AMBIGUITY AVERSION DECREASES THE IMPACT OF PARTIAL INSURANCE: EVIDENCE FROM AFRICAN FARMERS

Gharad Bryan
London School of Economics

Abstract
Indemnifying smallholder farmers against crop loss is thought to play an important role in encouraging the adoption of new technologies and facilitating productivity growth, but to be infeasible due to information problems. Consequently there is interest in developing alternative, partial, insurance products. Examples include rainfall insurance and the limited liability inherent in credit contracts. I argue that although these products may reduce information asymmetry, ambiguity averse farmers struggle to assess whether the contracts reduce risk. This problem is most pronounced when the production technology is ambiguous, as is likely the case for new technologies. I formalize this argument and test the theory using data from two RCTs, conducted in Malawi and Kenya. Comparative statics from the theory are consistent with both sets of data, and I argue that income losses from ambiguity aversion may be substantial. (JEL: D03, D81, G22, O12, O16, Q12, Q14)

1. Introduction

Low rates of technology adoption may account for much of the agricultural productivity gap between rich and poor countries. Risk is an oft cited explanation: poor farmers might be unwilling to trade-off higher risk for higher return.[1] This argument implies large development returns to agricultural insurance, but asymmetric information makes complete insurance contracts hard to provide. Partial insurance products, such as index insurance and limited liability credit, have been suggested as alternatives that lower risk but raise fewer informational problems.[2] Although studies have shown positive

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E-mail: g.t.bryan@lse.ac.uk

1. See Feder et al. (1985) and Foster and Rosenzweig (2010) for reviews.

2. See Morduch (2006) for a call for index insurance and Eswaran and Kotwal (1989) and Bryan et al. (2014) for the case for limited liability.

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impacts of these products,[3] the literature has documented low adoption rates.[4] It is the claim of this paper that although partial insurance products suffer less from problems of asymmetric information they create ambiguity. This ambiguity is especially important when insuring an income stream from a new technology, and limits both the demand for partial insurance products and their usefulness in encouraging technology adoption.

The core argument is simple. Partial insurance makes payment conditional on a specific state of the world, so the value of a contract depends on the probability of that state occurring and earnings in that state.[5] Objective information that would help to determine the relevant probabilities will often be unavailable, especially when income comes from a new technology. Thus the value of insurance is ambiguous, and insurance is less useful to those that do not tolerate ambiguity, that is, the ambiguity averse. To model this I follow Gilboa and Schmeidler (1989) and assume that ambiguity averse farmers entertain a set of beliefs about yields and act as if the worst of these beliefs determines outcomes (maxmin expected utility or MEU).[6] I argue that this "worst case" belief will differ depending on whether the farmer is insured, and that the change in worst case beliefs associated with the provision of insurance will lower the value of insurance.[7]

To build a theoretical and empirical case I concentrate on two examples. First, I consider rainfall insurance. I argue theoretically that rainfall insurance will increase adoption of a new crop less for ambiguity averse farmers than for ambiguity neutral farmers and that this difference in impacts will be larger for farmers that are more risk *averse* and that have the least experience with the new crop. The smaller relative impact for the ambiguity averse is due to differences in the perception of basis risk. Clarke (2016) models the extent of basis risk as the probability a farmer receives a low yield, but rainfall is high so insurance does not pay out. In Clarke's model, an increase in basis risk leads to a mean preserving increase in risk for those who purchase insurance. In a setting where the correlation between yield and rainfall is ambiguous, as

3. For example, Mobarak and Rosenzweig (2012), Karlan et al. (2014) and Bryan et al. (2014).

4. For example, Giné and Yang (2009) and Cole et al. (2013).

5. The value of complete insurance, in contrast, depends only on the value of certainty and not on the probabilities of payments.

6. The MEU model does not provide an explicit psychology for the behaviour it captures. Several authors have provided foundations. For example, Fox and Tversky (1995) propose "that people's confidence is undermined when they contrast their limited knowledge about an event with their superior knowledge about another event, or when they compare themselves with more knowledgeable individuals". This interpretation may lead to a richer set of policy implications if confirmed.

