Ambiguity aversion and the adoption of weather index-based insurance: experimental evidence from Uganda

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Abstract

Purpose – This study aims to estimate farmers' ambiguity aversion and analyze its impact on the adoption of weather index-based insurance in Uganda.

Design/methodology/approach – The research question we address is: Does the ambiguity of insurance contract outcomes affect farmers' decisions to adopt weather index-based agricultural insurance (WII)? To explore this, we use incentivized choice experiments to elicit ambiguity preferences and insurance adoption decisions. Our sample includes 291 small-scale coffee farmers from Central and Western Uganda. Given the panel data and the dependence of adoption decisions over time, we employ a dynamic probit model to analyze how ambiguity aversion influences WII uptake. Additionally, we use a pooled binary probit model to test the robustness of our results to different model specifications.

Findings – The results indicate that the adoption of WII decreased with each round of the choice experiment, particularly among ambiguity-averse farmers. We found that 58% of respondents were ambiguity-averse and that ambiguity aversion is negatively associated with WII adoption. Conversely, tertiary education positively influences the likelihood of adopting WII.

Practical implications – The results imply that farmers are not likely to invest in risk management strategies whose outcomes are not predictable with some level of certainty. Also, the negative effect of ambiguity aversion can be reduced as farmers gain more knowledge about the insurance products. Our findings highlight the need to provide sufficient information and education about the use of WII.

Originality/value – This study contributes to the limited literature on the role that behavioral factors play in the adoption of index-based agricultural insurance.

Keywords Uncertainty, Adoption, Weather

Paper type Research paper

1. Background

In many developing countries, the agricultural sector faces risks and uncertainties resulting from extreme weather changes, which reduce farm productivity and the welfare of households

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Declaration of interest: The authors declare no conflict of interest.

Ethical statement: This study focused on collecting survey data from coffee farmers to explore their preferences. As the study did not present any physical, psychological, social, economic, or legal risk to the participants, the Institutional Review Board (IRB) granted a waiver for ethical approval. The study was designed such that the ethical principles such as voluntary participation, no respondent identification, informed consent, protection and confidentiality of data were observed.

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whose livelihoods depend on farming. One alternative to overcoming the adverse effects of extreme weather changes is the use of index-based insurance. Index-based insurance is an innovative approach to providing insurance that compensates farmers for losses based on a predetermined threshold for the loss of assets and investments resulting from catastrophic events (Mobarak and Rosenzweig, 2013). It serves as an alternative to indemnity-based insurance, with indices based on parameters such as area yield, vegetation index, soil quality, and weather. Weather index-based insurance (WII) is increasingly being adopted as a tool to mitigate losses associated with climate variability and extreme weather events. The payouts are not based on the extent of the loss; rather, they are determined by predefined thresholds for rainfall and temperature to compensate policyholders.

Weather index insurance (WII) has been piloted in several Sub-Saharan African countries, including Ethiopia, Rwanda, Kenya, Malawi, and Uganda. Despite the potential benefits of these insurance products, adoption rates remain low. Factors that increase the likelihood of adoption include cultural beliefs, wealth, and social networks (Sibiko *et al.*, 2018). Conversely, high premium prices, cultural beliefs, and basis risk reduce the likelihood of adoption (Jensen and Barrett, 2017; Hill *et al.*, 2017; Lin *et al.*, 2015; Carter *et al.*, 2014; Miranda and Farrin, 2012). Behavioral factors, such as perceptions, beliefs, and attitudes, play a critical role in the adoption of agricultural insurance but are often under-explored (Carter *et al.*, 2016). A few studies have analyzed how behavioral factors affect the use of different agricultural technologies and risk management tools. For instance, Rippo and Cerroni (2023) examined the acceptability of income stabilization schemes as risk management tools for farmers. There is a need to expand the existing literature to understand how behavioral factors affect the adoption of agricultural insurance. Adjabui *et al.* (2019) analyzed how farmers' attitudes towards weather index insurance affected their willingness to pay for it. Studies such as Dougherty *et al.* (2020) and Hill *et al.* (2016) analyzed risk preferences and how they impact adoption of insurance using the expected utility theory (EUT). The EUT posits that, when presented with alternatives, individuals will choose options that maximize their expected utility, taking into account potential outcomes, their probabilities, and individual risk preferences (Green *et al.*, 1986). However, Carter *et al.* (2016) and Babcock (2015) show that the EUT does not accurately predict farmers' behavior. They show that a substantial number of farmers were sensitive to the basis risk in insurance contracts, given that insurance premiums are certain but benefits are unknown and stochastic. In cases of uncertainty, the probability of the events is not known, and therefore judgments about uncertain events are often based on subjective probabilities, drawn from personal experiences rather than statistical data (Kahneman and Tversky, 1979). An alternative theory is the cumulative prospect theory (CPT) by Tversky and Kahneman (1992), which shows that subjective probability weighting affects decision-making under risk and uncertainty. The CPT has been applied to assess the uptake of agricultural insurance. For example, Babcock (2015) used the CPT to show that farmers often perceive insurance payments as investments rather than risk management tools. Other studies include Brick and Visser (2015), who demonstrated that loss aversion, a key component of CPT, makes farmers more cautious about adopting insurance products. Dalhaus *et al.* (2020) recommended designing insurance products based on behavioral factors using CPT. However, the CPT, while influential in understanding decision-making under risk and uncertainty, has some limitations. It assumes that individuals evaluate potential losses and gains relative to a reference point, which can be subjective and varies among individuals, leading to inconsistencies in predictions. The theory also struggles to account for decision-making in situations involving ambiguity or uncertain probabilities.

Ambiguity theory is increasingly justified in decision-making contexts. The ambiguity theory recognizes that individuals often face uncertainty about probabilities and outcomes, and they would prefer alternatives whose outcomes are known with some level of certainty compared to those with uncertain outcomes (Dimmock and Kouwenberg, 2013; Ellsberg, 1961). Because of limited technologies for weather prediction, there are uncertainties in weather predictions and the correlation of index measurements with farmers' losses, creating ambiguity. In this study, we estimate farmers' aversion to ambiguity and use econometric analyses to examine its impact on adoption decisions for WII. The research question addressed is: Does farmers' ambiguity aversion significantly affect their decision to adopt WII? We assume that ambiguity aversion influences farmers' perceptions of insurance products, thereby affecting their adoption decisions.

