity aversion using a within subjects experimental design. But when the study subjects evaluate one prospect in isolation using a between subjects design, the evidence of ambiguity aversion was not revealed. These authors argue that such effects are due to the comparative ignorance. Fox and Weber (2002) further argue that due to order effects, if a participant makes two decisions, the first decision will be analysed non-comparatively whereas the second will be analysed comparatively. Accordingly, measures of ambiguity aversion are lower in experiments such as ours where the ambiguous bet comes before the risky bet. This suggests that we may underestimate ambiguity and risk-aversion.

Table 3
Effects of risk and ambiguity aversion on probability of IBI adoption.

	(1)	(2)	(3)	(4)	(5)	(6)
Risk aversion	0.149**		0.122*	0.163**		0.138*
	(0.060)		(0.064)	(0.071)		(0.075)
Ambiguity aversion		−0.110**	−0.070		−0.108*	−0.063
		(0.054)	(0.058)		(0.064)	(0.068)
Age				0.018***	0.018***	0.018***
				(0.006)	(0.006)	(0.006)
Sex				−0.125	−0.097	−0.123
				(0.214)	(0.213)	(0.214)
Education				0.159**	0.152**	0.157**
				(0.075)	(0.075)	(0.075)
Dependency ratio				0.071	0.092	0.070
				(0.355)	(0.354)	(0.355)
Time preference				−0.522	−0.529	−0.562*
				(0.328)	(0.330)	(0.331)
IBI promotion				1.891***	1.903***	1.893***
				(0.166)	(0.166)	(0.167)
Peer influence				0.812***	0.786***	0.801***
				(0.164)	(0.163)	(0.164)
IAS				0.464***	0.457***	0.462***
				(0.141)	(0.141)	(0.141)
Land size in qarxi				0.033***	0.033***	0.033***
				(0.011)	(0.011)	(0.011)
Livestock size (TLU)				0.030***	0.030***	0.030***
				(0.010)	(0.010)	(0.010)
Distance from market				0.070	0.062	0.067
				(0.074)	(0.074)	(0.074)
Extension contact				0.471	0.485	0.470
				(0.306)	(0.305)	(0.306)
CPS zone				−0.026*	−0.026**	−0.026*
				(0.013)	(0.013)	(0.013)
District 1				−0.396	−0.410	−0.398
				(0.270)	(0.270)	(0.270)
District 2				−0.411*	−0.393*	−0.408*
				(0.215)	(0.215)	(0.216)
Constant	0.071	0.062	0.055	−3.494***	−3.493***	−3.477***
	(0.060)	(0.061)	(0.062)	(0.637)	(0.637)	(0.637)
Observations	1139	1139	1139	1139	1139	1139

Note: ***$p<0.01$, **$p<0.05$, *$p<0.1$. Robust standards errors indicated in brackets. Estimations in Table 3 were made using logistic regressions. The dependent variable is uptake, a discrete choice that takes on a value of 1 if households have ever purchased IBI; 0 otherwise. IAS refers to intertemporal adverse selection.

family size. Moreover, IBI-adopters are more distant from markets and make more frequent contact with extension agents compared with non-adopter households. Adopters and non-adopters also differ on the basis of their local climate conditions.

4.3. Empirical strategy

We estimate the effects of risk and ambiguity aversion on IBI adoption decision of the households as follows:

$$d_i^* = \alpha + \theta(\eta)_i + \delta(\tau)_i + \beta Z_i + \varepsilon_{i;} \quad d_i^* = 1,\ \text{if } d_i > d_i^* \tag{2}$$

where d_i^* is adoption decision of individual household i; η and τ are the respective CRRA and CRAA values (directly measured from the experiments); Z_i is a vector of covariates affecting IBI adoption including household specific demographic characteristics like age, sex, education and dependency ratio; factors influencing IBI purchase decisions like time preference, trust in the insurer, marketing (promotion), peer influence and intertemporal adverse selection; household resources like land and livestock size, household services like access to market and extension services as well as crop production zone; and ε_i is the error term.