7. The basic insight is likely to extend to other models of ambiguity aversion. For example, Klibanoff et al. (2005) provide a smooth model of ambiguity that effectively weights all possible beliefs using a weighting function similar to expected utility. Ambiguity aversion implies the concavity of the weighting function with the implication that worse beliefs will get more weight. To the extent that these worse beliefs change in response to provision of insurance the basic point of the paper will go through. A recent contribution, Elabed and Carter (2015), makes use of the smooth model to study demand for index insurance. They argue that basis risk leads to the possibility that farmers who fail to compound lotteries will suffer from "compound risk aversion". They infer compound risk aversion from choices to remove basis risk and argue that it is quantitatively important. The results of that paper are complementary to those presented here, and I discuss reduction of compound lotteries in more details when presenting the results in what follows.

it is likely to be for new technologies, ambiguity averse farmer's worst case beliefs will lead them to perceive a high level of basis risk. Ambiguity averse farmers, therefore, differ from the ambiguity neutral in seeing more risk in an insured income stream with the implication that insurance has a smaller impact on the ambiguity averse. Further, because the ambiguity averse see the insured income as more risky, it is among the more risk averse farmers that the impact of insurance is expected to differ most. Finally, as experience with the new crop grows, ambiguity about the correlation between income and rainfall will reduce and the beliefs and behaviour of ambiguity averse and ambiguity neutral farmers will converge.

Second, I consider the insurance inherent in a credit contract. I argue that limited liability should increase adoption of a new crop less among ambiguity averse farmers than among ambiguity neutral farmers and that this difference in impacts should be largest for farmers that are most risk *loving* and that have the least experience with the new crop. Suppose that repayment of credit is enforced by the threat of punishment by the lender. If punishment for non-repayment is not too large, then farmers will not repay when yield is low. Further, if punishment is costly for the lender and the lender observes (at least partially) crop yields, then lenders will not chase farmers who have very low yields. Hence farmers have the ability to renege and not be punished, which forms a type of insurance. The value of this insurance depends on the variability of crop yield, which is likely to be uncertain or ambiguous for new crops. Without credit, an ambiguity averse farmer's worst case belief is that a new crop has a highly variable yield. With credit, however, the worst case belief is that yield is never low enough to allow the farmer to renege without cost. This difference in worst case beliefs reduces the value of limited liability for ambiguity averse farmers: ambiguity averse farmers perceive limited liability as reducing risk, whereas ambiguity neutral farmers see limited liability as a payout in the worst states of the world. Further, because of this difference in perceptions, the value of limited liability is predicted to increase with risk aversion for the ambiguity averse but not for the ambiguity neutral, meaning that it is risk *loving* ambiguity averse farmers that will benefit least from limited liability, the opposite of the case for index insurance. Finally, as with index insurance any difference in behaviour between ambiguity averse and ambiguity neutral farmers should reduce with experience.

I test these predictions using data from two randomized controlled trials run by other researchers. One study, reported in Giné and Yang (2009), was run in Malawi and required a treatment group to purchase rainfall insurance in order to adopt a new crop type, the control group did not have to purchase insurance. The second experiment, reported in Ashraf et al. (2009), and run in Kenya considers the adoption of a bundle of services including new crop types and gave a treatment group access to credit (which is implicitly limited liability) while not providing credit to the control group.[8] In both settings the research teams used simple lab experiments to elicit the

8. Although I have no direct evidence of default on the loans during the Kenya experiment, Ashraf et al. (2009) report that *all* farmers defaulted on their loans the year after the experiment, due to a reduction in price when an export buyer could not be found. This event clearly shows that default is possible.

degree of ambiguity and risk aversion. In both data sets the theory is verified. In the case of rainfall insurance the ambiguity averse decrease adoption in response to the provision of insurance, whereas the ambiguity neutral do not. This difference in impacts is strongest among the most risk averse farmers, reducing as risk aversion decreases or experience growing similar crops increases. In the case of limited liability the ambiguity neutral increase adoption in response to the availability of credit whereas the ambiguity averse do not. This difference in impacts is strongest for those measured to be close to risk neutral and decreases as risk aversion rises, and as experience growing the relevant crop increases.