There is an emerging literature on the applicability of ambiguity aversion in analyzing the uptake of agricultural insurance. Cecchi *et al.* (2024), Bryan (2019), and Elabed and Carter (2015) found that ambiguity aversion reduces the adoption of rainfall insurance. Belissa *et al.* (2020) show that farmers' ambiguity aversion significantly reduces the uptake of index insurance. Farmers who are ambiguity-averse shy away from these products because they perceive the uncertain correlation between the index and their actual losses as a significant risk. The concept of ambiguity aversion has also been used when analyzing farmers' adoption of agricultural technologies. Di Falco and Vieider (2022) examined how ambiguity aversion affects the use of adaptation practices to rainfall shocks. Wu *et al.* (2023) analyzed how ambiguity aversion affects the adoption of improved seed, whereas Amanuel and Tewodros (2023) analyzed how ambiguity aversion affects the adoption of improved land management practices. These studies all show that farmers who are ambiguity-averse are less likely to take up new or improved agricultural practices. We therefore hypothesize that ambiguity aversion has a significant and negative effect on the decision to adopt WII.

We use panel data obtained through choice experiments in simulated markets because the use of index-based agricultural insurance is relatively new in Uganda, and the market is not yet well developed. At the time the data was collected, index-based insurance programs were in the early stages of being implemented. Panel data collected over three rounds of choice experiments were used to analyze the adoption decisions over time and whether the effects of ambiguity aversion change over time as farmers gain new knowledge about how index-based insurance contracts are implemented. For the choice experiments, we use simulated markets with real money payments and payoffs. Simulated markets enable the respondents to think about their investment decisions and weigh alternative options before taking up insurance contracts (Lusk, 2019).

To estimate how ambiguity aversion affects the adoption of index insurance, we use a dynamic probit model. The dynamic probit model accounts for the influence of past outcomes on current binary decision-making, capturing the persistence and lagged effects in the data. The findings show that ambiguity aversion reduced the likelihood of adopting index insurance by the farmers, and the results remain consistent when the estimation is done by region and using a binary probit model. The findings underscore the need to provide information and education about how index insurance operates. The findings are useful in informing the development of programs to upscale the delivery of index insurance products. The study also contributes to the growing literature on how farmers' attitudes towards uncertainty can affect the uptake of index-based insurance.

2. Context of the study region

Coffee is important as a cash crop for increasing household income and contributes 10% to Uganda's agricultural Gross Domestic Product (NDP, 2020). However, the study areas comprised three districts: Masaka, Bushenyi, and Ishaka. The districts were selected because they are among the main coffee-producing districts in Uganda. Masaka, located in Central Uganda, experiences a tropical rainforest climate characterized by warm temperatures and significant rainfall throughout the year. The average annual temperature is 23 °C (73 °F), with minimal variation between seasons (UBOS, 2020). Masaka has two main rainy seasons: the long rains from March to May and the short rains from September to November. These periods bring substantial rainfall, supporting the region's agricultural activities, particularly coffee cultivation. The dry seasons, occurring from June to August and December to February, are relatively mild with less precipitation, but still retain sufficient humidity. This consistent and favorable weather pattern makes Masaka a productive agricultural hub, especially for crops like coffee, bananas, and various subsistence crops.

Ishaka and Bushenyi districts, located in Western Uganda, experience a moderate tropical climate characterized by relatively stable temperatures and significant rainfall. The region typically enjoys an average annual temperature of around 20 °C–25 °C (68 °F–77 °F), with slight variations due to its higher altitude (UBOS, 2020). Bushenyi and Ishaka districts have two main rainy seasons: the long rains from March to May and the short rains from September to November, which provide ample moisture for agriculture. The dry seasons, from June to August and December to February, are less pronounced but still bring lower rainfall, maintaining a generally humid environment.

The two regions primarily produce Robusta coffee, which thrives in the warm, tropical climate with adequate rainfall and fertile soils. Smallholder farmers typically manage plots averaging one to two hectares and rely on traditional farming practices, though there is a growing trend towards adopting improved techniques to enhance yield and quality. Robusta coffee production is, however, vulnerable to climate change, whereby exposure to temperatures above 28 °C during the critical growth seasons leads to significant reductions in productivity (Jarrod *et al.*, 2021). As a response to climate risks faced by coffee farmers, the National Union of Coffee Agribusiness Enterprises (NUCAFE) is promoting the use of a coffee weather index-based insurance program. The insurance program aims to enhance farmers' capacity to adapt to drought and extreme rainfall risks, and it is currently being piloted in the selected districts.

3. Methods

We collected data using both a survey and choice experiments. The survey data included the farmers' socioeconomic characteristics, agricultural production activities, and the risk management strategies used in coffee production. We conducted the choice experiments in two phases: the first phase aimed to elicit the levels of ambiguity aversion, and the second phase focused on eliciting farmers' adoption of index insurance products.

3.1 Eliciting farmers' ambiguity aversion

The common method for eliciting ambiguity preferences is by using the Ellsberg urn experiment. Ellsberg (1961) shows that a decision-maker who chooses an alternative with a known probability over one with an unknown probability is ambiguously averse. This can be illustrated by the preference relation $g \succ b$ that shows that a good outcome (g) is strictly preferred to a bad outcome (b). However, the ambiguity aversion theory shows that a lottery with both a good and bad outcome with known probabilities (P) and $(1-P)$ respectively, is preferable to a lottery with an unknown probability g' (Mas-Colell *et al.*, 2006). Therefore, a subject is ambiguity averse if $(P)g + (1-P)b \succcurlyeq g'$ and ambiguity seeking if $g' \succcurlyeq (P)g + (1-P)b$.

The Ellsberg experiment involves the use of urns, one with known odds and the other with unknown odds of selecting a specific color of beads. The proportion of the colored beads is varied, and respondents select a specific color of bead. In this study, respondents were presented with two containers containing 100 beads. One container was transparent, with a known proportion of red and white beads, whereas the other was opaque, with an undisclosed proportion of red and white beads. The game was played over three rounds, with each round featuring different proportions of white beads: 30%, 50%, and 70% for games 1, 2, and 3, respectively. For each round of the game, the respondents were presented with one transparent container and one opaque container to randomly pick a white bead from their preferred container. The illustration of the game is shown in S1 of the supplementary section. However, the order of the containers was randomized to reduce order bias. Order bias refers to the tendency of respondents to be influenced by the order in which options or questions are presented, potentially affecting their choices and responses (Nguyen *et al.*, 2021).