We use Eq. (2) to estimate the effects of risk and ambiguity aversion on IBI adoption in three different ways. First, decision d_i^* is a discrete choice with $d = 1$ for adopters and $d = 0$ for non-adopters. Thus, we estimate the effects of risk and ambiguity aversion on the probability of IBI adoption decision of the households using a binary logit. Second, limiting d_i^* to a mere binary adoption choice imposes the restriction that ambiguity or risk aversion has the same effect on every level of adoption. But we expect that the effect of risk or ambiguity aversion can vary with the intensity or frequency of adoption. Hence, to examine the effect of risk and ambiguity aversion on intensity of IBI adoption, we estimate OLS model where the dependent variable is the number of months that the smallholders have been adopting IBI over the period 2013–2017. Third, a common characteristic of smallholders in technology adoption is that after a group of farmers start adoption

Table 4
Effects of risk and ambiguity aversion on intensity of IBI adoption.

	(1)	(2)	(3)	(4)	(5)	(6)
Risk aversion	0.963*		0.445	0.918*		0.534
	(0.572)		(0.612)	(0.494)		(0.527)
Ambiguity aversion		−1.463***	−1.316**		−1.173***	−1.000**
		(0.522)	(0.559)		(0.452)	(0.483)
Age				0.150***	0.145***	0.145***
				(0.045)	(0.045)	(0.045)
Sex				−2.720*	−2.615*	−2.693*
				(1.527)	(1.523)	(1.525)
Education				1.459***	1.407***	1.425***
				(0.532)	(0.531)	(0.532)
Dependency ratio				−0.819	−0.792	−0.875
				(2.488)	(2.483)	(2.484)
Time preference				−3.412	−3.938*	−4.070*
				(2.312)	(2.327)	(2.330)
IBI promotion				15.184***	15.251***	15.191***
				(1.147)	(1.144)	(1.146)
Peer influence				7.901***	7.739***	7.775***
				(1.185)	(1.184)	(1.184)
IAS				4.010***	3.971***	3.997***
				(1.003)	(1.001)	(1.001)
Land size in qarxi				0.132**	0.139**	0.139**
				(0.060)	(0.060)	(0.060)
Livestock size (TLU)				0.146**	0.149**	0.147**
				(0.063)	(0.063)	(0.063)
Distance from market				1.516***	1.455***	1.476***
				(0.526)	(0.525)	(0.525)
Extension contact				3.882*	3.912*	3.887*
				(2.055)	(2.052)	(2.052)
CPS zone				−0.055	−0.065	−0.061
				(0.094)	(0.094)	(0.094)
District 1				2.978	2.837	2.890
				(1.905)	(1.902)	(1.903)
District 2				−1.757	−1.658	−1.715
				(1.531)	(1.528)	(1.529)
Constant	19.098***	18.827***	18.800***	−12.307***	−12.042***	−11.981***
	(0.585)	(0.596)	(0.598)	(4.242)	(4.239)	(4.239)
Observations	1139	1139	1139	1139	1139	1139
R-squared	0.002	0.007	0.007	0.289	0.291	0.292

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors are in parentheses. Regressions in Table 4 are undertaken using OLS. The dependent variable is the number of months that the household have been adopting IBI over the period 2013−2017.

in a given year, some of them may continue while others tend to dropout. In IBI adoption, some households who adopted during the initial phase continued while others dropped out. Accordingly, the effects of risk and ambiguity aversion on IBI adoption can vary overtime. For instance, due to learning, the effect of ambiguity aversion on insurance adoption can decrease overtime (Bryan 2010). To understand this, we run separate binary logit regressions measuring the effects of risk and ambiguity aversion on late, dropout and persistent adoption decisions of the households.

