Behavioural Factors and Technology Adoption: Experimental Evidence from Ghana

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Abstract

This paper investigates the effect of trust and of an ambiguous environment on fertiliser investments under index insurance. These two behavioural factors were studied by means of a framed field experiment conducted with Ghanaian cocoa farmers. The subjects had an option to invest in a package of fertiliser bundled with index insurance with a positive level of basis risk. The returns depended both on the subjects´ investment choices and a stochastic weather realization. The key ingredient of the study was that for different subjects, the nature of the basis risk was framed differently. Substantially fewer subjects adopted fertiliser when possible losses of fertiliser investment were framed as resulting from the insurer´s failure to meet its contract obligations, compared with an alternative in which the losses were framed as resulting from a mismatch between their own weather realizations and those on which the index insurance was based. A large negative effect on fertiliser investments was also found in treatments with either a small or large ambiguity regarding the exact level of basis risk. Both negative treatment effects were strongly significant. This may suggest that technologies with which farmers are relatively more experienced are more likely to be adopted under index insurance schemes. The overall experimental findings provide evidence that trust and ambiguity may be significant factors other than basis risk, limiting the effectiveness of index insurance in promoting agricultural innovation.

Keywords: behavioural finance, index insurance, trust framing, framed field experiments, technology adoption.

JEL Classification: C93, D14, G22, G41, O12.

Acknowledgements

I thank Daniel Clarke, Stefan Dercon, Michalis Drouvelis, Marcel Fafchamps, Douglas Gollin, Donhatai Harris, Glenn Harrison, Michael Kosfeld, Johannes Lohse, Sujoy Mukerji, Ganna Pogrebna, Pieter Serneels, and seminar audiences at CESS (Oxford University), Birmingham University, the 2017 SEEDEC conference (UEA), and the 2017 Workshop on Behavioural Game Theory (UEA) for very useful comments. I thank the enumeration team in Ghana for their excellent assistance in conducting the experiment. I am very grateful for generous financial assistance from the following sources: CSAE, ESRC, John Fell Fund and Williams College.

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1 Introduction

Why do innovative insurance schemes often fail to encourage farmers in developing countries to adopt new agricultural technologies? While few development economists disagree that basis risk is a fundamental non-price factor affecting demand for index insurance schemes, academics are increasingly exploring whether behavioural factors, ignored in the standard models of rationality, may also influence technology adoption decisions.

Duflo et al. (2011) provide evidence that some farmers may be present-based and have time-inconsistent preferences. These farmers may be willing to innovate, but they defer incurring the cost until the final moment at which the technology must be employed. Cole et al. (2013) argue that trust in an insurer may also play a very significant role. Several recent RCTs show that at the start of a given season, farmers are more willing to adopt a new technology under index insurance if payment of insurance claims had been experienced in the past either by themselves or by neighbouring farmers (Karlan et al., 2014; Cai et al., 2009). Other potential factors influencing agricultural innovation under index insurance are not only the resulting increased variability of harvest income, but also the uncertainty about the actual magnitude of the risks involved (Bryan, 2014). Farmers´ decisions to invest in new technology may be affected by the fact that exact yield variation may simply be unknown.

Trust and ambiguity may be important behavioural factors that limit the impact of index insurance on promoting technological change in agriculture. Nevertheless, it is challenging to study these aspects purely by RCTs. While recent field experiments show evidence that raising trust may be effective in raising insurance demand (Cole et al., 2013; Karlan et al., 2014) , the scope of studying trust via RCTs is limited due to ethical reasons. Studying ambiguity in the field is even more challenging, since unobserved heterogeneity prevents a precise calibration of ambiguity in the field. While Bryan (2014) shows that subjects with relatively higher rates of aversion to ambiguity are less likely to be encouraged by index insurance to adopt new technology, no field study has explored the impact of an ambiguous environment on insurance demand and technological choices.

The objective of this paper is to explore trust and an ambiguous environment as potential factors influencing agricultural innovation under an index insurance scheme. By means of a framed field experiment with a subject pool of cocoa farmers from Ghana, this paper investigates the importance of still understudied behavioural factors that RCTs cannot address directly.

This paper has four main contributions: 1) Addressing trust in an insurer as a factor influencing technological innovation under index insurance; 2) addressing an ambiguous environment as a factor influencing technological innovation under index insurance; 3) investigating the effect of a reduction in an ambiguous environment on technological innovation under index insurance; 4) providing new quantitative evidence that complements RCTs in the ongoing, highly policy relevant conversations over promoting agricultural modernization in developing countries.

The remaining structure of this paper is as follows: Section 3.2 summarises the existing literature on behavioural and non-behavioural factors, which may influence the take-up of agricultural technologies under index insurance. Section 3.3 describes in detail the experimental design. Section 3.4 presents the empirical strategy. The empirical results are presented in Section 3.5. Section 3.6 concludes and discusses some policy implications of the findings.

1.1 Literature Review

Encouraging the adoption of new agricultural technologies could significantly contribute to poverty eradication in developing countries (Gollin et al., 2002). While a new technology tends to raise average yields, yield improvements are not guaranteed for all adopters in a given region. Index insurance schemes are innovative financial products which may be attractive both to farmers and to insurers. An important advantage of an index insurance scheme relative to a traditional indemnity insurance is the possibility of it addressing the information problems of moral hazard and adverse selection. The payouts under index insurance are determined by an index trigger. This occurs when a particular weather condition, crucial for the crop yields,[1] is above a pre-determined threshold. The threshold is determined at a district level; therefore, the index insurance scheme is less susceptible to the problems of asymmetric information[2] and moral hazard.[3]

While index insurance schemes may be particularly effective in addressing important information problems, an insurance product may be unattractive to farmers due to basis risk (Mobarak and Rosenzweig, 2012; Clarke, 2016). Nevertheless, Cole et al. (2013) also stress the importance of non-price factors other than basis risk, which can fundamentally affect the demand for insurance. There is a large literature which argues that trust may hugely influence the demand for financial products (Doherty and Schlesinger, 1990; Guiso et al., 2008). Trust may be particularly relevant in the context of the insurance, as subjects pay premiums upfront and receive compensation later, but only under

[1] For instance, this may be the number of sunny days during the period of drying of cocoa beans on cocoa farms in Ghana.

[2] Under index insurance payouts are given to all farmers in a given district, if the pre-determined weather condition reaches the threshold (index triggered). The payouts are, therefore, not given merely to farmers, who are intrinsically less productive and have incentive to hide this from the insurer.

[3] The payouts under index insurance are determined by the index, which does not depend on the action of a particular farmer.

certain circumstances.

Another factor which can negatively affect the demand for financial products is the presence of ambiguity (Mukerji and Tallon, 2001). This occurs if risks faced by a subject are unknown. Ambiguity may influence an adoption decision, since, unlike traditional and familiar farming practices, the risks associated with new technologies may be unknown. This may be particularly important in the first years of adoption (Akay et al., 2012). Bryan (2014) notes that if a new technology is offered with an index insurance scheme, a farmer may also not know the correlation between his yields and the weather. This may substantially limit the effectiveness of an index insurance scheme in promoting the adoption of new technologies.

Trust and ambiguity may be important behavioural factors which influence technology adoption decisions under index insurance. Behavioural models relax the assumptions of rationality and self-interest.[4] For example, in a trust game,[5] the traditional models predict that none of the individuals is trustworthy, and that individuals never trust each another. However, lab experiments show evidence both for the trusting behaviour of senders and the trustworthiness behaviour of receivers (e.g. Berg et al., 1995; Falk and Kosfeld, 2006).

A subject's utility may be affected differently if, for instance, he loses money due to a random event, rather than due to a deliberate action of another subject. Bohnet et al. (2008) use a lab experiment to test whether subjects are averse to betrayal.[6] The experiment provides evidence that subject may be averse to betrayal. Despite the fact that uncertainty levels were identical across

[4]One of the core simplifying assumptions in the traditional models of decision making is that individuals are perfectly rational and act purely in their own interests.

[5]In a standard trust game (Berg, Dickhaut and McCabe (1995)), a sender, who receives an initial endowment, determines the proportion of the endowment to be sent to a receiver (trust behaviour). Subsequently, the receiver decides how much of this proportion he is willing to send back to the sender (trustworthiness behaviour).

[6]A subject is considered betrayal-averse, if a loss is caused by a random event is preferred to an identical loss caused by another subject.

the experimental treatments,[7] subjects accepted significantly less risk when it originated from other person rather than from nature.

By using experimental data on sow insurance in China, Cai et al. (2009) studied the demand for new technology under a government-sponsored sow insurance scheme.The dataset from this natural experiment shows that substantially higher rates of purchase of government sponsored insurance for sows were also found in these areas. This is interpreted by the authors as being due to a higher level of trust in the local government, which complied with its actuarial obligations. Cole et al. (2013) study insurance demand in a study with experimental variation in trust. Relative to subjects in control groups faced with unknown insurance educator, the insurance educator in the treatment group is endorsed by a trusted and well established local agent. Cole et al. (2013) found that this experimental variation substantially influences demand for index insurance, suggesting that being offered identical insurance by a trusted party can indeed influence farmers´ decisions.

It is worth noting that, apart from the fact that similar evidence for trust importance is found in studies based on RCTs (Cole et al., 2013) and natural experiments (Cai et al., 2009) studies, neither of these studies is directly relevant to the context considered here.[8] A recent RCT in northern Ghana by Karlan et al. (2014) is particularly relevant to our paper, as its key focus is also on the impact of index insurance on the adoption of new technologies. While the experiment did not involve explicit treatments related to trust, experimental subjects were revisited twice in this RCT. Karlan et al. (2014) found that demand for insurance in subsequent seasons was positively related both to farmers'

[7] Subjects assigned to control sessions played an adapted version of a trust game. Subsequently, the average probability of receiving endowment from senders was calculated, and this calibrated probability was used in risk games in experimental treatment sessions.