To estimate whether respondents are ambiguity-averse, ambiguity-loving, or neutral, matching probabilities can be used. The matching probability method involves asking individuals to state the probability at which they are indifferent between a risky option with a known probability and an ambiguous option. For instance, participants might be asked to choose between a lottery where the chance of winning is known and an ambiguous lottery where the chance of winning is unknown. The participant adjusts the known probability until they are indifferent between the two options (Cecchi *et al.*, 2024; Cerroni, 2020). However, adjusting probabilities to find an indifference point can be cognitively demanding for participants. Furthermore, the participants' responses can be influenced by initial values or starting points provided in the experiment. If the initial probability is set too high or too low, it can anchor participants' adjustments, leading to biased measurements.

We therefore used a simplified alternative to the matching probability method, following Ali *et al.* (2021). When provided with a container with a 50% proportion of white beads and an opaque container whose proportions are not known, a subject is categorized as ambiguity-averse if he or she chooses the option whose odds of selecting a white bead are known, ambiguity-seeking if they select the option whose odds are not known, and neutral if the subject is indifferent between the two options. Setting the probability threshold at 50% is arbitrary; however, it provides a natural and theoretically sound midpoint for comparing risk and ambiguity. Additionally, it allows for consistency and standardization across studies, enhancing comparability.

3.2 Design of index insurance choice experiment

We conducted the choice experiments by offering a hypothetical coffee weather index insurance product for a coffee-growing season to farmers in a simulated insurance market, with actual monetary payments for premiums and payoffs. Simulated markets were designed to create incentives for the respondents to think about their investment decisions. Williams *et al.* (2021) and Hill and Viceisza (2012) show that liquidity is a constraint in the payment of insurance premiums. However, for this study, the liquidity constraint was reduced, as all the respondents who participated in the choice experiment for eliciting ambiguity aversion were rewarded with a payout of 0.27 United States Dollars (USD) for participation and an additional 0.27 USD for each white bead selected. Therefore, the earnings ranged from 0.27 USD to 1.10 USD. To make the premium payments affordable, the insurance premium was set at 0.13 USD for each round of the experiment, which was less than the payouts earned from the ambiguity aversion experiment.

Because of limited funding, the value of the premium payments used in the choice experiments was less than the actual premium rate in the market. The actual premium rate for coffee drought insurance in Uganda was estimated at an average of 7 USD per hectare per coffee season. For each round of the game, a payoff of 0.4 USD was given if the index was above the threshold. The design of the experimental games closely follows that used by Hill and Viceisza (2012) and is summarized in Figure A1 of the supplementary material.

3.3 Theoretical framework

The cumulative prospect theory (CPT) by Tversky and Kahneman (1992) suggests that farmers evaluate insurance options based on perceived gains and losses relative to a reference point, such as their expected yield or income without insurance. A key component of CPT is loss aversion, which means that farmers are more sensitive to potential losses than to gains (Babcock, 2015). This sensitivity makes them particularly cautious about insurance scenarios where they might have to pay premiums without receiving payouts, perceiving this as a loss. Weather index-based insurance (WII), which provides payouts based on an index, such as rainfall levels rather than actual losses, introduces both risk and uncertainty.

Risk refers to situations where probabilities of adverse events are known or can be reliably estimated, such as using historical weather data to calculate the likelihood of droughts.

In contrast, uncertainty arises when probabilities are ambiguous, unclear, or unknown, such as doubts about whether the index will trigger payouts during adverse weather events or concerns about the reliability of the insurer. These two concepts, risk and uncertainty, are critical for understanding farmers' decision-making under WII, as they face both quantifiable risks and ambiguous probabilities.

The theoretical framework for this study, therefore, incorporates concepts of ambiguity aversion, subjective probability, and loss aversion to explain the adoption of index-based insurance. Ambiguity-averse individuals prefer situations where the likelihood of outcomes is clear and tend to avoid options with ambiguous probabilities, even if these might offer higher returns. As a result, ambiguity-averse individuals may overestimate the likelihood of unfavorable outcomes when the probabilities of their occurrence are unknown. CPT incorporates a probability weighting function to account for how individuals perceive the likelihood of uncertain events. The function $\pi(P)$ is S-shaped indicating that people tend to over-weigh small probabilities and under-weigh large probabilities (Babcock, 2015). To incorporate ambiguity aversion into the model, the probability weighting function is modified to reflect an individual's attitude towards ambiguous probabilities. The probability-adjusted weighting function is expressed as;

$$\pi_A(P,t) = \pi(P) * (1 + \gamma(t)A) \tag{1}$$

Where $\pi_A(P,t)$ is the probability weighting function applied dynamically to represent changes in farmers' ambiguity aversion over time, $\pi(P)$ is the original probability weighting function, $\gamma(t)$ is the ambiguity aversion parameter and A is the degree of uncertainty in the probability. This formation accounts for farmers' evolving attitudes towards ambiguity, reflecting their increasing or decreasing trust in the reliability of WII payouts as they gain knowledge and experience with the product. The term $\gamma(t)A$ increases the perceived weight of probabilities when ambiguity is present.

Without insurance, a subject considers the subjective perception of loss as follows;

$$U_{without} = \pi_A(P,t) * v(-L) + \pi_A(1-P,t) * v(0) \tag{2}$$

Where $\pi_A(P,t)$ and $\pi_A(1-P,t)$ represent the weighted probabilities of loss and no loss respectively, adjusted for ambiguity aversion. The value function v captures the subjective valuation of gains and losses. Specifically, $v(-L)$ represents the perceived loss in case of adverse events without insurance, while $v(0)$ presents the neutral reference point where no loss occurs. $\pi_A(1-P)$ is the probability that the adverse event does not occur.

With insurance, the utility function incorporates the cost of premium and perceived utility of the payout as

$$U_{with} = \pi_A(P(t)) * v(I-C) + \pi_A(1-P,t) * v(-C) \tag{3}$$

Where $v(I-C)$ is the subjective value function of the payout (I) from insurance minus the cost of insurance premium (C). If the averse weather events do not occur, the value function is $v(-C)$. If the adverse event occurs and the farmer is uninsured, the value function is $v(-L)$. A farmer will therefore adopt insurance if the utility with insurance is greater than the utility without insurance as shown in Equation (4).

$$\pi_A(P(t)) * v(I-C) + \pi_A(1-P,t) * v(-C) > \pi_A(P,t) * v(-L) + \pi_A(1-P,t) * v(0) \tag{4}$$

The left-hand side represents the weighted utility of receiving the insurance payout after paying the premium C, while the right-hand side represents the dynamic weighted utility of incurring the loss L without insurance, adjusted for ambiguity. The value function v, consistent with CPT, reflects loss aversion where losses $v(-L)$ are weighted more heavily than equivalent gains. This dynamic framework captures how farmers' preferences and adoption decisions evolve over time as they gain experience with insurance and adjust their perceptions of risk, probabilities and ambiguity.