5. Results

5.1. Impacts of risk and ambiguity aversion on the probability of IBI adoption

Table 3 suggests that an increase in risk aversion increases uptake of IBI while an increase in ambiguity aversion reduces the uptake of IBI. Both risk aversion and ambiguity aversion significantly affects adoption of IBI in the model without controls, as well as the specifications with a full set of controls. Note, however, that risk aversion and ambiguity aversion are borderline significant if both variables are included simultaneously in the specification with the full set of controls (see column 11 and 12). Our findings suggest that risk-averse smallholders try to insure against production risks by adopting IBI. Yet, due to basis risk, ambiguity-averse smallholders are reluctant to buy IBI.

5.2. Impacts of risk and ambiguity aversion on intensity of IBI adoption

Table 4 indicates that an increase in risk aversion increases the number of months that households stay in IBI adoption while an increase in ambiguity aversion decreases the number of months that households stay in IBI adoption phase, with and without including all covaraites.

The marginal effects with full set of covaraites indicate that a unit increase in the experimental risk measure (as households become more risk-averse), increases households' stay in adoption by 0.963 months. Table 4 also shows that ambiguity

Table 5
Effects of risk and ambiguity aversion on number of IBI policy purchased (Tobit estimates).

	(1)	(2)	(3)	(4)	(5)	(6)
Risk aversion	0.979***		0.685***	0.724***		0.535***
	(0.132)		(0.137)	(0.111)		(0.116)
Ambiguity aversion		−1.016***	−0.825***		−0.701***	−0.557***
		(0.117)	(0.122)		(0.099)	(0.103)
Age				0.046***	0.045***	0.045***
				(0.010)	(0.010)	(0.010)
Sex				−0.585*	−0.589*	−0.628*
				(0.337)	(0.337)	(0.335)
Education				0.449***	0.425***	0.441***
				(0.115)	(0.115)	(0.114)
Dependency ratio				0.130	0.102	0.078
				(0.553)	(0.553)	(0.550)
Time preference				0.058	−0.302	−0.309
				(0.488)	(0.492)	(0.490)
IBI promotion				5.085***	5.147***	5.049***
				(0.281)	(0.281)	(0.280)
Peer influence				2.492***	2.406***	2.422***
				(0.272)	(0.272)	(0.271)
IAS				1.181***	1.105***	1.149***
				(0.218)	(0.217)	(0.217)
Land size in qarxi				0.042***	0.045***	0.044***
				(0.012)	(0.012)	(0.012)
Livestock size (TLU)				0.041***	0.041***	0.039***
				(0.013)	(0.013)	(0.013)
Distance from market				0.323***	0.291***	0.301***
				(0.113)	(0.113)	(0.112)
Extension contact				1.621***	1.595***	1.592***
				(0.533)	(0.531)	(0.528)
CPS zone				−0.030	−0.030	−0.029
				(0.021)	(0.021)	(0.021)
District 1				0.333	0.355	0.398
				(0.410)	(0.409)	(0.407)
District 2				−0.581*	−0.460	−0.510
				(0.327)	(0.326)	(0.325)
Constant	1.095***	0.955***	0.905***	−9.375***	−9.251***	−9.207***
	(0.145)	(0.148)	(0.148)	(1.019)	(1.017)	(1.011)
Sigma	5.636***	5.605***	5.572***	4.578***	4.570***	4.544***
	(0.132)	(0.131)	(0.131)	(0.106)	(0.105)	(0.105)
Observations	1139	1139	1139	1139	1139	1139

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors are in parentheses. Regressions in Table 5 are undertaken using Tobit estimations. The dependent variable is the number of IBI policies that the households purchased over the period 2013–2017.

aversion significantly decreases the adoption of IBI. The marginal effects indicate that an increase in the experimental ambiguity measure (as smallholders become more ambiguity-averse) decreases the households' stay in IBI adoption by 1.298 months (p-value < 0.001), controlling for all covariates (see column 5). Risk aversion, however, is not significant if it is included with ambiguity aversion and wth all set of covariates (See column 6). Likely, in making their IBI purchase decisions, smallholders might give due weight for the ambiguity surrounding the IBI contract, and they might give relatively less attention for the stochastic occurrence of production risk. Similar to this study, Braham et al. (2014) finds that risk aversion has only a small impact on the timing of adoption of agricultural technologies, while ambiguity aversion has a large impact on adoption. Ross et al. (2012) also finds that risk aversion does not impact farmers' adoption of rice varieties in Mali while ambiguity aversion does.