The paper contributes to several literatures. First, I provide some of the first field evidence on the relevance of models of ambiguity aversion.[9] The two insurance schemes—index insurance and limited liability—each provide important advantages. First, ambiguity aversion can usually be thought of an increased degree of risk aversion when facing a specific source of uncertainty.[10] Hence risk aversion and ambiguity aversion have similar implications and often the same comparative statics. As argued previously this is not true in the context of index insurance where the ambiguity averse are predicted to behave as though they are risk tolerant (demanding little insurance) and to have insurance demand that is *decreasing* in risk aversion. Second, ambiguity aversion is conceptually very similar to a lack of trust. This is clear in the usual Ellsberg two urn experiment—the explanation may lie in aversion to ambiguity or in a mistrust of the experimenter. In the context of limited liability credit, however, trust is unlikely to play a role: the borrower does not need to trust the lender at all to benefit from limited liability. I believe these advantages allow me to provide reasonably compelling micro level evidence on the relevance of ambiguity.

Second, the results relate to a small but growing literature studying demand for index insurance (e.g., Cole et al. 2013). Three contributions are particularly closely related. Clarke (2016) argues that low demand can be rationalised in an expected utility model with basis risk. In his model basis risk is parameterized as the probability that yield is low, but the index insurance does not pay out. Increasing basis risk leads to a mean preserving spread in the distribution of outcomes, so with enough basis risk index insurance will be risk increasing. He argues that this could account for the common finding that risk aversion is negatively or weakly correlated with insurance demand. I make use of his basic framework. In my analysis of rainfall insurance ambiguity is about the extent of basis risk as modelled by Clarke (2016). I show empirically that insurance is ineffective at increasing adoption among the ambiguity averse, and that it is among the ambiguity averse that risk aversion is negatively correlated with the take-up of insurance. In my setting risk aversion positively predicts the impact of

9. The decision theoretic literature on ambiguity aversion is very large. Classics include Ellsberg (1961), Gilboa and Schmeidler (1989), Bewley (2002) and Klibanoff et al. (2005). See Ghirardato (2010) for a brief review. There is also a large literature in applied theory. For example, Dow and da Costa Werlang (1992), Rigotti and Shannon (2005) and Epstein and Schneider (2008). There is less direct empirical relevance, although see Barham et al. (2014) and Engle-Warnick et al. (2011).

10. See Strzalecki (2011) for a formalisation of this idea.

insurance among the ambiguity neutral, implying that basis risk is more important for the ambiguity averse. I see the two contributions as complementary. Giné et al. (2008) also collect data on ambiguity aversion in India using surveys similar to those I use, and correlate the measure with demand for rainfall insurance. They find no correlation, but suggest this may be because of measurement error and a lack of power. In contrast, Chantarat et al. (2009) study the willingness to pay for livestock insurance in which payment depends on area average grass coverage. They find that willingness to pay is negatively correlated with ambiguity aversion, consistent with ambiguity about the extent of basis risk in their setting, perhaps because herders are unclear about how grass coverage in their area will relate to the average.[11]

Third, several recent papers provide field evidence on the role of ambiguity aversion. Engle-Warnick et al. (2011), Barham et al. (2014) and Ross et al. (2012) all study the correlation between measures of ambiguity aversion and the cropping choices of farmers.[12] Engle-Warnick et al. (2011) find that ambiguity averse farmers are less likely to diversify among crop varieties and Ross et al. (2012) find that Laotian farmers measured to be ambiguity averse plant less of their fields to non-glutinous rice (the ambiguous choice in their interpretation), whereas Barham et al. (2014) find that the ambiguity averse are *faster* to adopt GM corn. The different findings in these papers highlight a difficulty in the literature: assessing the relevance of ambiguity aversion seems to require knowing whether any particular "new" crop is more or less ambiguous than an old crop. Relative to these papers I make progress be specifying a model of technology adoption and using it to derive comparative statics that hold regardless of the relative ambiguity of the new and old crops.

Fourth, the model tested is related to a large theoretical literature studying the impact of ambiguity aversion on insurance markets. Dow and da Costa Werlang (1992), Mukerji and Tallon (2001), Rigotti and Shannon (2005) and many others consider theoretically whether ambiguity aversion will lead to incomplete markets. I provide empirical evidence that ambiguity limits the extent of insurance markets. A second literature considers the comparative statics of insurance demand in response to increases in ambiguity aversion (e.g., Alary et al. 2013; Mihm 2010). To this literature I add empirical work documenting the direction of comparative statics. The model that I present is particularly closely related to the work of Mukerji and Tallon (2004b) and Mukerji and Tallon (2004a). These papers consider whether ambiguity aversion can explain the lack of a market in inflation indexed wages and bonds. The papers show that an ambiguity averse agent (modelled in their case as a Choquet expected utility maximiser)[13] may not value an indexed contract because the contract leaves open the

11. In the setting of Chantarat et al. (2009) herders have been using the same technology for many years and have ample room to learn. What will matter is whether they have had a chance to learn about the facts relevant to understand basis risk as presented by the contract.