[8] The study by Cole et al (2013) investigates the demand factors purely for a commercial non-agricultural index insurance scheme. The experiment by Cai et al. (2009) investigates the impact of a subsidised index insurance scheme on farming investment decisions.

own experience of receiving insurance compensation and to insurance compensation received by others within the farmers´ social network. This suggests that having been compensated in the past may substantially raise trust in receiving insurance payouts in the future.[9]

Ambiguity may be another behavioural factor affecting decisions both in abstract games and in investment decisions in real-world environments. Ambiguity occurs when certain outcomes are not only subject to risk but the exact level of the risks involved is not known either. As with trust and betrayal aversion, preferences over ambiguous environment are also not present in traditional decision theory. Ellsberg (1961) proved with two thought experiments that people may be averse to lotteries involving unknown, ambiguous probabilities. The Ellsberg paradox resulting from these experiments showed that subjects may violate axioms of subjective expected utility models (Savage, 1954). Subsequently, new models of decision-making taking account of ambiguity aversion were developed, such as Choquet expected utility (Schmeidler, 1989) and Maxmin expected utility (Gilboa and Schmeidler, 1989).

A number of laboratory experiments have investigated the presence of ambiguity aversion in preferences (e.g. Magdeldorff and Weber (1994), Moore and Eckel (2003)). Our paper studies investment decisions of farmers from developing countries; hence, it is of interest whether similar patterns of preferences are also to be observed among subjects from developing countries. Akay et al. (2012) found evidence both for RA and for AA among Ethiopian farmers, yet the data was obtained only in the gain domain. Apart from identifying AA among the subjects, the authors also claim that agricultural innovation may lead to a highly ambiguous environment.[10] Warnick et al. (2011) found sup-

[9] However, Karlan et al. (2014) also note that trust in an insurer may be particularly hard to establish at the beginning when farmers have no personal experience of whether their compensation claims are going to be respected or not.

[10] While farmers using traditional technologies are familiar with yield distribution, switching to new technologies may not only involve higher variability in yields but also unknown yield

portive evidence that Peruvian farmers are also risk averse and ambiguity averse in the gain domain.[11]

Exploring quantitatively the importance of ambiguity in investment decisions is challenging in the field since the scope of controlling precisely for ambiguity levels is very limited. Bryan (2014) uses the data in Gine and Yang (2009) on Malawi groundnut farmers to study whether AA affects the uptake of new technologies under mandated index insurance. Relative to more elaborate elicitation techniques in studies such as those by Warnick et al. (2011) and Barham et al. (2014), the data used by Bryan (2014) does not enable the distinction between ambiguity-averse, ambiguity-neutral and ambiguity-loving subjects. Nevertheless, the author shows evidence that the impact of mandated index insurance on technological innovation is greater among subjects who are relatively less ambiguity averse. This suggests that ambiguity-averse subjects may indeed value the index insurance less and, hence, remain unaffected in their choice of agricultural technology in the presence of index insurance.[12]

The RCTs may provide valuable insights into the importance of trust and ambiguity in technological innovation under index insurance schemes. Nevertheless, the scope of answering certain research questions by means of this methodology is limited. First, treatments involving contract violation should not be implemented in the real world on ethical grounds, as it would generate real income losses for experimental subjects. Second, the precise calibration of insurer trustworthiness may be very difficult. Moreover, introducing exper-

distributions. The uncertainty about this distribution of harvest outcomes under innovation may discourage ambiguity-averse farmers from experimenting with new technologies in the first place.

[11]This study also links risk and ambiguity preferences with post-experimental survey data on farmers´ decisions whether to plan more than one variety of the main crop. Warnick et al. (2011) found that crop diversification is less likely among ambiguity-averse farmers, and no evidence was found that RA affects diversification decision.

[12]Bryan (2014) also found that the difference in insurance impact on technological innovation between more and less ambiguity-averse subjects is increasing in risk aversion and, interestingly, becomes negligible as farmers gain experience with new technology.

imental variation in ambiguity as part of an RCT study appears even more challenging. It is almost impossible in the field to measure precisely the level of basis risk in newly introduced index insurance schemes. Therefore, any attempt to convincingly control for ambiguous environment in technological innovation under index insurance is likely to fail. To the best of my knowledge, no RCT explicitly studies the impact of an ambiguous environment on the adoption of new technologies.

The above-mentioned obstacles faced by RCTs may be overcome by means of a framed field experiment. The latter methodology can provide a complementary picture to RCTs, as it can introduce experimental treatments in a highly controllable environment. Depending on the treatment in the lab, potential losses deducted from experimental winnings may be framed as either due to a basis risk or due to contract violation. If these two frames occur with identical probabilities, the challenge of precise probability calibration under both treatments is also resolved. Furthermore, as long as all subjects are guaranteed sufficient monetary winnings from attending the experiment, the ethical concerns of conducting treatments on trust are also addressed. Finally, although RCTs are unable to precisely measure and introduce variation in the level of ambiguity in the environment, this treatment may be easily implemented in a laboratory setting.

This paper provides one of the first pieces of field evidence documenting the importance of trust and ambiguity in agricultural innovation under index insurance. An increasing number of RCTs aim to better understand non-price factors determining the demand for index insurance. By introducing the framing effect of trust and an ambiguous environment in a controllable setting, this framed field experiment enables me to ask and potentially answer questions that are either challenging or impossible to be addressed by means of RCTs. By studying the potential demand effects of two understudied behavioural factors, this framed field experiment provides a complementary picture to the important policy debate in development economics.

Table 1: Sub-samples across Treatment Groups

	'Basis´	**'Trust´**	**'Small Ambiguity´**	**'Large Ambiguity´**	Total
subjects	116	117	117	116	466
sessions	6	6	6	6	24

1.2 Sample Description

The experiment was conducted in 12 randomly selected villages from the cocoa-growing Ashanti region in central Ghana. A total of 466 subjects were randomly selected for the experiment from lists of farmers selling cocoa harvest to all Licensed Buying Companies operating in a given village. Due to an excellent advance team from COCOBOD, attrition was non-existent in the experiment. Depending on village accessibility, experimental sessions took place in different locations, such as schools and churches.[13] There were altogether 24 experimental sessions. Four different types of sessions were conducted depending on treatment ('Basis´, 'Trust´, 'Small Ambiguity´ or 'Large Ambiguity´). Table 1 shows the number of subjects in each treatment group as well as the number of different sessions of each treatment group. Session types were allocated randomly across 24 sessions of the experiment. Six sessions of each session type were conducted.[14]

Table 2 shows summary statistics both for fertiliser non-adopters (left column), fertiliser adopters (middle column) and two combined sub-samples (right column). Standard deviations are in parentheses. Adoption rates of fertiliser in the real world are higher among married subjects and females. Adopters are also slightly older and more educated. They also have substantially higher yields, which is reasonable due to the potential of yield increases due to fertiliser adoption.

It is very promising that the sample size included primarily head households

[13] We conducted only two sessions in each village (one in the morning and one in the afternoon), and the type of each session was assigned randomly.

[14] In Table 9 in Appendix we report results from regressing session types on our set of controls. The coefficients on controls are not statistically significant, suggesting that assignment to a particular session group was randomised fairly successfully.

Table 2: Descriptive Statistics

	No Fert	Used Fert	Total
Yield (t/ha)	.15	.21	.18
	(.13)	(.23)	(.18)
If household head	.78	.75	.77
	(.41)	(.44)	(.42)
If male	1.5	1.7	1.6
	(3.1)	(3.8)	(3.4)
Age	48	53	50
	(14)	(16)	(15)
Number of children	6.1	6.4	6.2
	(3.2)	(3.5)	(3.3)
Education level	3	3	3
	(1.4)	(1.4)	(1.4)

Main statistic is the mean. Standard deviation is in parenthesis.
Sample size is equal to 467.
266 farmers did not use fertiliser in the last season (column (1)).
201 farmers did not use fertiliser in the last season (column (2)).

that were middle-aged. This appears to be the group of farmers that are most likely responsible in the household for making decisions on whether to invest in fertiliser or not. This is the key question of interest in this paper; hence, this sample appears to be good for the purpose of the study. It is worth stressing that the experimental sample is relatively representative as the key sample descriptive statistics are comparable with the five-wave nationwide panel of cocoa farmers from 2002 to 2010.

1.3 The Experiments

The experiment was conducted with cocoa farmers in Ghana. Cocoa farming is the dominant cash crop in Ghana but cocoa cultivation is rather labour intensive and does not require the use of sophisticated machinery. One of the key investment decisions a farmer may consider is whether to apply fertiliser on their farm. The experimental subjects were cocoa farmers, who were asked to think of their decisions as investment choices on their farm; hence, the experiment falls into the category of framed field experiments (Harrison and List, 2004). The following subsections describe the design and implementation of the experiment.

1.3.1 The structure of the experiment

The between-subject design of the experiment implied that each experimental subject was randomly assigned to either a control group or to one of the treatment groups. Hence, each subject of the 467-subject sample made only one farming investment decision. Subsequently, the risk preferences of each experimental subject were elicited via the Binswanger (1980) procedure. Only after all the decisions were collected and the actual decision was played out was the payout determined randomly for each subject. Since it was not known until the very end which decision would determine the experimental winnings; the experimental subjects had to make careful choices in all parts of the experiment. Moreover, this experimental design did not allow for wealth effects and, hence, the design incentivised subjects to treat each decision independently. Each subject was given a 2 GHC show-up fee and he could win up to an additional 10 GHC. The eventual game earnings depended on the choices made, the decision problem that was played out, and the random elements within the decision problem that was played out.

1.3.2 Fertiliser investment games

Irrespective of the random assignment of farmers to either control group or any of the three treatment groups, each experimental subject was asked to make a binary decision in the single-season farming investment game. He could either choose ‘Old´ technology or take a loan for fertiliser investment with mandated index insurance (‘Fertiliser´). A farmer´s returns would be determined both by his choice of technology and by the stochastic realisation of weather. Under all treatment, 'Fertiliser´ technology had the same higher expected yields relative to 'Old´ technology. However, it was also a more risky technological choice since the fertiliser investment was entirely ineffective in bad weather. The individual weather realisation was also identical across the control and all treatments. With a probability of 0.75, the weather conditions on farmers´ land were good, implying high yields. With a probability of 0.25, the weather conditions on farmers´ land were bad, implying low yields.