5.3. Impacts of risk and ambiguity aversion on late, dropout and persistent IBI adoption decisions

Table 5 shows that risk aversion is positively associated with late adoption decision without covariates as well as with inclusion of all set of covariates while ambiguity aversion has no a statistically significant impact on late adoption decisions at 5 percent level (see columns 1–4). Table 5 also indicates that an increase in risk aversion as well as an increase in ambiguity aversion significantly decreases the rate of dropout for households who have adopted IBI (see columns 5–8). Thus, from the prespective of sustained uptake, both risk and ambiguity aversion behaviour of smallholders matter for their dropout decisions once they enaged in IBI adoption. Further, Table 5 also reveals that risk aversion as well as ambiguity aversions has insignificant effect on persistent adoption decisions of the households at 5 percent level (see columns 9–12). While ambiguity about the IBI contract is potentially high in the initial periods of adoption due to inadequate information, the effect can reduce overtime due to learning.

Table 6
Heterogeneous effects of risk and ambiguity aversion on categories of adopters.

Variables	Late adopters				Dropouts				Persistent adopters			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Risk aversion	0.334***	0.256***		0.312***	−0.186**	−0.177**		−0.236***	0.092	0.146*		0.108
	(0.078)	(0.077)		(0.083)	(0.080)	(0.079)		(0.085)	(0.089)	(0.083)		(0.090)
Ambiguity aversion	0.170**		0.056	0.164	−0.176***		−0.076	−0.150**	−0.082		−0.139*	−0.099
	(0.081)		(0.078)	(0.085)	(0.067)		(0.070)	(0.074)	(0.084)		(0.083)	(0.090)
Age		0.009	0.010	0.010		0.011	0.010	0.010		0.006	0.006	0.006
		(0.008)	(0.008)	(0.008)		(0.007)	(0.007)	(0.007)		(0.009)	(0.009)	(0.009)
Sex		0.505*	0.546*	0.503*		−0.305	−0.329	−0.299		−0.271	−0.249	−0.266
		(0.282)	(0.280)	(0.282)		(0.230)	(0.230)	(0.231)		(0.295)	(0.294)	(0.295)
Education		0.018	0.011	0.023		0.035	0.042	0.029		0.207**	0.198**	0.204**
		(0.090)	(0.089)	(0.091)		(0.079)	(0.079)	(0.079)		(0.098)	(0.098)	(0.098)
Dependency ratio		0.589	0.656	0.610		−0.079	−0.115	−0.079		−0.295	−0.280	−0.299
		(0.437)	(0.435)	(0.438)		(0.385)	(0.384)	(0.386)		(0.468)	(0.468)	(0.468)
Time preference		−0.390	−0.219	−0.306		0.714**	0.576*	0.616*		−1.772***	−1.844***	−1.841***
		(0.411)	(0.409)	(0.417)		(0.340)	(0.341)	(0.343)		(0.505)	(0.506)	(0.508)
IBI promotion		0.927***	0.946***	0.933***		1.742***	1.706***	1.752***		1.049***	1.061***	1.046***
		(0.230)	(0.228)	(0.230)		(0.245)	(0.244)	(0.245)		(0.269)	(0.269)	(0.269)
Peer influence		−0.095	−0.093	−0.063		0.871***	0.858***	0.845***		0.734***	0.715***	0.722***
		(0.205)	(0.204)	(0.206)		(0.212)	(0.212)	(0.213)		(0.273)	(0.273)	(0.273)
IAS		0.004	0.001	0.010		0.312**	0.307**	0.310**		0.412**	0.410**	0.412**
		(0.170)	(0.168)	(0.170)		(0.152)	(0.152)	(0.153)		(0.186)	(0.186)	(0.186)
Land size in qarxi		0.016*	0.015*	0.015*		0.004	0.005	0.005		0.008	0.009	0.009
		(0.009)	(0.009)	(0.009)		(0.008)	(0.008)	(0.008)		(0.010)	(0.010)	(0.010)
Livestock size (TLU)		0.010	0.011	0.010		0.011	0.009	0.011		0.010	0.011	0.010
		(0.010)	(0.010)	(0.010)		(0.009)	(0.009)	(0.009)		(0.010)	(0.010)	(0.010)
Distance from market		−0.233**	−0.226**	−0.225**		0.199***	0.196**	0.195**		0.066	0.068	0.065
		(0.094)	(0.094)	(0.094)		(0.076)	(0.076)	(0.076)		(0.094)	(0.093)	(0.094)
Extension contact		−0.268	−0.260	−0.267		0.290	0.255	0.274		2.284**	2.280**	2.278**
		(0.335)	(0.332)	(0.336)		(0.350)	(0.349)	(0.350)		(1.020)	(1.019)	(1.020)
CPS Zone		−0.058***	−0.058***	−0.058***		0.007	0.008	0.007		0.008	0.008	0.008
		(0.018)	(0.018)	(0.018)		(0.014)	(0.014)	(0.014)		(0.017)	(0.017)	(0.017)
District 1		−1.672***	−1.657***	−1.669***		0.593**	0.604**	0.604**		0.152	0.161	0.157
		(0.361)	(0.360)	(0.362)		(0.287)	(0.286)	(0.288)		(0.325)	(0.324)	(0.325)
District 2		−0.793***	−0.743***	−0.808***		0.429*	0.400*	0.441*		−0.368	−0.353	−0.365
		(0.251)	(0.248)	(0.251)		(0.230)	(0.230)	(0.231)		(0.259)	(0.258)	(0.259)
Constant	−1.665***	−1.690**	−1.800**	−1.757**	−1.252***	−5.058***	−4.929***	−5.022***	−1.941***	−5.913***	−5.912***	−5.889***
	(0.085)	(0.748)	(0.745)	(0.753)	(0.074)	(0.732)	(0.730)	(0.733)	(0.094)	(1.285)	(1.282)	(1.285)
Observations	1139	1139	1139	1139	1139	1139	1139	1139	1139	1139	1139	1139