12. Less directly related Tanaka et al. (2010) study the correlation between several parameters derived from a prospect theory model and income and Liu (2013) looks at the correlation between these same parameters and crop choice.

13. The Choquet model coincides with the MEU model that I use in the case of a convex capacity.

risk that the relative prices of goods change. The intuition for their result is similar to the intuition for my results, faced with the option to purchase an indexed bond or to take an indexed wage contract, the individual will believe that risk related to relative price changes dominates aggregate risk with respect to inflation and will choose not to purchase. Mukerji and Tallon (2004a,b) show how this basic intuition can lead to the endogenous break down of trade in these markets. The present paper can be seen as an empirical test of these predictions, and the model presented a simple translation of this work to the particular setting of agricultural production.

The remainder of the paper is structured as follows. Section 2 discusses the data and empirical settings. Section 3 introduces a simple model of technology adoption with ambiguity aversion and insurance, and derives testable implications. Section 4 provides the empirical results, Section 5 discusses alternative interpretations of the data and Section 6 offers some brief conclusions.

2. Data and Settings

2.1. Malawi

The first data set I use comes from an experiment in Malawi designed to test the efficacy of rainfall insurance in promoting the take-up of HYV (High Yielding Variety) seeds—in this case groundnut seeds. I give a brief description of the experiment here, a more full account can be found in Appendix C and in Giné and Yang (2009). The sample consisted of 771 Malawian groundnut and maize farmers who were members of the National Smallholder Farmers Association of Malawi (NASFAM). These farmers were approached through local farmers' clubs and provided with the opportunity to purchase a package of HYV groundnut seeds.[14] Field tests showed that the seed variety "had higher yields, was less susceptible to drought, had a shorter maturation period, exhibited greater disease resistance, and had higher oil content".[15] The experiment randomly divided the sample into treatment and control and treatment farmers were *required* to take-up rainfall insurance in addition to the seeds. All participants were also offered a credit contract. The availability of credit is consistent across treatment and control and I argue in Section 3.4 that there are no interesting interactions between the insurance provided through the credit contract and the insurance provided through the rainfall insurance. Details of the insurance product can be found in Appendix C and Giné and Yang (2009), but the essential ingredient is that it is an index insurance product paying out an amount that depends on rainfall measured at a village rainfall gauge. The payout is zero above a pre-specified trigger point and then increases linearly as rainfall falls until a second trigger below which the payout remains constant. The insurance was also intended to be actuarially fair with the calculation based on historic

14. The offer also included the option to purchase HYV maize seeds, but this offer was rarely taken up.

15. Giné and Yang (2009), page 5.

rainfall data. In order to recoup costs, however, a lump sum additional payment was required.

The data set includes measures of take-up of the new crop (my main outcome variable), past experience with related groundnut varieties (although not the one offered in the experiment that was new) and measures of ambiguity aversion and risk aversion for 730 of the farmers. This enables me to use the experimental variation to determine how insurance affects the take-up decision, and how this impact differs according to measured ambiguity aversion, risk aversion and experience. The method for eliciting risk and ambiguity preference is discussed in what follows. I concentrate my analysis on these 730 farmers.[16]

2.2. Kenya

The second data set I use comes from a Kenyan experiment that aimed to understand what prevents farmers from growing export crops. The details of the experiment are reported in Appendix C and Ashraf et al. (2009). The authors worked with DrumNet, an NGO that works through farmer self-help groups to provide information, marketing and credit to encourage small scale farmers to grow export crops. A farmer who takes up the DrumNet offer receives a package of seeds for an export crop (French beans, passionfruit or baby corn) as well as assistance with marketing. In practice there was no interest in passion fruit, and little interest in baby corn. The experiment consisted of several treatments, but only one is relevant for the current study: a subset of farmers were randomly chosen to receive credit from DrumNet, in addition to the seeds and marketing.[17] The data set provides information on the take-up decision, past experience growing French beans and measures of risk aversion and ambiguity aversion.[18] Ambiguity aversion and risk aversion measures are only available for 409 of 450 farmers and I restrict my analysis to these subjects.[19]