The unique experimental variation was a second-stage lottery under a bad weather scenario. Bad weather could result in either basis risk (control group), a bad type of insurer ('Trust Frame´ treatment) or an uncertain likelihood of basis risk ('Large Ambiguity´ and 'Small Ambiguity´ treatments). The subsequent paragraphs describe the payoff structure and explain the experimental variation in greater detail. This is followed by a statement of the game theoretical predictions as well as the four main hypotheses of this paper.

Control Treatment T0: $Takeup_{T0}$ (Fertiliser with Basis Risk)

Subject choosing 'Fertiliser´ in the control group ($Takeup_{T0}$) would not be protected by insurance under the basis risk scenario. This would happen if bad weather turned out to be localised. The index would not be triggered; therefore, the farmer would not receive any insurance compensation. An alternative second-stage lottery scenario would be bad weather turning out to be common. This would imply that bad weather had affected the surrounding area and the index would be triggered. Under this scenario of bad weather, the farmer would receive full compensation for a failed fertiliser investment. Localised bad weather and common bad weather were equally likely to occur. Since bad weather occurred with a probability of 0.25, the probability of basis risk (localised bad weather) was equal to 0.125

Index insurance was not available for the ´Old´ technology; hence, in this

Table 3: Payoff Table

Weather	Weather Probability	Payoffs 'Old´	Payoffs 'Fertiliser´
good	0.75	6	6.5
bad & common	0.125	4	6.5
bad & localised (basis risk)	0.125	4	0.5

Comparisons across the two technologies:

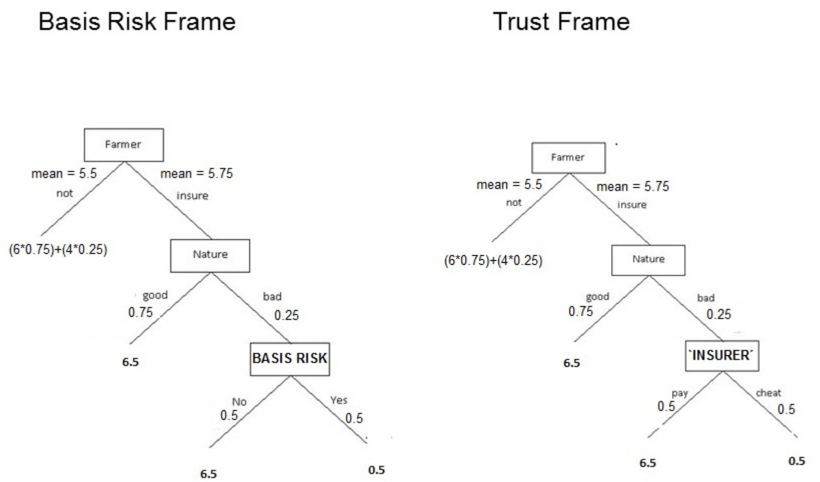
Technology	Mean	Variance
'Old´	5.5	1.75
'Fertiliser´	5.75	2.67

case, it was irrelevant whether bad weather was common or localised. Choosing 'Old´ technology would generate GHC 6 under good weather and GHC 4 under both types of bad weather. Adopting fertiliser would result in yield improvement under good weather, generating GHC 6.5. Despite being a failed investment in bad weather, fertiliser adopters would still receive GHC 6.5 if the bad weather was common – implying that the index would be triggered. However, if bad weather was localised, fertiliser was a failed investment with no insurance compensation. Since the subject was still obliged to repay loan with interest and insurance premium, this would result in very low outcome of GHC 0.5. Table 3 summarises the payoffs under each weather scenario for both types of technologies (simple mathematical equations showing benefits and costs of fertiliser investment are shown in the implementation section).

Treatment T1:$Takeup_{T1}$ (Fertiliser under the Trust Frame)

The subject choosing 'Fertiliser´ in the Trust Frame treatment group ($Takeup_{T1}$) would not be protected by insurance under a bad type of insurer. This would happen if the farmer faced bad weather but was informed that the insurer had denied insurance compensation. The experiment involved no real subjects playing the role of insurer; hence, under this treatment, the lack of insurance compensation was framed as facing a bad type of insurer (rather than facing basis risk as in the control group). Under an alternative second-stage lottery scenario, the farmer would face bad weather and a good type of insurer. Under this scenario, the farmer would be informed that the insurer type was good and the farmer would receive full compensation for a failed fertiliser investment. Bad and good types of insurers were equally likely to occur.

Figure 1: Game tree: Control and Trust Frame



Game theoretically, people should be indifferent between the risk generated by nature and the risk generated by human beings, as long as the involved risks are identical. All payoffs under a Trust Frame treatment were identical to payoffs under the control group shown in Table 3. Figure 1 shows that the probabilities of weather outcomes and second-stage lottery were also identical. This implied an identical mean of GHC 5.5 and variance of 'Old´ technology, as well as an identical mean of GHC 5.75 and a variance of more risky ´Fertiliser´ technology. Therefore the preferences across 'Old´ and 'Fertiliser´technology should be identical for expected utility maximisers.

The only difference between the control group and Trust Frame treatment was whether the second-stage lottery was framed as a weather type or an insurer type. Even if the probability and size of the loss is identical, subjects´ utility may be affected differently if the source of the loss is a random event or the unethical action of another human. This treatment tests for the presence of betrayal aversion in framing. Instead of introducing the actions of real insurers, the experimental design enables us to investigate whether farmers are less likely to adopt fertiliser if a possible lack of protection is framed in terms of a bad insurer rather than in terms of localised weather.

Hypothesis I Farmers are less likely to adopt fertiliser with index insurance if the source of risk of denial of insurance claims is framed as a bad insurer type ($Takeup_{T1}$) rather than as basis risk ($Takeup_{T0}$).

$Takeup_{T1} < Takeup_{T0}$

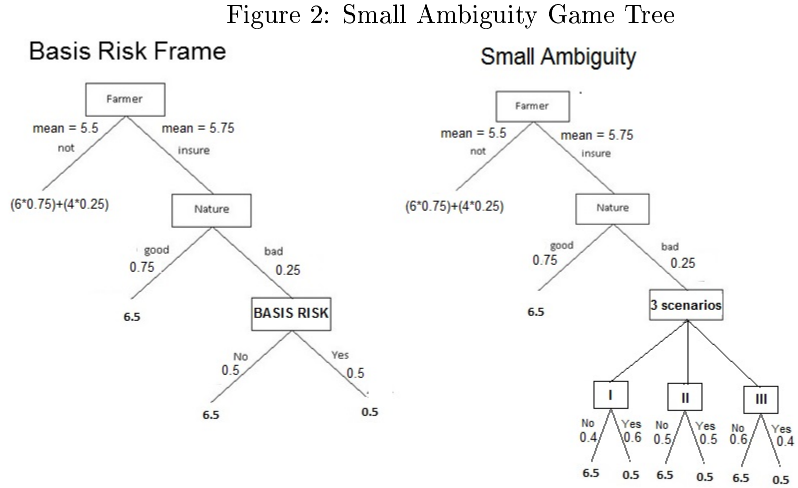
Treatment T2 :$Takeup_{T2}$ (Fertiliser under Small Ambiguity)

Subject choosing 'Fertiliser´ in the Small Ambiguity treatment group ($Takeup_{T2}$) would not be protected by insurance under the unknown probability of a basis risk scenario (localised bad weather). While subjects in the control group ($Takeup_{T0}$) knew that common and localised type of bad weather were equally likely, subjects in the Small Ambiguity treatment group knew that this probability distribution was only one of three possible scenarios. Under the second scenario, bad weather would be localised with a probability of 60% and common with a probability of 40%. Finally, under a third scenario, bad weather would be localised with a probability of 40% and common with a probability of 60%. Therefore, subjects knew an interval by which the probability of basis risk was bounded but the exact probability of basis risk remained unknown. Each of the three above-mentioned scenarios was equally likely.

Game theoretically, people should be indifferent between known and unknown probabilities of outcomes as long as the expected value of the lotteries are identical. Fertiliser adoption under Small Ambiguity treatment ($Takeup_{T2}$) involved three different possible probabilities of basis risk. However, the aggregate probability of basis risk was identical to the probability of basis risk in the control group ($Takeup_{T0}$). Therefore, the mean and variance of fertiliser investment was also identical in the treatment and control group, and expected utility maximisers should be indifferent between these two options.

The only difference between the control group and the Small Ambiguity treatment was whether the probability of basis risk was exactly known or whether it was bounded by a small interval. Even if the overall probability of basis risk was identical across the two groups, subjects´ utility might be affected differently if the likelihood of basis risk is known. This treatment tests for the presence of subjects who are ambiguity-loving or ambiguity-averse. The experimental design enables us to investigate whether farmers are less likely to adopt fertiliser if the probability of basis risk is not entirely known.

Figure 2: Small Ambiguity Game Tree



Hypothesis II Farmers are less likely to adopt fertiliser with index insurance if the probability of basis risk involves a small level of ambiguity ($Takeup_{T2}$) rather than no ambiguity ($Takeup_{T0}$).

$Takeup_{T2} < Takeup_{T0}$

Treatment T3 :$Takeup_{T3}$ (Fertiliser under Large Ambiguity)

Subjects choosing 'Fertiliser´ in a Large Ambiguity treatment group ($Takeup_{T3}$) would not be protected by insurance under the unknown probability of basis risk scenario (localised bad weather). As with the Small Ambiguity treatment, the exact probability of basis risk was not known, as it depended on three equally likely scenarios. One of the scenarios was identical to the control group ($Takeup_{T0}$) where common and localised types of bad weather were equally likely. However, under the second scenario, bad weather would be localised with a probability of 80% and common with a probability of 20%. Finally, under the third scenario, bad weather would be localised with a probability of 20% and common with a probability of 80%.