Note: $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$. Standard errors are in parentheses. Regressions in Table 7 are undertaken using logit. The dependent variables are adoption dummies for late adopters, dropouts and persistent adopters. We categorized households who joined the adoption process during the last 3 cycles as late adopters. Similarly, we considered households who dropped the adoption for at least 3 cycles as dropouts, and those who did not dropout for more than 3 cycles as persistent adopters. Variables.

Table 7
Interaction effects among risk aversion, ambiguity aversion and year of adoption.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Risk aversion	0.149** (0.060)							0.180** (0.080)
Ambiguity aversion		−0.110** (0.054)						−0.073 (0.069)
Risk aversion*Ambiguity aversion			0.003 (0.047)				0.103* (0.062)	
Risk aversion*Year				−0.149** (0.060)			−0.180** (0.080)	
Ambiguity aversion*Year					0.110** (0.054)		0.073 (0.069)	
Risk aversion*Ambiguity aversion*Year						0.003 (0.047)		0.103* (0.062)
Age							0.018*** (0.007)	0.018*** (0.007)
Sex							−0.125 (0.215)	−0.125 (0.215)
Education							0.161** (0.075)	0.161** (0.075)
Dependency ratio							0.086 (0.356)	0.086 (0.356)
Time preference							−0.679** (0.338)	−0.679** (0.338)
IBI promotion							1.892*** (0.167)	1.892*** (0.167)
Peer influence							0.798*** (0.164)	0.798*** (0.164)
IAS							0.466*** (0.141)	0.466*** (0.141)
Land size in qarxi							0.033*** (0.011)	0.033*** (0.011)
Livestock size (TLU)							0.030*** (0.010)	0.030*** (0.010)
Distance from market							0.077 (0.075)	0.077 (0.075)
Extension contact							0.454 (0.305)	0.454 (0.305)
CPS Zone							−0.026* (0.013)	−0.026* (0.013)
District 1							−0.398 (0.270)	−0.398 (0.270)
District 2							−0.437** (0.217)	−0.437** (0.217)
Constant	0.071 (0.060)	0.062 (0.061)	0.094 (0.063)	0.071 (0.060)	0.062 (0.061)	0.094 (0.063)	−3.415*** (0.637)	−3.415*** (0.637)
Observations	1139	1139	1139	1139	1139	1139	1139	1139