I argue that the credit contract, as with most in developing countries, is characterised by limited liability. As a consequence credit also provides a form of insurance, because the farmer does not pay back if crop yield is too low.[20] This setting allows me to use experimental variation to test how the availability of limited liability affects the take-up

16. The results are robust to considering all farmers and including dummy variables for missing data.

17. The farmers in the credit treatment did not have to make use of the credit option, unlike in the Malawi case where insurance was required to purchase the new seeds. The other treatment arms were not cross cutting with the credit treatment considered here and so it is not necessary to control for other elements of the study design. The experimental intervention was a clustered trial, with self-help groups being assigned to different treatments arms. All analysis clusters standard errors at the cluster level.

18. Of the total set of farmers surveyed by Ashraf et al. (2009), which includes farmers outside my sample, about 12% of farmers grew French beans in the past season. No farmers grew baby corn or passionfruit. Some 45% of farmers in total grew export crops, which includes crops such as coffee, bananas and tomatoes.

19. The results are robust to considering all farmers and including dummy variables for missing data.

20. That credit contracts with limited liability provide insurance is essential to the literature on moral hazard (see, e.g., Stiglitz and Weiss 1981). The loan offered in Kenya was formally a joint liability loan. Discussion with the NGO suggests that this was largely seen as a formality and most borrowers did not

decision and how this impact differs according to measured ambiguity aversion, risk aversion and experience.

2.3. Measuring Ambiguity and Risk Aversion

Both data sets have farmer level measures of ambiguity aversion and risk aversion that were elicited at baseline before insurance and seed offers were made. Risk aversion is measured using a standard question in which farmers chose from a list of 50:50 gambles as in Binswanger (1980). The gambles were not incentivized (i.e., the questions were hypothetical). I briefly discuss how to interpret these unincentivized gambles in Section 2.4.

In the Kenyan experiment, ambiguity aversion is measured by the following question:

> *You are going to play a game where you draw a ball out of a bag without looking. If the ball you choose is the "right" colour, then you win 50 shillings. You get to decide which bag to choose the ball from.*
> Bag One: *In Bag One there are 4 RED balls and 6 YELLOW balls. You must pick a RED ball in order to win.*
> Bag Two: *In Bag Two there are 10 balls—some are RED and some are YELLOW. You decide what colour ball wins. You must then pick this colour ball to win.*
> *Which bag would you like to choose from?*

The question was the same in Malawi, except the number of balls differed (5 in each bag 2 red and 3 yellow) and the value of the prize was left unspecified with players simply being told that they would "win" the game.[21] Decision makers were also given a visual aid and, again, the question was not incentivized. Those who chose bag one are treated as being ambiguity averse or MEU and those who chose bag two are identified as ambiguity neutral or subjective expected utility (SEU) maximisers.[22] Because the probability of winning from the risky bag is only 0.4, the question identifies those who show a *strict* preference for the risky urn in the Ellsberg two urn example. This is important as simply preferring the risky bag when the probability of winning is 0.5 is consistent with indifference between the two bags and therefore consistent with SEU. The measure may, therefore, categorise some farmers who are ambiguity averse as ambiguity neutral, and it is also possible that those who chose the ambiguous bag are in fact ambiguity seeking individuals.[23] Although both the Malawi and Kenya questions

expect it to be enforced. In Section 3, I model the loan as though it were an individual loan, but comment on the extent to which the results would apply to a joint liability setting.

21. Specifically the words "...then you win 50 shillings" are replaced with "... then you win".

22. The questions replicates the two urn example from Ellsberg (1961). Choosing the risky urn is not consistent with SEU because there is no prior that the decision maker could hold that would lead the risky urn to be strictly preferred.

23. The preferred method of elicitation for these preferences, as well as whether risk aversion and ambiguity aversion are stable personal characteristics, are currently open research topics, for example,

measure aversion to ambiguity, the two questions are not identical and estimated effects of ambiguity aversion should not be directly compared across the contexts.