While the probability of basis risk was known in the control group, the probability of basis risk under a Large Ambiguity treatment was unknown and bounded by a large interval (substantially larger than under Small Ambiguity treatment). However, the overall probabilities of basis risk were identical, implying an identical expected value and variance of fertiliser investment in the control group and the Large Ambiguity group. While expected utility maximisers would be indifferent across these two options, an ambiguity-averse individual would prefer to invest in fertiliser where the probability of basis risk is known.

Hypothesis III Farmers are less likely to adopt fertiliser with index insurance if the probability of basis risk involves a large level of ambiguity ($Takeup_{T3}$)

rather than no ambiguity ($Takeup_{T0}$).

While an unknown probability of basis risk in Large Ambiguity treatment was bounded by a substantially larger interval relative to the Small Ambiguity treatment, the overall probability of basis risk was identical. Introducing even a relatively low level of ambiguity would discourage subjects with the highest level of aversion to ambiguity, yet the overall impact on adoption rates would be substantially higher in an environment with a large level of ambiguity.

$Takeup_{T3} < Takeup_{T0}$[15]

The empirical specification

In order to investigate these three hypotheses, I estimate the basic specification:

$$Takeup_i = Takeup_i = \beta_0 + \beta_1 TreatT1_i + \beta_2 TreatT2_i + \beta_3 TreatT3_i + \beta_4 LowRA_i + X_i^{\mathrm{k}} \beta_5 + \varepsilon_i \tag{1}$$

In this equation, the variables are defined as follows:

1. $Takeup_i$ is a dummy variable taking value 1 if a subject i adopted the fertiliser,

2. $TreatT1_i$ is a dummy variable taking value 1 if a subject i made the adoption decision in the treatment group T1 ($FERT_{T1}$: Fertiliser under the Trust Frame),

3. $TreatT2_i$ is a dummy variable taking value 1 if a subject i made the adoption decision in the treatment group T2 ($FERT_{T2}$:Fertiliser under the Small Ambiguity),

4. $TreatT3_i$ is a dummy variable taking value 1 if a subject i made the

[15] Given that the level of ambiguity is larger under the treatment T2 than under the treatment T1, one would expect $Takeup_{T3} < Takeup_{T2} < Takeup_{T0}$. Also, since treatment T1 did not involve any level of ambiguity (T1 treatment was based on the Trust Frame), it is not clear a priori how the takeup rates under T1 would compare to the takeup rates under T2 or T3 (according to Hypothesis I, one expects $Takeup_{T1} < Takeup_{T0}$).

adoption decision in the treatment group T3 ($FERT_{T3}$:Fertiliser under the Large Ambiguity),

5. $LowRA_i$ is a dummy variable taking value 1 if subject i´s CRRA coefficient $\sigma_i \leq 0.18$.[16]

6. X_i^k is a vector of control variables,

7. ϵ_i is a mean zero error term.

The specification (1) enables me to test Hypothesis I while controlling for Hypothesis II and for Hypothesis III. and vice versa. All three hypotheses can be tested by means of Student´s t-test (Student, 1927).

1.3.3 Implementation of the experiment

The experiment was conducted with a non-standard subject pool of Ghanaian cocoa farmers with low levels of formal education. The greatest effort was put into ensuring the understanding of the decision problems by the experimental subjects. The following paragraphs discuss how key information was conveyed to the experimental subjects.

Weather description (same across all treatments)

The experiment was designed to resemble the agricultural practices of experimental subjects as closely as possibly. Cocoa seasonal farming consists of several stages, such as planting, tree spraying, pod ripening, pods collection, beans fermenting and beans drying. At these farming stages, different weather conditions were viewed optimally. Sunny weather may be good for beans drying but not necessarily for pod ripening. Pilots of the experiment revealed that optimal seasonal conditions could not be defined purely by one weather condition. However, farmers´ understanding was clear when a high seasonal harvest outcome

[16]The CRRA coefficients were elicited by the standard Binswanger procedure: the CRRA coefficients $\sigma_i$which are interpreted as follows: $\sigma_i < 0 \implies i$ is risk-loving, $\sigma_i = 0 \implies i$ is risk-neutral, $\sigma_i > 0 \implies i$ is risk-averse.

occurred with a high number of harvested beans, and a low seasonal harvest occurred with a low number of harvested beans. Moreover, farmers associate good farming conditions with healthy orange pods producing many cocoa beans and bad farming conditions with unhealthy black pods producing little cocoa beans. Given this information, good weather was described as healthy orange pods producing many cocoa beans at the end of the harvesting season. Bad weather was described as unhealthy black pods producing few cocoa beans at the end of the harvesting season.

Good weather was calibrated at 75% and bad weather was set at 25%. However, due to the fact that the experimental sample was non-standard with subjects primarily having little formal education, use of probabilities was limited in order to maximise the understanding of the experiment. Subjects were told that six out of eight pods would symbolise good weather and two out of eight pods would symbolise bad weather. In order to familiarise the subjects with the probabilities involved, real orange pods (six orange and two black pods) were displayed throughout the experiment. Subject were also given individual visualisation depicting each weather outcome. However, the actual weather draws were made from a bag containing eight small equal-sized marbles,out of which six were orange and two were black. The small bag was used both for several demonstration draws before decision making as well as for the actual weather determination at the end of experiment. In order to ensure subjects´ familiarity with the probabilities involved, farmers could see real cocoa pods and individual weather cards at all stages of the experiment.

Payoff description (the same across all treatments)

Another common feature across all treatment groups were payoffs. Subjects were asked to think that their choice of technology together with the weather realisation would determine their seasonal harvesting income. Subjects could choose traditional, safer ‘Old´ technology. Alternatively, they could invest in new technology of fertiliser investment with mandated index insurance. This would generate a higher mean for the harvest, but also a higher harvest variability. The payoff calibrations incorporated the idea that fertiliser was effective in raising yields in good weather, yet it could be failed investment when the weather was bad (Dercon and Christiaensen, 2011). Due to the fact that no formal insurance products were present in the area of study, insurance was explained by enumerators as a protection mechanism linked to fertiliser investment. This concept was understood well by the experimental subjects.

Table 4 displays all payoffs under ‘Old´ and ‘Fertiliser´ technology. In order to ensure subjects' understanding of the technological investments, all payoffs were explained with basic mathematical equations, including summations and subtractions. Fertiliser involved costs and benefits that were presented with reference to baseline payoffs under ´Old´ technology.

Fertiliser investment was positive in good weather leading to final payoff of GHC 6.5. Nevertheless, fertiliser was completely ineffective in bad weather. Subjects were asked to think of this scenario as corresponding to an event such as unexpected torrential rain completely washing away the fertiliser. Fertiliser investment could then give either more (6.5 GHC) or less (0.5 GHC) relative to ‘Old´ technology. The final payoff for fertiliser adopters under bad weather was determined by the second-stage lottery, where the treatment variation was introduced. The implementation of different experimental treatments is described below.

1.3.4 Treatment implementation

Following the investment decision, each experimental subject determined his individual weather realisation by drawing a marble. Drawing a black marble implied that weather on a farm was bad. While payoffs under the ‘Old´ tech-

Table 4: Payoff Table Detailed

Weather	**Weather Probability**	**Payoffs 'Old´**	**'Fertiliser´ relative to 'Old´**	**Payoffs 'Fertiliser´**
good	0.75	6	$6 + r - c - i - m$	6.5
bad & common	0.125	4	$4 + 0 - c - i - m + P_{common}$	6.5
bad & localised	0.125	4	$4 + 0 - c - i - m + P_{localised}$	0.5

Legend:

	Description	**Calibrated values**
r	fertiliser benefit	4
c	fertiliser cost (loan)	2
i	interest	1
m	premium	0.5
P_{common}	insurance payout (bad, common)	6
$P_{localised}$	insurance payout (bad, localised)	0

Comparisons of two technologies:

Technology	good (0.75)	bad & common (0.125)	bad & localised (0.125)	**Mean**	**Variance**
'Old´	6	4	4	5.5	1.75
'Fertiliser´	6.5	6.5	0.5	5.75	2.67

nology would already be known (insurance was bundled for fertiliser adopters only), payoffs under 'Fertiliser´ would need to be determined by the second-stage lottery. This additional draw from another type of bag would depend on experimental treatment.

Second-stage draw under control group (Basis Risk)

Under the control group, a fertiliser adopter experiencing bad weather would receive insurance compensation if bad weather was common. Bad weather could be common or localised (basis risk) with equal probabilities. The type of bad weather would be determined by drawing district weather from a bag containing 10 tokens.

Five black tokens represented bad district weather. Drawing a black token implied common bad weather. Under this scenario, failed fertiliser investment was compensated by insurance, implying a final payoff of GHC 6.5. Similarly, five orange tokens represented good district weather. Drawing an orange token implied localised bad weather and basis risk. Under this scenario, failed fertiliser investment was not compensated by insurance, implying a final payoff of GHC 0.5.

Second-stage draw under a Trust Frame treatment

Under a Trust Frame treatment, a group fertiliser adopter experiencing bad weather would receive insurance compensation if the type of insurer was good. The insurer could be either good or bad, with equal probability. The type of insurer would be determined by a draw from a bag containing 10 tokens.

Drawing one of five tokens with positive face expression implied a good insurer. Under this scenario, failed fertiliser investment was compensated by insurance, implying a final payoff of GHC 6.5. Similarly, drawing one of five tokens with a negative face expression implied a bad insurer. Under this scenario, failed fertiliser investment was not compensated for by insurance, implying a final payoff of GHC 0.5.

Additional draw under Small Ambiguity treatment

Under the Small Ambiguity treatment, a fertiliser adopter experiencing bad weather would receive insurance compensation if bad weather was common. The exact probability of common and localised bad weather would be determined by one of the scenarios. Under the first scenario, bad weather was common or localised with equal probabilities (one bag contained five black tokens for common bad weather and five orange tokens for localised bad weather). Under the second scenario, common weather was slightly more likely (the second bag contained six black tokens and four orange tokens). Under the third scenario, localised weather was slightly more likely (the third bag contained four black tokens and six orange tokens).

Payoffs of fertiliser adopters under bad weather would be revealed firstly by subjects´ choices across identical bags determining one of three scenarios. The subsequent draw of tokens was identical as under the control group.