Note: ***p<0.01, **p<0.05, *p<0.1. Robust standards errors indicated in brackets. Estimations in Table 6 were made using logistic regressions. The dependent variable is uptake, a discrete choice that takes on a value of 1 if households have ever purchased IBI; 0 otherwise. The variable *Year* takes the value 1 if the household is adopter in 2017; 0 otherwise.

To this end, though the level of literacy of smallholders is low in the study area, the insurance firm (OIC) offered different training and awareness creation activities through which learning, experience sharing or information diffusion can be effected. Thus, with increased information and understanding about IBI overtime, the ambiguity of households might have been clarified overtime.

Some control variables were observed to influence IBI uptake decisions of the smallholders. Age and education of the household head, trust in the insurer, IBI poduct promotion and intertemporal adverse selection postitively affect IBI adoption decisions. Larger larger livestock size and frequent contact with extension agents alos increases enhances IBI adoption. Trust in the insurer, distance from the market and crop production zone were also influenced late adoption decisions. Similarly, trust in the insurer, peer influence, distance from the market and IBI product promotion affect dropout decisions of the households. Level of education, time preference, trust in the insurer and peer influence also determined persistent adoption decisions. This seems to be a promising avenue for future investigation with a larger panel dataset. Although we do control for many variables, t here is still a potential for omitted variables. But we do not have data on social networks. We might think that people who are more well-connected in social networks may likely adopt IBI and they may also tend to be less ambiguity-averse. Experimental data on social networks would have further strengthened our findings.

6. Conclusion

Using data from lab-in-the field experiments and household survey, this study examines whether risk and/or ambiguity aversion can explain the low uptake of IBI by smallholders in Ethiopia. Though risk-averse smallholders attempt to insure against stochastic production risks, the main problem in adoption of IBI is the ambiguity due to basis risk. Because of a higher potential degree of ambiguity associated with the failure of the IBI contract to accurately reflect loss realizations of smallholders, we hypothesized that, on top of risk aversion, ambiguity aversion might play a large role in hampering adoption of IBI in the study area. First, we tested the effects of risk and ambiguity aversion on incidence of IBI adoption using a discrete choice adoption model. Our analyses suggest that an increase in risk aversion increases while an increase in ambiguity aversion reduces the probability of IBI adoption among the smallholders. In contrast with most of the previous empirical tests of the roles of risk aversion on technology adoption, we find that risk aversion speeds-up rather than delays the adoption of IBI. This difference may be due to the fact that most empirical literature so far has been considering the whole uncertainty as risk in their analysis, without having a split look at risk and ambiguity that sums up to uncertainty. Second, we estimated an OLS model to measure the effect of risk and ambiguity aversion on intensity of IBI adoption measured by the number of months that households have stayed in adoption phase. Results reveal that risk aversion increases while ambiguity aversion decreases the number of months that the smallholders have stayed in IBI adoption over the 2013–2017 periods. Thirdly, we estimated the effects of risk and ambiguity aversion on late, dropout and persistent adoption decisions of the smallholders. This analysis is important from the perspective of sustained uptake. Our results suggest that risk aversion increases while ambiguity aversion has no effect on late adoption decisions. Both risk and ambiguity aversions also decrease dropout decisions once the households adopted IBI. However, our results evidence that risk aversion as well as ambiguity aversion has no significant effect on persistent IBI adoption decisions of the households.