3.4 Empirical framework

The weighted utilities are not observed. However, we observe choices or decisions made by the subject that reflect their underlying preferences. We used this data to analyze the factors affecting the adoption of index-based insurance using a dynamic probit regression model. The dynamic probit model takes into account the correlation between the binary dependent variable y_{nt} and the unobserved heterogeneity u_{nt} (Grotti and Cutuli, 2018). The subscripts n and t indexed individuals and time (rounds) respectively, where $n = 1, \ldots, N$ and $t = 1, 2, 3$. The dynamic specification also accounts for state dependence processes modeled as a t-1 lag in the outcome variable, and these show the likelihood that an individual that adopts in one period will adopt in the subsequent period. The latent dependent variable for the dynamic probit model was therefore specified as shown in Equation (2) and it included the lagged dependent variable (y_{nt-1}) as a covariate. The variable y^*_{nt} indexed the latent dependent variable and it expressed the likelihood that an individual n will pay for insurance, whereas y_{nt} was the observed binary outcome variable. Z_{nt} was a vector of time-varying explanatory variables that are strictly exogenous, R_n which is the unit-specific unobserved effect, and u_{nt} is the idiosyncratic error term that is assumed to be serially independent.

$$y^*_{nt} = \gamma y_{nt-1} + \beta Z_{nt} + \theta X_n + R_n + u_{nt} \tag{5}$$

The independent variables included time-invariant variables such as the locations and respondent characteristics $(X_{n.})$. The respondent characteristics included the education level, age, sex, ambiguity aversion, and these are described in Table 1. Location variables R_n were

Table 1. Description of variables

Notation	Description	Measurement
y_{nt}	Dependent variable for insured adoption	Binary variable (1 = If subject n paid a premium C for insurance at a time t, 0 otherwise)
Time variant covariates		
y_{nt-1}	Lag insurance if subject n paid a premium for insurance in previous round	Binary variable (1 = If subject paid a premium for insurance in time $t-1$, 0 otherwise)
Z_{nt}	Savings for subject n at time $tZ_{nt} = Z_{nt-1} - C + I$	Continuous variable in USD equivalent
Time invariant covariates		
X_{1n}	Ambiguity aversion	Binary variable (1 = ambiguity averse, 0 = Ambiguity seeking)
X_{2n}	Age in completed years	Continuous variable in completed years
X_{3n}	Highest level of education attained by the subject	Categorical variable (1 = Primary level, 2 = secondary level, 3 = Post-secondary level)
X_{4n}	If subject identifies as male or female sex	Binary variable (1 = Male, 0 = Female)
X_{5n}	Sub-county location	Categorical variable
Covariates for unobserved heterogeneity		
y_{n0}	Initial values for the dependent variable y_{nt}	Binary variable showing whether the subject adopted insurance at the start of the games
Z_{n0}	Initial value for time-variant explanatory variable Z_{nt}.	Continuous variable showing amount of savings that the subject had at the start of the game
$\overline{Z}_l$	Within unit averages for the savings variable Z_{nt}.	Continuous variable showing the average savings for the subjects

Source(s): Authors' own work

included to capture unobserved differences in socio-economic factors and cultural practices across the different locations. These characteristics were invariant because they did not change across the three rounds of the choice experiments. The time-variant characteristics included the savings that a respondent had at the start of each round of the choice experiment.

The transition probability for individual n at time t, given R_n is given by Equation (6) where $\Phi = (.)$ is the distribution function of the standard normal distribution.

$$Pr(y_{nt}|Z_{nt}, y_{nt-1}, X_n, c_n) = \Phi(\gamma y_{nt-1} + \beta Z_{nt} + \theta X_n + R_n) \tag{6}$$

Following Rabe-Hesketh and Skrondal (2013), the unit-specific unobserved effect R_n can be written as shown in Equation (4) where y_{n0} and Z_{n0} represent the initial value of the response variable and of the time-varying explanatory variables respectively. $\overline{Z}_l$ stands for the within unit averages of the explanatory variables where averages are based on time $t = 2, \ldots, T$, and α_n is a unit-specific time-constant error term, normally distributed with mean 0 and variance σ_a^2.

$$R_n = \alpha_0 + \alpha_1 y_{n0} + \alpha_3 Z_{n0} + \alpha_2 \overline{Z}_l + \alpha_n \tag{7}$$

Unobserved heterogeneity is addressed by including in the model the initial period value of the dependent variable and the initial period unit averages of time-varying explanatory variables. Since unobserved heterogeneity is captured by R_n, the $t-1$ lag value of the response variable can be interpreted as state dependence which is the causal effect exerted by the use of insurance in one period, on its use in the subsequent period.

$$\begin{aligned} Pr\left(y_{nt}\middle|Z_{nt}, y_{nt-1,}c_n\right) &= \Phi(\gamma y_{nt-1} + \beta Z_{nt} + \theta X_n + R_n) \\ &= \Phi\left(\gamma y_{nt-1} + \beta Z_{nt} + \theta X_n + \alpha_0 + \alpha_1 y_{n0} + \alpha_2 \overline{Z}_l + \alpha_3 Z_{n0} + \alpha_n\right) \end{aligned} \tag{8}$$

The estimation of the dynamic probit model was based on the marginal maximum likelihood random parameters approach. A STATA software package developed by Grotti and Cutuli (2018) was used to estimate the effects and post estimation commands used to estimate the steady-state expected dynamics for significant time-invariant covariates.

4. Results

The characteristics of the respondents are presented in Table 2, and these are disaggregated by their ambiguity preferences as well as their regional locations. For continuous variables, *t*-tests were conducted to determine if there were significant differences in characteristics between the two groups. For categorical variables, Pearson Chi-square tests were utilized to assess significant differences between the groups.

Even though the methodology used sought to identify three categories of ambiguity preferences, we only estimated two levels: ambiguity-averse and ambiguity-seeking. Only five respondents were identified as being ambiguity-neutral, and this sample size was too low to allow for additional statistical and econometric analysis. The results for the whole sample show that 58.08% of respondents were ambiguity-averse. There is also a statistically significant regional difference in ambiguity aversion, with a proportion of 33.95% in the Western region and 72.53% in the Central region. The difference between the two regions was significant at a 1% level.