2.4. The Use of Unincentivized Questions

The fact that both risk and ambiguity aversion are measured without incentives raises the possibility of measurement error in these key variables. If this measurement error is classical, it will tend to make it harder to detect effects. Because I show in what follows that these measures are significantly correlated with the outcomes of interest this is not a large concern. However, if not classical, the measurement error may cause bias. For example, it may be that those that chose the risky urn were those that do not understand the question well, so that my measure of ambiguity aversion is correlated with intelligence. I pursue three strategies to test if this drives the results. First, I use the model in what follows to derive comparative statics. To the extent that ambiguity aversion and intelligence have different comparative statics I can rule out alternative explanations. Second, in Section 5, I directly control for other characteristics and show that the results are robust to these controls, in particular I can control for literacy in the Kenyan data that may be a good proxy for basic intelligence as well as controlling for a measure of how well the individual understands the insurance product in the Malawian data. Third, other studies have shown that unincentivized elicitation methods give results that are highly correlated with incentivised lotteries (e.g., Dohmen et al. 2011). As my goal only requires correlation between true preferences and my measure, this fact is of some comfort. A concern that remains is that Dohmen et al. (2011) use a sample of Germans in their work, and their results may not directly apply to my two settings. To shed some light on this concern, I note that Dohmen et al. (2011) show that risk aversion is strongly correlated with age and gender (older people and women are more risk averse) as well as height. These correlations between risk aversion, gender and age have been shown in numerous other experiments and Table 1 shows the relevant correlations in my settings with risk aversion coded as a discrete variable taking on value 1 if the farmer has higher than median risk aversion.[24] Overall, the familiar correlations hold: in the Malawi data set, both gender and age are correlated with measured risk aversion. In Kenya, gender is again correlated, but age is not correlated. In the Kenyan data set I know the gender of the survey respondent, but only the age of the household head, which may account for the lack of correlation. Overall, these results tend to support the claim that the risk aversion measures, while unincentivized, are measuring a relevant characteristic. Unfortunately, there are few

Abdellaoui et al. (2011), Andreoni et al. (2013), Dimmock et al. (2016) and Einav et al. (2012). These particular questions were used because the data is available, and were chosen by the researchers collecting the data because of their simplicity. To the extent that ambiguity and risk attitudes are not stable characteristics it is hard to explain the set of empirical results found in this paper, although variability in attitudes would tend to mean that estimates are downward biased.

24. I do not have measures of height. I use the discrete measure of risk aversion as it increases power, and my sample is small relative to Dohmen et al. The coefficients have the same sign but higher p-values when a more continuous measure of risk aversion is used.

TABLE 1. Correlates of measured risk aversion.

	Malawi	Kenya
Female	0.085**	0.095*
	(0.034)	(0.053)
Age (10 years)	0.021*	– 0.013
	(0.013)	(0.020)
Income controls	Yes	Yes
R^2	0.012	0.012
N	730	409

Notes: Robust standard errors in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$.

known robust correlates of ambiguity aversion, so I am unable to make a similar case for that measure.

2.5. *Summary Statistics*

Tables 2 and 3 provide some basic summary statistics for the two data sets. The columns present the means of each variable within the ambiguity neutral (*AN*) and ambiguity averse (*AA*) groups. Orthogonality with respect to the treatment is established in the papers documenting the main effects of each of the experiments. The main take-away point from Tables 2 and 3 is that measured ambiguity aversion is not correlated with many household characteristics, making the strong correlation between ambiguity aversion and insurance demand documented in what follows quite surprising.[25]

3. Model

In this section I model the interaction between technology adoption, partial insurance and ambiguity aversion. I aim to provide a straightforward formalization of the intuition presented previously: crop insurance is often sold with the aim of encouraging technology adoption, but when there is important ambiguity regarding the new crop—related either to the correlation between an index and yield or the riskiness of yield—partial insurance will be relatively ineffective at increasing adoption. I also aim to present a model that is simple enough to provide clear empirical implications, which can be taken to data.

3.1. *MEU Preferences, Partial Insurance and Technology Adoption*

I model a farmer who must choose between a traditional crop and a modern crop. I first describe the modern crop, before turning to the traditional crop.