There is interplay between risk and ambiguity aversion in IBI adoption decisions of smallholders. Since farmers are averse to production risk, most of them can be fundamentally willing to insure such risk using the IBI contract. However, in the presence of basis risk, farmers can remain ambiguous about whether the contract accurately reveals their actual loss realizations. This means, though risk-averse smallholders are willing to buy IBI in order to hedge their production risk, their actual uptake may not be effective due to the ambiguity surrounding the validity of the contract to payout in the future. Ambiguity aversion thus dictates uptake decisions of smallholders in a sort of dominance effect. However, the effect of ambiguity aversion on IBI adoption diminishes overtime, because farmers' learning and experience in adoption gradually clarifies their ambiguity regarding the nature of the contract. In addition, overtime improvement in the design of IBI that inherently reduces basis risk like improvement in IBI design helps to reduce the ambiguity surrounding the validity of IBI contract overtime.

Several implications for future studies on technology adoption can be drawn from this study. The first is the need to distinguish between risk and ambiguity in analysis of technology adoption. Second, the effects of risk and ambiguity aversion on technology adoption can vary over time. These implications underscore the need for future studies to theoretically distinguish and empirically test the relative relevance of the effect of risk and ambiguity aversion in technology adoption decisions. Our study also has methodological implications in designing studies related to the adoption of rural technologies. Combining experimental methods to measure variables that are otherwise difficult to identify like risk and ambiguity aversion with survey methods helps to better understand the role of the behavior of decision making units. In addition, the fact that the effect of ambiguity aversion on IBI adoption diminishes overtime suggests the importance of learning mechanisms such as training in shaping the behavior and capacity of individual smallholders to manage uncertainty through adoption of new technologies. Since large numbers of rural producers and entrepreneurs inherently face challenges of managing uncertainty in an increasingly volatile global economy, the imperative to deepen our understanding in this regard seems high.

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Supplementary materials

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References

Akay, A., Martinsson, P., Medhin, H., Trautmann, S.T., 2012. Attitudes toward uncertainty among the poor: an experiment in rural Ethiopia. Theory Decis. 73, 453–464.
Barham, B.L., Chavas, J.-P., Fitz, D., Salas, V.R., Schechter, L., 2014. The roles of risk and ambiguity in technology adoption. J. Econ. Behav. Organ. 97, 204–218.
Barnett, B.J., Barrett, C.B., Skees, J.R., 2008. Poverty traps and index-based risk transfer products. World Dev. 36, 1766–1785.
Barrett, C.B., 2011. Covariate catastrophic risk management in the developing world: discussion. Am. J. Agric. Econ. 93, 512–513 aaq134.
Biazin, B., Sterk, G., 2013. Drought vulnerability drives land-use and land cover changes in the rift valley dry lands of Ethiopia. Agric. Ecosyst. Environ. 164, 100–113.
Binswanger, H.P., 1980. Attitudes toward risk: experimental measurement in rural India. Am. J. Agric. Econ 62, 395–407.
Brick, K.A., Visser, M., Burns, J., 2012. Risk Aversion: experimental evidence from South African fishing communities. Am. J. Agric. Econ. 94 (1), 133–152.

Bryan, G. (2010) Ambiguity and insurance. *Unpublished manuscript*. Yale University Department of Economics, see url for more information: https://pdfs.semanticscholar.org/131f/224c121a377b0d675f43155f0f2245a3041a.pdf?_ga=2.125464524.732340984.1564399767-2060515288.1564399767

Camerer, C., Weber, M., 1992. Recent developments in modeling preferences: uncertainty and ambiguity. J. Risk Uncertain 5, 325–370.