The results in Table 1 show that, overall, for the whole sample, the percentage of respondents who purchased insurance was 73.54%. When disaggregated by ambiguity preference, the ambiguity-seeking farmers had a higher percentage of 81.66% compared to the ambiguity-averse, who were estimated at 61.3%. The disaggregation by region shows that the highest percentage of farmers paying premiums was in the Central region, estimated at

Table 2. Characteristics of the respondents

Respondent characteristics	All (n = 291)	Ambiguity seeking (n = 122)	Ambiguity averse (n = 169)	Chi-square/t-test statistic	Western (n = 109)	Central (n = 182)	Chi-square/t-test statistic
Respondents that are ambiguity averse (%)	58.08				33.95	72.53	125.04***
Respondents that paid insurance premiums (%)	73.54	81.66	62.3	40.95***	37.92	94.87	40.89***
Education level of respondents							
Primary level (%)	63.92	563.11	64.5	3.07	70.64	59.89	12.68***
Secondary school level (%)	27.15	29.51	25.44		23.85	29.12	
Tertiary level (%)	8.93	7.38	10.06		5.50	10.99	
Sex of the respondents (%)	57.73	59.84	56.21	0.29	40.37	68.13	64.61
Mean age of respondents (years)	46.38	45.3	47.16	−2.00**	40.65	49.81	−10.25***
	(13.53)	(13.89)	(13.22)		(12.00)	(13.24)	
Mean savings (USD)	0.33	0.344	0.32	2.07**	0.34	0.32	1.60
	(0.16)	(0.15)	(0.16)		(0.14)	(0.17)	
Mean number of times respondents paid premium	2.71	2.16	3.11	−8.19***	1.00	3.00	−46.27***
	(1.14)	(1.21)	(1.02)		(0.88)	(0.57)	

Note(s): ***, **, *Significance at 1%, 5%, 10% level. Standard deviation in parenthesis
Source(s): Authors' own work

94.87%, compared to the Western region, which was estimated at 37.92%. The Chi-square test indicates a highly significant difference in adoption between the groups of respondents disaggregated by ambiguity preferences and by region, and this difference was statistically significant at a 1% level. However, the proportion of respondents who paid insurance premiums decreased for each round of the experiments, as shown in Figure 1.

The mean number of times that the respondents paid for insurance premiums was 3, with ambiguity-seeking individuals averaging 2.16 times and ambiguity-averse individuals averaging 3.11 times. In the Western region, the average is 1.9 times compared to 4.2 times in the Central region.

The table shows that the average age of respondents is 46.38 years, with ambiguity-seeking individuals averaging 45.3 years and ambiguity-averse individuals averaging 47.16 years. The *t*-test statistic of -2.00 shows a significant difference at the 5% level. Regionally, the Western region has an average age of 40.65 years, while the Central region has a significantly higher average of 49.81 years.

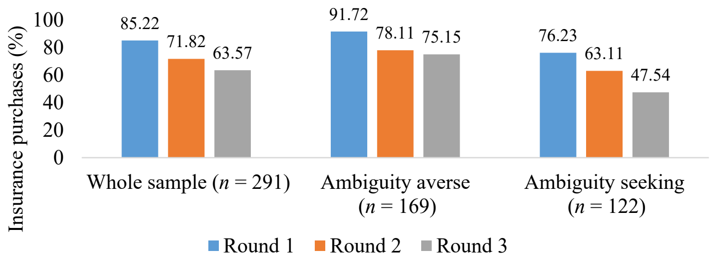
The mean savings for all respondents is USD 0.33, with ambiguity-seeking individuals having USD 0.344 and ambiguity-averse individuals having USD 0.32. Regionally, there is no significant difference in savings between the Western and Central regions, with the Western region having an average of USD 0.34 and the Central region, USD 0.32. This suggests that savings levels are relatively consistent across regions and ambiguity preferences.

The results for educational attainment show that 63.11% of the total sample has primary education or less, 27.15% have secondary education, and 8.93% have post-secondary education. There are significant regional differences, with 59.89% in the Central region having primary education compared to 70.02% in the Western region.

4.1 Factors affecting adoption of weather index insurance

We used the Maximum Likelihood method to estimate the dynamic probit model to assess the effect of ambiguity aversion on the likelihood that a farmer adopts index insurance contracts, and the results are presented in Table 3. For comparison, we also estimated a static pooled probit model. The results for the pooled probit model are presented in Column I, whereas the results for the dynamic probit model are presented in Columns II, III, and IV. The results show that the coefficients for the variables for both the probit and the dynamic probit models have the same signs. However, the dynamic model provides better estimates, as shown by the values for the log-likelihood. The dynamic model accounts for the effect of the previous adoption and unobserved heterogeneity in the likelihood of the adoption of insurance. Table 3 also reports the results for the estimations for the whole sample and for the samples disaggregated by regions.

The first coefficient, lag insured, is the lagged value of the dependent variable, capturing the state dependence. It shows the effect of adoption in a previous period on the likelihood of