Second-stage draw under Large Ambiguity treatment

Implementation of Large Ambiguity treatment was identical to the Small Ambiguity treatment except that the token composition of second and third bag was different (the second bag contained eight black tokens and two orange tokens; the third bag contained two black tokens and eight orange tokens).

The experiment aimed to better understand the farming investment decisions of Ghanaian cocoa farmers. Therefore, a lot of effort was put into ensuring that experimental subjects made decisions related to farming problems rather than abstract games. The framed protocol of the experiment encouraged subjects to think of their decisions as farming investments and that experimental winnings depended on investment choice and weather realisation. Importantly, subjects were encouraged to view different choices as investment options since costs and benefits were clearly displayed by mathematical equations written on large boards by enumerators. Subjects were incentivised to make careful decisions as average experimental winnings equalled approximately two days' wages at local rates. Weather outcomes were explained in detail to mimic the real weather outcomes faced by farmers in the studied area. A substantial use of visualisation devices was essential in ensuring high experimental understanding, including the use of real orange and black cocoa pods, symbolising either a good or bad harvest.

1.4 Experimental Results and Discussion

This part of the paper analyses the between-subject experimental data using both parametric and non-parametric empirical approaches. Firstly, the adoption decisions of control group are compared with different treatment groups using several parametric and non-parametric methodologies. These early results are then followed by regression analysis estimates where the fertiliser adoption decision is the dependent variable. Subsequently, the data are interpreted with reference to existing evidence and policy discussion on agricultural technology adoption under index insurance.

1.4.1 Preliminary Results

Parametric and Non-Parametric Tests of 'Trust´ Treatment

We first investigate whether fertiliser adoption rates (measured here as the mean of the binary adoption choice variable) differed across subjects assigned to 'Basis´and 'Trust´ groups. Depending on different distributional and variance assumptions, all tests displayed in Table 5 tested the null hypothesis of whether the means in the two samples under considerations were equal.

Table 5 shows that the mean of the 'Basis' group is 0.5897, compared to the mean of 0.4051 in the 'Trust´ group. We first test the null hypothesis of the mean equality by using parametric unpaired two-sample t-tests.[17] The null hypothesis of the mean equality is strongly rejected against the two-sided alternative, even at the 1% significance level.

This result remains unchanged in two non-parametric tests[18]: the null hy-

[17]The test is unpaired due to the fact that the design of the experiment was between-subject. Each experimental subject was assigned to either the control group or to one of the treatment groups; hence, only one fertiliser adoption decision per individual was collected and data points across to sample cannot be assigned to the same individual.

[18]The two tests are substantially less restrictive in assumptions, since non-parametric tests do not impose strong normality assumptions on the distribution of the two underlying samples. While the Mann-Whitney test stills keeps the original assumption of equal variance, the Kolmogorov-Smirnoff test does not impose either normality or variance equality assumptions.

Table 5: Mean Equality Tests (´Basis´and ´Trust´ groups)

	'Basis´ Group	**'Trust´ Group**
mean	**0.5897**	**0.4051**
standard deviation	0.0457	0.0458
observations	116	117

Parametric Tests

	t-test (equal variance)	t-test (not equal variance)
statistic	t = 2.8543	t = 2.8543
p-value	0.0047	0.0047

Non-Parametric Tests

	Mann-Whitney test	Kolmogorov-Smirnoff test
statistic	z = 2.811	K-S = 0.1846
p-value	0.0049	0.038

pothesis of mean equality is strongly rejected both in Mann-Whitney test and in Kolmogorov-Smirnoff test.

Parametric and Non-Parametric Tests of 'Small Ambiguity´ Treatment

The first key feature shown in Table 6 is that approximately 53% subjects adopted fertiliser under an index insurance scheme with a small level of ambiguity in the environment. Relative to the 'Trust ´group, this value is substantially closer to the 59 % proportion of adoption rates among subjects in the 'Basis´ group. This indicates that the ´Small Ambiguity´ treatment is less powerful than the 'Trust' treatment described above. Indeed, the unpaired t-test does not reject the null hypothesis of the mean equality among the 'Basis´and 'Small Ambiguity´groups, as the minimal significance level for rejecting the null hypothesis is 39.74%. Non-parametric versions of both types of t-tests also fail to reject the null hypothesis of mean equality. All tests suggest that there is not enough statistical evidence to claim that the sample means of the 'Basis´and 'Small Ambiguity´ groups are different.

Table 6: Mean Equality Tests (´Basis´and ´Small Ambiguity´ groups)

	'Basis´ Group	**'Small Ambiguity´ Group**
mean	**0.5897**	**0.5345**
standard deviation	0.0457	0.0465
observations	116	117

Parametric Tests

	t-test (equal variance)	t-test (not equal variance)
statistic	t = 0.8478	t = 0.8477
p-value	0.3974	0.3975

Non-Parametric Tests

	Mann-Whitney test	Kolmogorov-Smirnoff test
statistic	z = 0.848	K-S = 0.0553
p-value	0.3963	0.994

Parametric and Non-Parametric Tests of 'Large Ambiguity´ Treatment

Table 7 shows that approximately 42% of subjects adopted fertiliser under an index insurance scheme with a large level of ambiguity in the environment. This is substantially lower than the rate of approximately 59% among subjects from the 'Basis´ group. Both parametric and non-parametric results in Table 7 confirm this. The null hypothesis of the mean equality among the 'Basis´ and 'Large Ambiguity´ samples is rejected in unpaired t-tests with or without equal variance assumptions, even at the 1% significance level. Refraining from a normality assumption and performing a non-parametric version of either t-test with the variance equality assumption maintained (Mann-Whitney test) or the t-test with the variance equality assumption relaxed (Kolmogorov-Smirnoff test) confirm this finding. All tests show strong evidence that the means of 'Basis´ and 'Large Ambiguity´ are most likely not equal. This indicates that there may be a 'Large Ambiguity´ treatment effect and subjects´ decision-making may be affected by the presence of a large ambiguity in the environment.

Table 7: Mean Equality Tests (´Basis´and ´Large Ambiguity´ groups)

	'Basis´ Group	**'Large Ambiguity´ Group**
mean	**0.5897**	**0.4188**
standard deviation	0.0457	0.0458
observations	116	116

Parametric Tests

	t-test (equal variance)	t-test (not equal variance)
statistic	t = 2.6427	t = 2.6427
p-value	0.0088	0.0088

Non-Parametric Tests

	Mann-Whitney test	Kolmogorov-Smirnoff test
statistic	z = 2.609	K-S = 0.1709
p-value	0.0091	0.066

The Main Results

Table 8 presents the main results of the following empirical specification (equation 1):

$$Takeup_i = \beta_0 + \beta_1 TreatT1_i + \beta_2 TreatT2_i + \beta_3 TreatT3_i + \beta_4 LowRA_i + X_i^{\mathrm{k}} \beta_5 + \varepsilon_i$$

In this equation, the dependent variable is $Takeup_i$ (taking the value of 1 if fertiliser is adopted by a subject i and 0 otherwise). The binary variables $TreatT1_i$, $TreatT2_i$ and $TreatT3_i$ describe whether a subject i participated in either treatment T1, T2 or T3 respectively (1= participated in the given treatment, 0 otherwise).

To recap, treatment T1 studies the effect of trust frame.[19] Treatments T2 and T3 introduce an ambiguous level of basis risk.[20] $LowRA_i$ is a dummy vari-

[19]Under the treatment T1 the subjects were told that the potential loss under insurance scheme would be due to insurer´s contract violation (under the control group this potential loss would be due to the basis risk).

[20]Under the treatments T2 and T3 the exact level of the basis risk was uncertain. The treatments introduced the mean preserving spread of the probability of basis risk. Under the control group the level of basis risk was known and occurred with the probability 0.5. Under the treatment T2 (´Small Ambiguity´) the basis risk could occur with the probability either 0.4, 0.5 or 0.6. Under the treatment T3 ('Large Ambiguity´) the basis risk could occur with

Table 8: Key Results: Dep Var is Takeup

	(1) OLS	(2) Probit	(3) OLS	(4) Probit	(5) OLS	(6) Probit
TreatT1	-0.192***	-0.205***	-0.169***	-0.182***	-0.181***	-0.182***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TreatT2	-0.117***	-0.134***	-0.119***	-0.145***	-0.099*	-0.114*
	(0.001)	(0.001)	(0.000)	(0.000)	(0.019)	(0.011)
TreatT3	-0.258***	-0.263***	-0.251***	-0.259***	-0.261***	-0.254***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LowRA			0.155***	0.177***	0.151*	0.254
			(0.004)	(0.006)	(0.042)	(0.146)
Yield (t/ha)			0.084	0.095	0.081	0.095
			(0.377)	(0.440)	(0.391)	(0.433)
If household head			0.063	0.059	0.061	0.058
			(0.279)	(0.253)	(0.285)	(0.251)
If male			0.004+	0.007*	0.004	0.007+
			(0.062)	(0.034)	(0.101)	(0.050)
Number of children			0.001	0.001	0.002	0.001
			(0.867)	(0.866)	(0.806)	(0.836)
Education level			-0.013	-0.012	-0.012	-0.012
			(0.287)	(0.302)	(0.332)	(0.308)
Age			-0.002	-0.002	-0.002	-0.002
			(0.136)	(0.137)	(0.119)	(0.114)
Site			0.007*	0.009*	0.007*	0.008*
			(0.028)	(0.030)	(0.045)	(0.048)
Understanding			0.171	0.186	0.166	0.174
			(0.450)	(0.366)	(0.465)	(0.393)
LowRA*TreatT1					0.101	0.018
					(0.435)	(0.932)
LowRA*TreatT2					-0.121	-0.219
					(0.275)	(0.246)
LowRA*TreatT3					0.094	-0.016
					(0.501)	(0.944)

Robust standard errors clustered at site level.

TreatT1-T3 take values 1 if the decision is made in T1-T3, respectively, and 0 otherwise.

LowRA equals 1 if a respondent chooses A in the Binswanger lottery, and 0 otherwise.