Carter, M., de Janvry, A., Sadoulet, E., Sarris, A., 2014. Index-based weather insurance for developing countries: a review of evidence and a set of propositions for up-scaling. Annu. Rev. Resour. Econ. 9, 421–438 2017.

Clarke, D.J., 2011. A Theory of Rational Demand For Index Insurance. Department of Economics, University of Oxford.

Cummins, J.D., Lalonde, D., Phillips, R.D., 2004. The basis risk of catastrophic-loss index securities. J. Financ. Econ. 71, 77–111.

De Bock, O. & D.U. Ontiveros (2013) Literature review on the impact of microinsurance. 35, publisher: impact Insurance See also url: http://www.impactinsurance.org/publications/rp35

Dercon, S., 2004. Growth and shocks: evidence from rural Ethiopia. J. Dev. Econ. 74, 309–329.

Elabed, G., Carter, M.R., 2015. Compound-risk aversion, ambiguity and the willingness to pay for microinsurance. J. Econ. Behav. Organ. 118, 150–166.

Ellsberg, D., 1961. Risk, ambiguity, and the savage axioms. Q. J. Econ. 643–669.

Feder, G., Just, R.E., Zilberman, D., 1985. Adoption of agricultural innovations in developing countries: survey. Econ. Dev. Cult. Change 33, 255–298.

Foster, A.D., Rosenzweig, M.R., 2010. Microeconomics of technology adoption. Annu. Rev. Econom. 2, 395–424.

Fox, C.R., Tversky, A., 1995. Ambiguity aversion and comparative ignorance. Q. J. Econ. 110, 585–603.

Holt, C., Laury, S., 2002. Risk aversion and incentive effects. Am. Econ. Rev. 92, 1644–1655.

Hulme, M., Doherty, R., Ngara, T., New, M., Lister, D., 2001. African climate change: 1900-2100. Clim. Res. 17, 145–168.

Jensen, N.D., A. Mude & C.B. Barrett (2014) How basis risk and spatiotemporal adverse selection influence demand for index insurance: evidence from northern Kenya. *Available at SSRN 2475187*. Food Policy, 74, 2018, 172-198. https://www.researchgate.net/publication/322395375_How_basis_risk_and_spatiotemporal_adverse_selection_influence_demand_for_index_insurance_Evidence_from_northern_Kenya

Klibanoff, P., Marinacci, M., Mukerji, S., 2005. A smooth model of decision making under ambiguity. Econometrica 73, 1849–1892.

Meinke, H., Stone, R.C., 2005. Seasonal and inter-annual climate forecasting: the new tool for increasing preparedness to climate variability and change in agricultural planning and operations. Clim. Change 70, 221–253.

Porth, P.L., ßKen Seng Tan Professor, A., Carter, M., Elabed, G., Serfilippi, E., 2015. Behavioral economic insights on index insurance design. Agric. Finance Rev. 75, 8–18.

Pratt, J.W., 1964. Risk aversion in the small and in the large. Econometrica 32, 122–136.

Ross, Nicholas & Santos, Paulo & Capon, Timothy, 2012. Risk, ambiguity and the adoption of new technologies: experimental evidence from a developing economy, 2012 Conference, August 18-24, 2012, Foz do Iguacu, Brazil 126492, International Association of Agricultural Economists. URL: https://ideas.repec.org/p/ags/iaae12/126492.html.

Skees J.R, Innovations in index insurance for the poor in lower income countries, *Agricultural and Resource Economics Review* 37, 2008, 1–15.

Takahashi, K., Ikegami M., Sheahan M. and Barrett, C.B., Experimental Evidence on the drivers of index-based livestock insurance demand in southern Ethiopia, *World Development*, 78, 2016, 324–340.

Thornton, P.K., Jones, P.G., Alagarswamy, G., Andresen, J., Herrero, M., 2010. Adapting to climate change: agricultural system and household impacts in Est Africa. Agric. Syst. 103, 73–82.

Zant W., Hot Stuff: Index insurance for Indian smallholder pepper growers, *World Development*, 36, 2008, 1585–1606.