Source(s): Authors' own work

Figure 1. Percentage of respondents paying insurance premium

Table 3. Regression output

Symbol	Description	Probit model (all sample)	Dynamic probit (all sample)	Dynamic probit (western region)	Dynamic probit (central region)
y_{nt-1}	Lag insurance: If subject paid for insurance in previous round		0.6939	0.6043	0.2694
			(0.1110)***	(0.0273)***	(0.1657)
Z_{nt}	Savings for subject n at time t (USD)	0.0274	−0.1604	−3.4546	0.1046
		(0.0717)	(0.3124)	(2.3778)	(0.1627)
X_{1n}	Ambiguity aversion (Base: ambiguity seeking)	−0.0477	−0.0633	−0.1243	−0.0472
		(0.0267)*	(0.0228)***	(0.0552)**	(0.0119)***
X_{2n}	Age of subject (years)	0.0007	0.0007	0.0002	0.0004
		(0.0011)	(0.0010)	(0.0022)	(0.0007)
X_{3n}	Highest level of education attained (base: primary level)				
	Secondary level	0.0687	0.0062	−0.0058	0.0234
		(0.0261)***	(0.0222)	(0.05518)	(0.0189)
	Post-secondary level	0.0588	0.0559	0.0552	0.0601
		(0.0349)*	(0.0239)**	(0.0719)	(0.0146)***
X_{4n}	Male subject (Base: female)	−0.0091	0.0137	0.0332	0.0116
		(0.0234)	(0.0242)	(0.0547)	(0.0184)
X_{5n}	Sub-county location				
	Kabonera	0.7842	0.4687		
		(0.0510)***	(0.1208)***		
	Kyabugimbi	0.2693	−0.1391	−0.0333	
		(0.0667)***	(0.1144)	(0.0729)	
	Kyanamukaaka	0.7479	0.3831		−0.0377
		(0.0500)***	(0.1256)***		(0.0328)
	Mukungwe	0.7974	0.4535		0.0082
		(0.0468)***	(0.1285)***		(0.0286)
	Nyakabirizi	0.2606	−0.1227	−0.0206	
		(0.0805)***	(0.1351)	(0.0842)	
	Ruhumuro	0.2637	0.0319	0.0654	
		(0.0690)***	(0.1437)	(0.0959)	
y_{n0}	Initial values for the adoption of insurance at the start of the game		−0.0580	−0.3037	0.6873
			(0.0560)	(0.0225)	(0.0526)***
Z_{n0}	Initial value for savings at the start of the game		−0.1099	−1.3575	−0.1942
			(0.2545)	(1.3745)	(0.1564)
$\overline{Z}_l$	Average savings amount (USD)		0.2177	4.9175	−0.0907
			(0.4986)	(3.5966)	(0.2790)
	N	873	582	218	364
	Log pseudo likelihood	−311.2369	−125.6690	−79.1333	−32.1721
	Wald chi-square	334.9300	301.2200	3943.9200	2315.6200
	Probability > χ^2	0.0000	0.0000	0.0000	0.0000

Note(s): ***, **, *Significance at 1%, 5%, 10% level. Standard errors in parenthesis
Source(s): Authors' own work

adoption in the subsequent period. The positive coefficient for the lagged adoption variable indicates the presence of significant dynamics of state dependence, and the results were significant for the whole sample and for the Western region. Farmers that adopt insurance in one period are 0.69 times more likely to purchase insurance in the subsequent period, and the result is significant at the 1% level.

The coefficient of interest was that associated with the binary variable showing whether farmers were ambiguity-averse. When comparing the coefficient estimates across the three models, the signs for the coefficient for ambiguity aversion are the same. The coefficient associated with ambiguity aversion was negative and significant, suggesting that the likelihood of adopting index insurance was lower for farmers who are ambiguity-averse as compared to those who are ambiguity-seeking. The pooled probit model shows that, holding other factors constant, farmers who are ambiguity-averse were 4.78% less likely to adopt index-based insurance compared to those who are not. The dynamic probit model estimates show that farmers who are ambiguity-averse are 6.33 times less likely to purchase insurance contracts, and the result was significant at the 1% level.

The results further show that higher levels of education increase the likelihood of adoption and renewal of index-based insurance. Farmers with secondary and tertiary levels of education are more likely to adopt index insurance compared to those with primary or lower levels of education. Additionally, farmers with tertiary or post-secondary education are more likely to purchase insurance contracts compared to those with primary levels of education.

The set of coefficients for the variables capturing unobserved heterogeneity includes the initial condition, the initial value, and the within-unit averages of time-varying savings variables. The results show a significant effect of the initial condition for insurance adoption, and the result was significant for the Central region. The initial adoption of insurance increases the likelihood of taking up insurance by 0.68, holding other factors constant.

5. Discussion

The results showed a high proportion of farmers purchasing insurance but with a clear trend of insurance purchases declining across successive rounds of the experiment, with the decline being higher for the ambiguity-averse respondents. This shows that ambiguity-averse individuals are less likely to sustain insurance purchases over time, possibly because of uncertainty about the benefits or distrust in the payout mechanism of index-based insurance. For policymakers, this highlights the need for targeted interventions to sustain insurance uptake, particularly among ambiguity-averse farmers. Strategies could include providing clearer information about how index insurance works, ensuring transparent and reliable payout processes, and possibly offering initial incentives or subsidies to build trust and demonstrate the insurance's value. These measures could help mitigate the effects of ambiguity aversion and encourage more consistent insurance adoption.

The results for the characteristics of the respondents show a significantly low proportion of ambiguity-averse farmers in the Western region compared to Central Uganda. The low proportion of ambiguity-averse farmers can be attributed to the social and cultural norms in the region. Social norms that foster or promote an ambiguity-seeking mindset among farmers can significantly influence their approach to risk and uncertainty in agricultural decision-making. In communities where risk-taking is culturally valued or where historical experiences have demonstrated the benefits of taking chances, farmers may be more inclined to embrace ambiguity. Gikunda *et al.* (2022) and Tanko and Ismaila (2021) show that culture plays a significant role in the uptake of new agricultural technologies and the effectiveness of agricultural extension. If local traditions celebrate new innovations, farmers might be more willing to experiment with new farming techniques or crop varieties despite uncertain outcomes. Additionally, social networks and peer influence can reinforce these norms; farmers observing their neighbors adopting ambiguous ventures may feel encouraged to follow suit. Therefore, in regions where cultural and social interactions highlight the rewards of risk-taking, farmers are likely to develop ambiguity-seeking attitudes that can affect their uptake of innovations such as WII.

However, the results also showed a significantly lower adoption of WII in Western Uganda compared to Central Uganda. This can be attributed to the differences in weather conditions between the two regions. Western Uganda experiences more predictable weather patterns, making droughts less frequent or severe compared to the Central region. If farmers perceive the risk of drought or other extreme weather events to be lower, they may see less value in purchasing drought insurance. This perception reduces the perceived benefits of WII, leading to its low adoption.

The results showed significant dynamics of state dependence. Farmers who purchase insurance are more likely to appreciate the benefits of index insurance, which induces them to renew their insurance contracts. The ambiguity attitudes of the farmers are conditioned by their recent experiences; therefore, their knowledge about the insurance is continuously updated as experience accumulates. Carter *et al.* (2014) also show that farmers not only learn from their own experiences but also from the experiences of other farmers within their social networks. As they gained more knowledge through participation or exposure to information, their confidence and ability to evaluate uncertain scenarios improves. However, learning about the value of index-based insurance is particularly difficult due to the stochastic and covariate nature of the product. This suggests that knowledge acquisition directly influences decision-making under ambiguity, rather than changes in perceived ambiguity levels.