Understanding is the fraction of correct answers to eight questions testing understanding.

Columns (3) and (4) include controls.

Columns (5) and (6) include controls, and interactions between 'LowRA' and the treatment dummies.

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

able taking a value of 1 if the subject i's CRRA coefficient $\sigma_i \leq 0.18$. The empirical results in Table 8 are based on the four specifications: columns (1) and (2) are linear-probability models (LPM) and columns (3) and (4) are Probit models.[21] The standard errors in all the specifications are robust to heteroskedasticity and are clustered at the session level.[22]

Results: Hypothesis I ($Takeup_{T1} < Takeup_{T0}$)

Hypothesis I tests whether the fertiliser take-up under the trust-frame treatment T1 ($Takeup_{T1}$) is lower than the fertiliser take-up under the control group ($Takeup_{T0}$). This is equivalent to testing whether $\beta_1 < 0$ in the (equation 1).

Hypothesis I is strongly rejected in all specifications in Table 8. The estimated value of the coefficient β_1 is in the range of -0.169 and -0.205. Therefore, the adoption rates drop substantially by approximately 17-20% when the source of incomplete insurance coverage is explained as the insurer´s contract violation (the trust-frame treatment T1).[23] This result is significant at 1% in all columns in Table 8.

Results: Hypothesis II ($Takeup_{T2} < Takeup_{T0}$)

Hypothesis II tests whether the fertiliser take-up under the small-ambiguity treatment T2 ($Takeup_{T2}$) is lower than the fertiliser take-up under the control

the probability either 0.2, 0.5 or 0.8.

[21]Under homoscedasticity, the LPM and Probit estimators are both consistent but the Probit estimator is more efficient (Wooldridge, 2002). Nevertheless, only the LPM will be consistent under heteroskedasticity. The Probit estimator will be inconsistent unless the problem of the heteroscedasticity is not actively addressed (Greene, 2012). Since either the LPM or the Probit model is preferred under different assumptions, both models are estimated in Table 8.

[22]The statistical inference can be invalidated if standard errors fail to account for the presence of the heteroskedasticity or the correlation among the observations within the session (Wooldridge, 2002). Heteroskedasticity-robust standard errors clustered at the session level are frequently applied in the experimental data to address this issue (e.g. Barr and Genicot, 2008; Clarke and Kalani, 2011).

[23]The fertiliser adoption rates in the control group (the source of incomplete insurance coverage explained as basis risk) are equal to about 58%.

group ($Takeup_{T0}$). This is equivalent to testing whether $\beta_2 < 0$ in the (equation 1).

The data does not support Hypothesis II. The estimated value of the coefficient β_2 is always negative. When the exact level of basis risk is unknown,[24] the estimated reduction in the fertiliser adoption rates ranges between 9.9% (column 5) and 14.5% (column 4).[25] Depending on the model, the result is significant either at 1% (columns 1-4) or at 5% (columns 5-6).

Results: Hypothesis III ($Takeup_{T3} < Takeup_{T0}$)

Hypothesis III tests whether the fertiliser take-up under the large-ambiguity treatment T3 ($Takeup_{T3}$) is lower than the fertiliser take-up under the basis risk control treatment ($Takeup_{T1}$). This is equivalent to testing whether $\beta_3 < 0$ in the (equation 1).

Hypothesis III is strongly rejected in the data. The estimate of β_3 in Table 8 is always highly negative and significant at 1%. Therefore, when the level of basis risk of the index insurance is highly ambiguous,[26] the drop in the fertiliser adoption is in the range of 25.1% (column 3 in Table 8) and 26.3% (column 2 in Table 8). This is a very high impact, given that the approximate fertiliser adoption rates are 58% when the level of basis is known to equal 0.5.

Additional Results (The Risk-Aversion Dummy $LowRA$ and the Interaction Terms)

The estimated coefficient β_4 of the dummy variable $LowRA$ is always positive in Table 8. The variable $LowRA$ identifies subjects who are relatively more

[24]Under the small-ambiguity treatment T2, the basis risk probability is either 0.4 or 0.5 or 0.6.

[25]The adoption rates are about 58% when the basis-risk probability is known to be equal to 0.5 (the control group).

[26]Under the large-ambiguity treatment T3, the basis risk probability is either 0.2 or 0.5 or 0.8.

willing to choose risky investment options[27]. This result is not surprising. In the experiment, fertiliser investment ($Takeup_i = 1$) is a risky investment (it has a higher mean and higher variance than the safe investment ($Takeup_i = 0$)). The subject i, who has a preference for risky lotteries (the CRRA coefficient $\sigma_i < 0.18$), is expected to invest in fertiliser irrespective of the experimental treatment.

The estimate $\hat{\beta}_4$ in Table 8 is significant at 1% in columns 1 and 3 or at 5% in column 2. However, it is marginally insignificant in column 4 (the p-value equals 0.127). The specification in column 4 estimates a Probit model, which may be inconsistent in the presence of heteroscedasticity (Greene, 2012).[28] Importantly, the estimate $\hat{\beta}_4$ is significant in the LPM models in columns 1 and 2. Since these results use heteroskedasticity-robust standard errors, which imply a valid statistical inference (Greene, 2012), we are inclined to conclude that the effect of $LowRA$ variable is positive and significant. The fertiliser adoption rates increase by between 15.4% and 17.4% if a subject is relatively less risk averse or risk loving ($LowRA_i = 1$ implies $\sigma < 0.18$).[29]

The specifications in column 5 (the LPM model) and in column 6 (the Probit model) in Table 8 in Table 8 also include the interaction terms between the dummy variable for risk preferences and the treatment dummies: $LowRA.TreatT1$, $LowRA.TreatT2$ and $LowRA.TreatT3$. While all these dummies are statistic-

[27] The risk preferences were elicited by the Binswanger elicitation procedure (Binswanger, 1981). Assuming the constant relative risk aversion (CRRA) utility function $U(x) = \frac{x^{1-\sigma}}{1-\sigma}$, the dummy variable $LowRA$ identifies subjects, whose CRRA coefficient $\sigma < 0.18$ (this includes all the risk-loving subjects ($\sigma < 0$), the risk-neutral subjects ($\sigma = 0$) as well as the subjects which are relatively less risk-averse ($0 < \sigma < 0.18$).

[28] The standard errors used in a Probit model are incorrect (and hence the statistical inference is invalidated) if the heteroskedasticity is not actively addressed (Greene, 2012). While modelling correctly the exact form of heteroskedasticity is challenging in a Probit model, the statistical inference in a LPM model are correct under heteroscedasticity-robust standard errors. Under the Probit model it is not possible to obtain heteroscedasticity-robust standard errors due to the model´s assumption of normal distribution (and hence non-linearity in the coefficients).

[29] In our regressions we use 'LowRA' as the control for risk preferences. Our empirical results are confirmed in an alternative specification with the CRRA control (see Table 10 in Appendix).

ally significant, none of the interaction terms is significant in Table 8.

1.4.2 Discussion of the Empirical Results

This section discusses the overall empirical findings both in the trust and the ambiguity treatments and compares these with the evidence in the related literature.

The Negative Effect of the Trust Treatment ($Takeup_{T1}$)

Both regression and mean equality results provide strong evidence that a trust frame may reduce the technological innovation under index insurance. According to the empirical results in Table 8, framing the potential lack of insurance payoff as trust (and not as basis risk) reduces the fertiliser take-up by approximately 17 percentage points.

Our interpretation of this finding is that experimental subjects may be averse to betrayal.[30] The one-period feature of the experiment enabled us to rule out reputations, punishment or collusion as explanations of subjects' decisions.[31] Furthermore, our experiment involves equally calibrated risks of losses in the treatment group and in the control group. However, in our treatment, the loss is framed as if caused by a human action. This is distinct from the experimental design in Bohnet and Zeckhauser (2004), where the loss is caused by the actions of the experimental subjects. We find new evidence that betrayal aversion may be present in a trust frame. Our framing implied that decisions made by experimental subjects ould only affect their own payoffs, and hence could not be

[30] Betrayal aversion is a behavioural departure from the expected utility theory (EUT). According to the EUT all subjects should be betrayal-neutral (i.e. subjects should be indifferent between losses due to nature and due to human action). The experimental evidence in Bohnet and Zeckhauser (2004) indicates that subjects may be betrayal averse. The experimental subjects are found to dislike substantially more risks of losses due to action by other subjects rather than risks of equally calibrated losses due to random event.

[31] Berg et al., (1995) note that a multiple-period trust game enables subjects to take advantage in later rounds of faking reputation for pro-social behaviour. Furthermore, players would also have a possibility to collude or to punish anti-social actions observed in earlier rounds of the game. These mechanisms are not motivated by trust and could explain investment decisions. This concern is addressed in a one-period version of the trust game addresses this concern.

influenced by other-regarding preferences or efficiency preferences.[32]

An individual may be averse to betrayal if he cares not only about his payoffs but also about how these payoffs were generated (Bohnet et al., 2008). A growing body of literature argues that utility may be affected not only by consequences but also by procedures (Rabin, 1993; Sen, 1997; Dufwenberg and Kirchberger, 2004). In our experiment, the identical consequences were generated either by a random event or by an equally likely framing of an action of an insurer. Our experimental treatment did not involve real insurers, therefore the decisions made by experimental subjects could not be influenced by intentions of others.[33] Nevertheless, our negative treatment effect can be explained by procedural utility theory (Frey et al., 2004; Stutzer and Frey, 2003). Our results could possibly be driven by subjects' aversion to procedures that involve betrayal. However, we also do not rule out a possibility that aversion to procedures distinct from betrayal could conceivably explain the pattern of decisions we observe in our data. For example, if our experimental subjects dislike institutions (such as insurance providers), they may prefer to experience an identical loss that is generated by nature.