The results show a negative effect of ambiguity aversion on the adoption of index-based insurance. Similar findings were obtained by Bryan (2019) and Slingerland (2017), who showed that ambiguity aversion significantly reduced the likelihood of adoption of index insurance in Mali and Kenya, respectively. Other studies, such as Carter *et al.* (2014) and Bryan (2019), show that a large proportion of farmers prefer alternatives whose outcomes are known with some level of certainty over those whose outcomes are not known, making them ambiguity-averse. An ambiguity-averse agent will prefer not to take up a contract rather than purchase one without clarity on when and how it will compensate for their losses.

Ambiguity aversion significantly impacts farmers' perceived benefits and valuation of WII, which in turn influences their adoption decisions and the extent to which they adopt such insurance. Ambiguity-averse farmers prefer clear, known risks over uncertain ones, leading them to view index insurance which bases payouts on external indices like rainfall levels rather than actual farm losses with uncertainty. This arises because the probability and size of payouts are perceived as uncertain, making farmers worry about paying premiums without receiving commensurate benefits. Consequently, ambiguity-averse farmers may overestimate the likelihood of adverse scenarios where they do not receive payouts despite paying premiums, thus perceiving the insurance as less beneficial. This diminished perceived value results in lower adoption rates and a reduced willingness to invest in comprehensive coverage. Giné *et al.* (2008) underscore the importance of farmers' trust and understanding of insurance mechanisms in their adoption decisions. Additionally, the complexity and novelty of weather index-based insurance require a higher level of understanding and familiarity, which many farmers might lack. This cognitive burden discourages farmers from engaging with the product.

The results further show that higher levels of education increase the likelihood of adoption of WII. Education increases access to knowledge, which enhances one's ability to take on risks and understand the value of the product. The results show that introducing a relatively complex insurance product in an environment where farmers have low levels of education, as is the case in many developing countries may be problematic. Index insurance is particularly difficult to understand because payments are not linked to individual farmers' losses but are instead linked to extreme weather changes. Therefore, encouraging its uptake by farmers with low levels of education requires continued education. Castellani and Vigano (2017), Cole *et al.* (2013), and Gine and Yang (2007) provide evidence that education and financial literacy increase the uptake of insurance and that social networks can also be used to diffuse knowledge among communities.

6. Conclusions and policy implications

Agricultural insurance is one of the innovations for mitigating risks and enhancing the resilience of farmers against adverse weather conditions and other uncertainties. Farmers, therefore, invest in insurance premiums to mitigate risks and safeguard their livelihoods against potential losses. However, the adoption of agricultural insurance in Uganda and several developing countries in Africa is still low. This research analyzes the factors affecting the adoption of index insurance, with a specific focus on the role of farmers' risk preferences measured by their level of ambiguity aversion. Consistent with the findings from other studies, our results show: (1) a high but decreasing rate of WII adoption over time, (2) a negative effect of ambiguity aversion on the likelihood of adopting index insurance, and (3) higher levels of education increase the likelihood of farmers adopting index insurance.

The finding that the uptake of index insurance decreases over time indicates a critical need for sustained engagement and continuous support to ensure long-term adoption. Policymakers and stakeholders should focus on building trust and demonstrating the consistent reliability of index insurance products. This can be achieved through regular communication and educational initiatives that keep farmers informed about how index insurance works, the benefits it provides, and real-world examples of successful payouts. Additionally, incorporating feedback mechanisms that allow farmers to voice concerns and suggestions will help tailor the products to better meet their needs, thereby encouraging sustained adoption.

The negative impact of ambiguity aversion on the likelihood of adopting index insurance underscores the importance of reducing perceived uncertainties associated with these products. Policymakers should consider strategies to make index insurance more transparent and easier to understand. This could involve providing clear, straightforward information about how indices are calculated and ensuring that payout mechanisms are perceived as fair and reliable. Technological innovations should be used to provide better estimates of weather predictions and their possible effect on crop productivity. Offering initial subsidies or financial incentives could also mitigate the impact of ambiguity aversion by reducing the financial risk for farmers trying insurance for the first time. Furthermore, integrating WII with existing risk management practices, such as credit, can help build familiarity and trust, making the concept less intimidating for ambiguity-averse farmers.

The positive correlation between tertiary education and the likelihood of adopting index insurance suggests that educational initiatives can play a crucial role in promoting these products. Policies that support agricultural education and financial literacy programs can equip farmers with the knowledge needed to make informed decisions about risk management tools. These programs should be designed to reach a wide audience, including those who may not have formal tertiary education, by using accessible and practical training methods.

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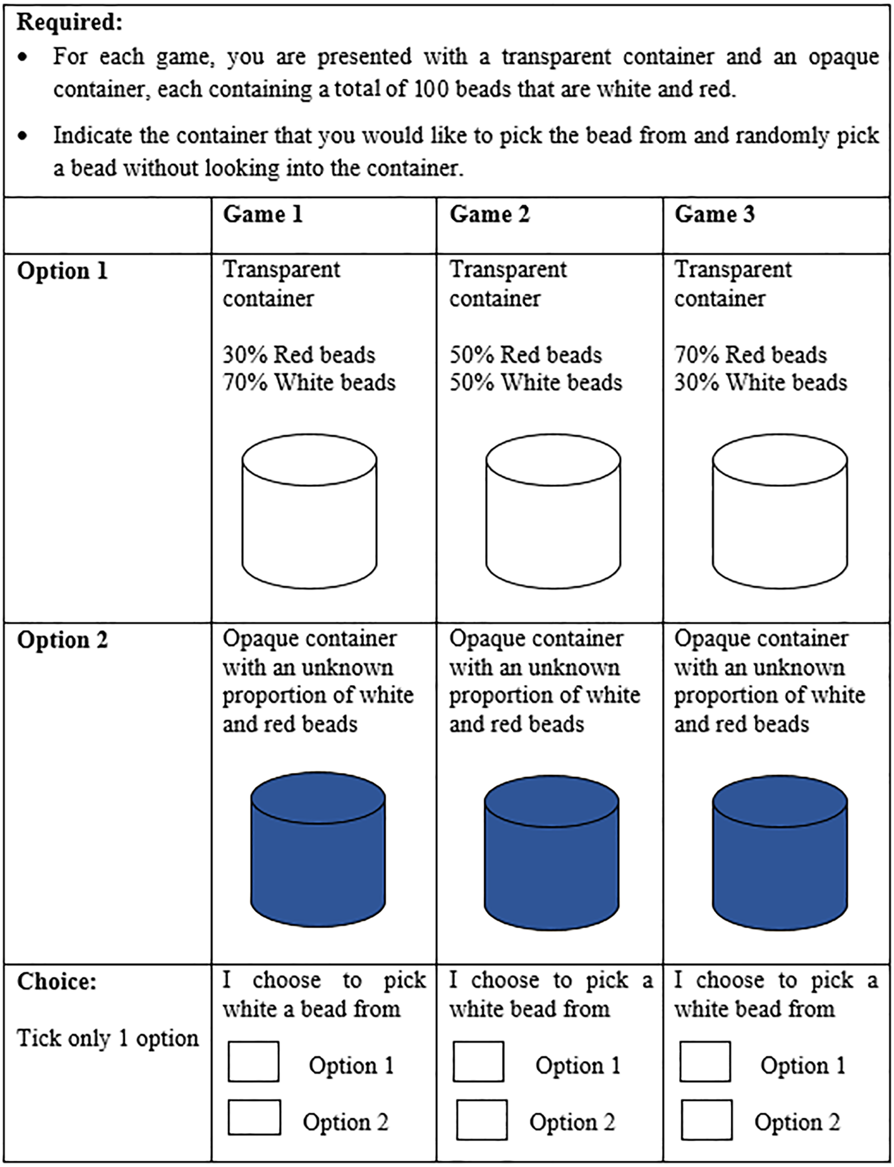
(The Appendix follows overleaf)

Supplementary material

S1: Design of experiment for ambiguity aversion



Required:

- For each game, you are presented with a transparent container and an opaque container, each containing a total of 100 beads that are white and red.
- Indicate the container that you would like to pick the bead from and randomly pick a bead without looking into the container.

	Game 1	Game 2	Game 3
Option 1	Transparent container 30% Red beads 70% White beads	Transparent container 50% Red beads 50% White beads	Transparent container 70% Red beads 30% White beads
Option 2	Opaque container with an unknown proportion of white and red beads	Opaque container with an unknown proportion of white and red beads	Opaque container with an unknown proportion of white and red beads
Choice: Tick only 1 option	I choose to pick white a bead from ☐ Option 1 ☐ Option 2	I choose to pick a white bead from ☐ Option 1 ☐ Option 2	I choose to pick a white bead from ☐ Option 1 ☐ Option 2

Source(s): Authors' own work

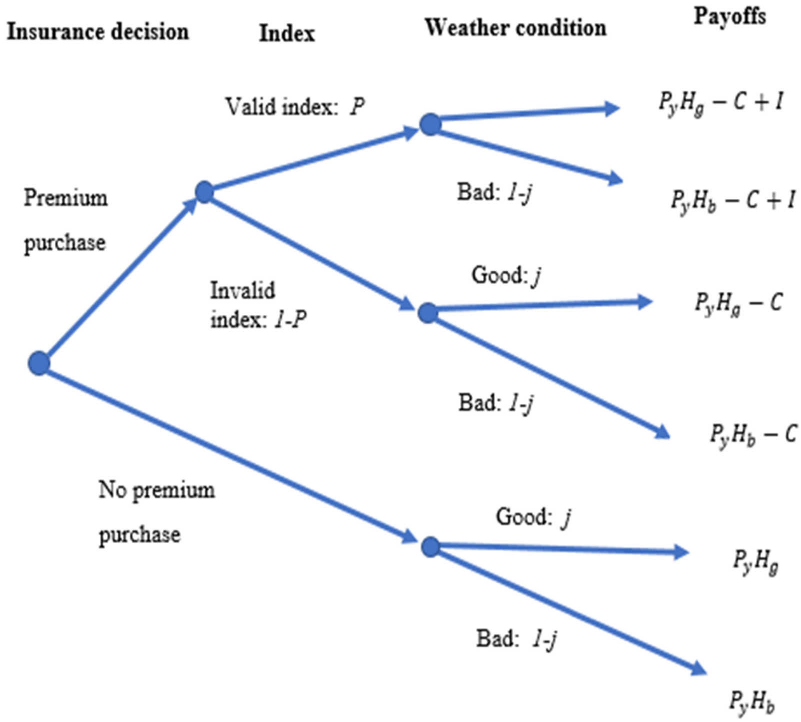
Figure A1. Choice sets for the ambiguity aversion game

S2. Decision of the index insurance uptake choice experiment

The choice experiments were based on a scenario where all the respondents are offered an opportunity to purchase an insurance contract for one hectare of coffee. The respondents then decided whether to purchase the insurance contract. The respondents make their insurance decision in a time t_1 but the outcome from the purchase is realized in the period t_2. If the farmer purchases the insurance contract, they pay a premium C in the time t_1 and receive a payoff I when an extreme weather changes occur at a later time t_2.

The possible outcomes from the farmers' decisions are summarized in Figure A2, where H_g and H_g show the yield outcomes obtained in time t_2. The yield obtained with favorable weather conditions is H_g, whereas the yield obtained with adverse weather is H_b. The probability of having a valid index is P and the probability of having good yields is j. However, the probabilities P and j are not known by the farmer, at the time of paying the insurance premium and that is what makes index insurance to be ambiguous. To represent the yield outcome for the coffee season, each subject was presented with a container containing an equal proportion of red and white beads. The respondents were required to randomly pick a bead from the container, whereby a red bead represented a bad coffee yield outcome whereas a white bead represented a good yield outcome.

If the farmer purchases weather index insurance, and if the weather conditions are extremely bad, they receive a payoff I, but with good weather conditions, they receive no payoff. The payoff depends on whether the weather variable reaches a predefined critical level, or trigger level, and therefore, $I \geq 0$. The farmer that chooses not to adopt insurance does not pay a premium and therefore does not get any payoff in case of bad weather. To represent index insurance against a covariate risk, respondents were divided into groups of ten to simulate a farming community. For each each group, a coin flip was used to determine whether the group was eligible for a payoff. If the coin turned out tails, that represents a severe drought season that triggers a payoff for the group. If the coin turns out heads, that represented a good weather season that does not trigger a payoff. The coin flip also represented the uncertainty regarding whether the changes in weather conditions would trigger an index payment. Also, payoffs were made depending on the outcome for the weather condition, regardless of whether the respondents had obtained a good or bad yield. The insurance game was played three times, with each round representing a coffee-growing season that required a payment of a premium to participate. The respondents were informed of the outcome of each round of the experiment before proceeding to the next.



Source(s): Adapted from Elabed and Carter (2015)

Figure A2. Illustration of outcomes and payoffs from the choice experiment

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