Our experimental design aimed to identify the lower bound of the treatment effect; hence, the framing of the treatment was neutral (i.e. 'insurers´). One could expect a stronger treatment effect under a negative loading of the

[32] A number of theoretical models and experimental evidence suggests that decision makers may care not only about their own payoffs, but also be altruistic (Andreoni and Miller, 2002), be averse to inequality (Bolton and Ockenfels, 2000), or be concerned out efficiency of outcomes (Charness and Rabin, 2002). In our experiment, a farmer's decision to enter an insurance contract could not affect payoffs of the insurer. Therefore, this decision should be motivated only by his own payoffs.

[33] Numerous studies find experimental evidence that a subject' utility and his response (either positive or negative reciprocity) to an action of the opponent may depend not only on the opponent's action but also on the intention behind this action (for example McGabe, Rigdon and Smith, 2003, Stutzer and Frey, (2003), Falk et al. (2006)). Falk and Fischbacher (2003) develop a theoretical framework in which a reciprocal behaviour can be explained both by outcomes (as in outcome-based models by Fehr and Schmidt, (1999), Bolton and Ockenfels, (2000)) and by intentions (as in intention-based models by Rabin (1993), Dufwenberg and Kirchsberger (2004)).

framing (e.g. 'cheating insurers´ or ´bad insurers´).[34] Burnham et al. (2000) found evidence that negatively loading the trust game (i.e. describing players as 'strangers, as opposed to 'partners') significantly changes both the trusting and trustworthiness behaviour.

Several related studies also investigate the framing effects in experimental samples of subjects from developing countries. Ross and Mittel (1998) found in a laboratory experiment that the demand for insurance is significantly affected whether an identical investment option is presented as an opportunity or as a threat. In a field experimental setting in South Africa, Bertrand et al. (2010) also found a strong framing impact on credit demand. Nevertheless, Cole et al. (2013) did not find a differential effect where index insurance offered in India is explained to pay in two out of 10 years relative to not paying in eight out of 10 years. The existing experimental evidence on framing effects among the experimental samples from developing countries appears to be context specific.

Our experimental findings indicate that trust may be a very significant factor reducing the take-up of new technologies under index insurance schemes. Our framing treatment revealed that subjects dislike it substantially more if insurance payouts are not received due to an insurer´s decision rather than due to an equally likely basis risk. These results are valuable and complementary to the findings emerging from recent RCTs that explore other reasons for low take-up of insurance. Certain trust treatments of interest would be unethical in the RCTs if subjects could experience losses. The trust treatment in our framed field experiments still ensured positive winnings for all subjects at the end of the experiment.

Our findings add more information to an important policy discussion. While

[34]One could also possibly expect a higher impact on subjects´ behaviour if the trust framing was replaced by an experiment involving real insurers. Bohnet et al. (2008) found evidence for betrayal aversion in such an experimental setting, and argue that the treatment effect could be magnified under different calibrations of probabilities in the studied games.

basis risk is often regarded as a crucial factor reducing the demand for index insurance, trust may be equally important. Investments in insurers' credibility may thus be as essential as investments in more precise indices reducing basis risk. If farmers are particularly reluctant to get insurance due to the lack of trust in insurers, policies aiming at raising the level of trustworthiness of insurance schemes could also successfully improve the demand for index insurance. A recent RCT by Cole et al. (2013) identified one policy successfully addressing the trust issue. While the index insurance studied by Cole et al. (2013) is not linked to technology, the demand for index insurance improves significantly when farmers are informed about an insurance policy by a trusted local organisation. While two other important RCTs (Karlan et al., 2014, and Cai et al., 2009) did not introduce trust interventions as part of their experimental treatment,these studies found evidence that observing insurance payouts in a given area in first season encourages farmers to purchase more index insurance in subsequent seasons.

A potentially successful policy would be to design index insurance contracts paying insurance claims of lower amounts but with sufficient frequencies. However, as noted by Cole et al. (2013), the scope of this approach should be limited. This is because farmers can typically manage small variations in weather through a variety of coping mechanisms, so that insurance payouts are really needed primarily to help manage weather scenarios that are less frequent but more severe. An alternative policy would be to consider selling insurance at the meso level, such as to cooperatives or to an entire village. Group management is more likely to be better educated and familiar with financial products and less biased with respect to (mis)trust in the insurer. Once index insurance is implemented in the early seasons and individual farmers are more experienced with index insurance and possibly receive insurance payouts, index insurance may later be more easily sold at the individual level. If index insurance is linked to technology adoption, it can significantly contribute to the aggregate agricultural modernisation.

The Negative Effect of the two Ambiguity Treatments

The experiment introduced ambiguous environment in the payoff distribution with the small ambiguity treatment T2 (the probability of basis risk equal to either 0.4 or 0.5 or 0.6) and the large ambiguity treatment T3 (the probability of basis risk equal to either 0.2 or 0.5 or 0.8). These treatment effects enables us to test for the presence of the ambiguity-aversion.[35]

The empirical results in Table 8 suggests that both the ´Small Ambiguity´ and the ´Large Ambiguity´ treatments reduce the demand for fertiliser under index insurance.[36] The estimated reductions in the fertiliser adoption rates are in the range of 9.8% and 14.6% under the ´Small Ambiguity´ and in the range of 25.1% and 26.3% under the 'Large Ambiguity´.

Our results suggest that an ambiguous environment may be a strong factor in addition to basis risk for reducing the effectiveness of index insurance in raising the adoption rates of new technologies. Akay et al. (2012) argue that the initial lack of knowledge of the yield distribution may discourage farmers from experimenting with the new technology. The farmers would not know the correlation between bad weather and yield. Index insurance may not be attractive due to the resulting ambiguity in the exact level of basis risk.

Bryan (2014) provides the first empirical evidence showing that ambiguity

[35]Distinction between known probabilities and unknown probabilities was first proposed by Knight (1921) and Keynes (1921). Ellsberg (1961) was first to show that decision makers may be affected by lotteries characterised by unknown (i.e. ambiguous) probabilities (Mas-Colell et al., 1995). Ambiguity-aversion is a behavioural departure from the expected utility theory (EUT). According to the EUT all subjects should be ambiguity-neutral (i.e. subjects should be indifferent between lotteries which have the same mean but different level of uncertainties with respect to the probabilities).

[36]In the control group the subjects new the exact probability of basis risk).

may negatively affect the uptake of new technologies. Based on elicited preferences for ambiguity in a RCT (Randomised Controlled Trial) among the Malawi maize and groundnut farmers (Gine and Yang, 2009), Bryan (2014) identified the subjects who were relatively more ambiguity averse. These farmers were then found to be less likely to adopt new technologies under index insurance.

Studying ambiguity by means of the RCTs is particularly challenging, however, since it is effectively impossible to precisely measure the ambiguity. It would be at least equally challenging to introduce a treatment variation in the level of ambiguity. However, precise calibration and variation in the level of ambiguous environment can easily be implemented in controlled laboratory settings. Our experimental design enabled us to precisely measure the ambiguity by introducing a mean preserving spread of the basis risk probability. Our experimental treatments also introduce variation in this level of ambiguity (the ´Small Ambiguity´ and the ´Large Ambiguity´ treatments). To the best of my knowledge, this is the first paper studying technology adoption choices under index insurance with a precisely calibrated ambiguous environment. The experimental findings provide a complementary picture to this early RCT evidence in Bryan (2014) on a still understudied area of ambiguity impact on technology adoption.

There could potentially be alternative explanations of our empirical results. It could be the case that our negative treatment effect is not due to aversion to ambiguity but due to subjects' lack of understanding of the experiment. In order to address this concern we measured subjects' level of understanding, and used it as one of explanatory variables in our regressions. However, the negative treatment effect we identify could be interpreted not as aversion to ambiguity but as aversion to compound lotteries.[37] The main focus of our

[37]A compound lottery is a two-stage lottery. A subject is averse to a compound lottery if he prefers a probabilistic equivalent single-stage lottery (Machina, 1989).

experiment was to study in detail farmers' fertiliser investment decisions under index insurance. We abstrained from elicitng preferences towards ambiguity and compound lotteries, as this would significantly prolong experimental sessions. Moreover, aversion to ambiguity is closely related to aversion to compound lotteries. A subject is confronted with unknown (ambiguous) probabilities if he cannot reduce compound lotteries to a single lottery (Segal, 1987). A number of recent experimental studies (e.g. Halevy, 2007; Chew, Miao, Zhong, 2017) show that subjects who are averse to compound lotteries are also averse to ambiguous lotteries. We find evidence that farmers may be less likely to adopt fertiliser under index insurance schemes that include risks that we interpret as either compound or unknown.

A successful policy which may address the problem of ambiguity in index insurance may be to subsidise initially the premium rates (Bryan, 2014). Farmers may be more willing to experiment with the new technology at subsidised premium rates. Over time, as they understand better the yield distribution and its correlation with the weather, the premium subsidies can be lowered and eliminated. Bryan (2016) found that the difference in the adoption rates between relatively more ambiguity-averse farmers and less ambiguity-averse farmers is decreasing with experience with new technology.

The results from our experimental treatments are in line with these findings. The reduction in the fertiliser investments were lower under the ´Small Ambiguity´ treatment relative to the ´Large Ambiguity´treatments. The short-term subsidised premium rates may encourage farmers to start experiment with new technologies. As the farmers gain more experience with the new technology, the farming environment becomes less ambiguous and the subsidies could be removed in the long run.

1.4.3 External Validity

This experiment focused primarily on the context of agricultural investment decisions; hence, it is essential that the experimental data was conducted in the area where future policies might be implemented. The aim of the experiment was to understand the choices of farmers from LDCs, and hence the external validity of this experiment should be viewed on the spectrum of developing countries. Ghanaian cocoa farming is rather small-scale, with little agricultural intensification, low productivity or low aggregate adoption rates of new technologies. Therefore, the experimental findings may be less applicable to those developing countries with agriculture characterised by large farms and capital intensity (parts of Latin America) or high agricultural productivity (parts of East and South East Asia). The results may perhaps be more generalisable to developing countries dominated by agricultural sectors with similar characteristics (for instance other African countries).

One of the key benefits of framed field experiments is the possibility to study the impact of a particular factor on the variable of interest in a controllable laboratory environment. Under all treatments of this experiment, subjects could choose between traditional technology with low yields or fertiliser with mandated index insurance (as in the experiment of Hill and Viceisza, 2012). Moreover, fertiliser investment in the experiment was financed with loans, and loan defaults were not allowed either. This depicts accurately a popular Abrabopa credit programme for fertiliser operating in Ghana, with highly successful repayment rates exceeding 90%. Limited liability was not studied in this paper, although it is also a possible factor limiting the effectiveness of insurance schemes linked to loans (see, for example, the Malawi maize farmers studied in Gine and Yang, 2009). Finally, the experimental subjects made private decisions and only played one round of the fertiliser investment games. The literature shows that farmers learn about the benefits of technology either from their accumulated experience over time (Conley and Udry, 2010) or from informal social networks (Mobarak and Rosenzweig, 2012). Studying peer learning, network or peer effects would substantially prolong and complicate the design. This experiment abstracted from issues such as learning and limited liability in order to focus more directly on aspects of trust and ambiguity that are still understudied in the development literature on technology adoption.

One of the challenges of any experiment studying index insurance is to explain complex basis risk to subjects. In this experiment, basis risk was explained with concepts of localised bad weather (basis risk occurs if only an individual farm is affected) and common bad weather (basis risk does not occur when farms on district level are affected). Similar descriptions of basis risk were also chosen in Clarke and Kalani (2011). This concept was clearly understood by participants, despite low levels of formal education. Cole et al. (2013) stress in their RCT that it is essential that an insurance educator spends enough time to explain how index insurance works. This approach was not taken in our framed field experiment, as it would have significantly prolonged experimental sessions and possibly would not have succeeded in ensuring sufficient understanding within a reasonable time. However, the details of the index were not specified either. In an experimental game, it was sufficient to give participants a rather general exposition of the insurance product and associated basis risk; this would not have been sufficient in an RCT in which subjects were making decisions about their actual livelihoods. For the purposes of FFE, the experimental results are generalisable to many different types of index insurance where index could be based either on yield on different types of weather or on a combination of yield and weather indices.

This paper focuses on the behavioural limits of index insurance in increasing the adoption of new technologies; therefore, a baseline index insurance with a moderate fixed basis risk of 0.125 was chosen. The study investigated whether factors other than basis risk may also play a role in discouraging technological adoption under index insurance. The trust treatment was a framing experiment where non-payment of claims by an insurer was had a neutral framing . Since treatment could be framed negatively or it could involve real insurers, one could argue that our finding is at the lower end of the scale for the negative impact of trust on insurance demand. Two different ambiguity treatments studied the role of index insurance in raising technology adoption if the environment was moderately or highly ambiguous.

Finally, it should be stressed that the role of this experiment was to complement a growing number of field experiments and provide new information about a highly popular policy discussion. While studying trust and ambiguity is very challenging in the context of RCTs, it is significantly easier to study in the highly controllable environment of a laboratory-in-field experiment. This experimental design enables us to investigate the importance of trust and ambiguity in influencing the effectiveness of index insurance in promoting agricultural innovation in developing countries.

1.5 Conclusion

This paper identifies betrayal-aversion and ambiguity-aversion as two behavioural factors which may reduce technology adoption under index insurance. The empirical results are based on a framed field experiment conducted with the cocoa farmers in Ghana. Studying trust and ambiguity by means of randomised controlled trials is challenging, if not impossible. Our experimental treatments introduce trust framing as well as precisely calibrating and varying the level of ambiguity. The findings provide new evidence that contributes to a growing policy discussion on how rural households in developing countries could benefit from promising index insurance schemes. Organisations familiar to farmers providing education on insurance (Cole et al., 2013) or building insurance regulatory frameworks may successfully improve trust. An initial experience with insurance payouts may also encourage farmers to view index insurance more reliably in future (Karlan et al., 2014). An ambiguous environment may also discourage farmers from innovating under index insurance schemes. The short-term subsidies of the insurance premium rates may reduce the level of ambiguity associated with the level of basis risk. Once farmers have more experience with new technology, the ambiguity gradually decreases and subsidies will no longer be necessary.

1.6 Appendix

Protocol and procedures

The experiment was conducted with a non-standard sample of 466 cocoa farmers from the Ashanti region in Ghana. All experimental sessions were conducted in the local Twi language by three enumerators. Enumerators were well trained during the several pilots undertaken in the cocoa villages close to the capital city, Accra. Enumerators also kept the same roles in all experimental sessions. An

Table 9: Randomisation test: Dep Var is Session Type

	(1) OLS	(2) Probit
Yield (t/ha)	0.004	0.002
	(0.380)	(0.700)
If household head	-0.080	-0.015
	(0.528)	(0.946)
If male	0.004	0.284
	(0.666)	(0.123)
Age	-0.000	-0.000
	(0.910)	(0.928)
Number of children	0.008	0.001
	(0.617)	(0.968)
Education level	0.051	0.042
	(0.167)	(0.358)
overall p-values	0.788	0.550

Dependent variable is Session Type.

Session Type takes values 1-3 for treatment sessions T1-T3, respectively, and 0 otherwise.

Overall p-values correspond to tests of overall significance in regression.

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

average experimental session took approximately 75 minutes and was followed by a short 10-minute questionnaire about general household characteristics and farming practices. Experimental subjects were given 2 GHC for showing up and they could win up to an additional 10 GHC depending on their choices and luck. The average experimental winnings were 8 GHC, which equalled approximately a two-day wage in the studied area. Instead of pen-and-paper methodology, subjects´ answers were collected with stickers and envelopes. Each envelope consisted of an answer sheet, where subjects would record their answers by placing a sticker in the indicated space. This method ensured privacy in decision-making as well as in the effective collection of responses by enumerators (we found in pilot sessions that many illiterate subjects struggled with recording their choices with a pen).

Enumerators assisted subjects by first showing on a large visualisation aid

Table 10: Results: Dep Var is Takeup (risk control is CRRA)

	(1) OLS	(2) Probit	(3) OLS	(4) Probit
TreatT1	-0.185***	-0.198***	-0.172***	-0.184***
	(0.000)	(0.000)	(0.000)	(0.000)
TreatT2	-0.115***	-0.133***	-0.121***	-0.144***
	(0.002)	(0.001)	(0.000)	(0.000)
TreatT3	-0.252***	-0.258***	-0.256***	-0.263***
	(0.000)	(0.000)	(0.000)	(0.000)
CRRA	0.104*	0.110*	0.103*	0.107*
	(0.031)	(0.026)	(0.047)	(0.043)
Yield (t/ha)			0.089	0.104
			(0.361)	(0.412)
If household head			0.070	0.067
			(0.227)	(0.190)
If male			0.004+	0.007*
			(0.060)	(0.043)
Number of children			0.001	0.000
			(0.937)	(0.962)
Education level			-0.014	-0.013
			(0.255)	(0.260)
Age			-0.002	-0.002
			(0.139)	(0.143)
Site			0.008*	0.009*
			(0.026)	(0.029)
Understanding			0.134	0.140
			(0.550)	(0.491)

Robust standard errors clustered at site level.

TreatT1-T3 take values 1 if the decision is made in T1-T3, respectively, and 0 otherwise.

CRRA is a midpoint of range corresponding to the preferred Binswanger lottery.

Understanding is the fraction of correct answers to eight questions testing understanding.

Columns (3) and (4) include controls.

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

where the sticker should be placed depending on the chosen option. This method was very successful as a proportion of sample size was illiterate and would have struggled with recording their choices with a pen. Moreover, subjects paid more attention to placing the sticker on their answer sheets and passing the envelope to the enumerator.

Ensuring privacy in the decision-making was one of the core objectives of the experiment. In addition to the sticker-and-envelope method of recording answers, subjects were randomly allocated across numbered and spaced out chairs at the beginning of each session. No talking was allowed during the decision-making. However, the enumerators´ role was to explain the games as clearly as possible. Group understanding questions were asked during the early parts of the experiment, and each subject could later ask enumerators private questions by raising their hands. Large visualisation aids included boards and blackboards for payoff descriptions, and subjects were given individual visualisation aids too. In farming investment problems, real cocoa pods were used to depict the farming environment more closely and to explain the probabilities of different weather outcomes more clearly. Another key feature of the experiment was that experimental subjects made all their decisions prior to knowing the actual weather situation that would affect their winnings. This enabled us to control for wealth effects, and the probability distribution related to each decision problem was explained by a number of demonstration draws made by experimental subjects.

Protocol of the Farming Investment Decisions

The protocol of the farming game was as follows:

1. Enumerators explained the farming weather and its probability distribution.

2. Subjects were told that choosing the Old technology would give GHC 6 in good weather and GHC 4 in bad weather.

3. Subjects had an option to borrow funds for fertiliser investment that would give payoffs shown in Table 4.

4. Subjects were told that under fertiliser adoption, the payoffs under bad weather would be determined by a second draw.

5. Different reasons for a second draw were explained, depending on the treatment session (‘Basis´, ‘Trust´, ‘Small Ambiguity´ or ‘Large Ambiguity´).

6. Farmers decided whether to adopt fertiliser or not.

7. If the farming investment decision determined individuals´ final experimental winnings, these were computed both by the choices made and weather draw.

Procedures of the Farming Investment Games

The procedures of the farming games were as follows:

1. Enumerators used cocoa pods and equivalently coloured marbles to describe the weather.

2. Several demonstration weather draws were made by subjects.

3. Enumerators used tokens to describe the second-stage draw under fertiliser investment.

4. Payoffs in Table 4 were shown on a large board by mathematical additions and subtractions.

5. Large board with pod types and final payoffs both under ‘Old´ and ‘Fertiliser´ technology were displayed.

6. Several additional weather draws were made by the subjects.

7. Subjects were given an envelope with stickers and decision cards and a summary of payoffs under both technologies.

8. Subjects made private decisions by placing stickers on a side of the decision card with the preferred technology.

9. Choices were collected by the enumerators and recorded by the experimenter.

10. Each subject determined which one of the experimental games was played out for him by drawing one of the numbered tokens.

11. Final experimental winnings were determined depending on the subject´s decision and his draw of random weather.