25. Dimmock et al. (2016) also find that ambiguity attitude is largely independent of demographic factors.

TABLE 2. Summary statistics: Malawi.

	AN	*AA*	*p*-value
Respondent age	40.416	40.492	0.937
	(13.102)	(12.467)	
Head female	0.120	0.121	0.961
	(0.325)	(0.327)	
Years schooling head	5.104	5.450	0.195
	(3.432)	(3.678)	
House quality	−0.048	0.015	0.510
	(1.248)	(1.293)	
Total acres of land owned	7.357	7.114	0.695
	(8.245)	(8.374)	
Total income	36.900	30.108	0.561
	(216.251)	(85.823)	
Saving account	0.196	0.237	0.177
	(0.397)	(0.426)	
Ever committee member	0.473	0.419	0.144
	(0.500)	(0.494)	
Years' experience with groundnut	9.127	8.074	0.096
	(8.752)	(8.168)	
Correct insurance	0.438	0.414	0.508
	(0.497)	(0.493)	
Risk tolerance	3.804	3.554	0.097*
	(1.927)	(2.083)	
Trust insurance	0.003	0.002	0.851
	(0.056)	(0.049)	
Trust finance	5.966	5.909	0.763
	(2.444)	(2.555)	
Trust gauge	5.755	5.660	0.726
	(3.527)	(3.379)	
Trust general	0.347	0.305	0.092*
	(0.338)	(0.329)	
N	317	413	
Distance to gauge	11.274	12.339	0.497
	(12.733)	(14.439)	
Missing dist. to gauge	0.594	0.530	0.084*
	(0.492)	(0.500)	
N	129	194	

Notes: Standard deviations in parentheses. *p*-values are for a *t*-test of the hypothesis that the mean value does not depend on measured ambiguity aversion. Correct insurance indicates the respondent was able to answer a hypothetical question about the insurance contract. Individual trust measures are self-reported "on a scale from 1 to 10 how much do you trust...". These are then divided by 10 to create a measure on a scale from 0 to 1. Trust insurance asks about insurance companies in general. Trust finance is a composite of three questions asking about trust in NASFAM and the two finance companies that provided the loan. Trust gauge asks whether the respondent trusts the measurements at the rainfall gauge. General trust measure is taken from the GSS. Committee member implies that the respondent was a member of a club committee. The clubs were the basic unit through which the insurance was organised. $^{*}p < 0.1$.

TABLE 3. Summary statistics: Kenya.

	AN	*AA*	*p*-value
Age member	40.980	41.466	0.698
	(11.743)	(12.956)	
Respondent female	0.450	0.408	0.406
	(0.499)	(0.493)	
Head female	0.083	0.050	0.181
	(0.276)	(0.218)	
Years school head	6.218	6.175	0.824
	(1.919)	(1.947)	
Literate member	0.781	0.858	0.042**
	(0.415)	(0.349)	
House quality	1.394	1.281	0.206
	(0.822)	(0.922)	
Land area	1.800	1.930	0.457
	(1.739)	(1.734)	
Saving account	0.696	0.675	0.659
	(0.460)	(0.469)	
Ever officer	0.160	0.200	0.302
	(0.367)	(0.401)	
Log income	3.340	3.372	0.807
	(1.296)	(1.278)	
Yield past year	25.587	25.309	0.950
	(45.061)	(43.335)	
Months with Shg	49.107	47.862	0.836
	(40.520)	(35.533)	
Distance to road	0.955	0.773	0.187
	(1.474)	(1.269)	
Optimism	2.363	2.434	0.059*
	(1.635)	(1.497)	
Impatient	0.160	0.146	0.700
	(0.367)	(0.354)	
Risk aversion	5.822	5.883	0.825
	(4.292)	(4.274)	
Grew export crop	0.533	0.525	0.881
Last year	(0.038)	(0.032)	
Household size	4.657	4.496	0.453
	(0.175)	(0.131)	
N	169	240	

Notes: Standard deviations in parentheses. p-values are for a t-test of the hypothesis that the mean value does not depend on measured ambiguity aversion. Officer refers to an officer of the self-help group through which Drumnet was distributed. Months with Shg measures the amount of time the farmer has been with the self-help group. Optimism is a psychometric measure of optimism. Impatient is an indicator for having above median discount rate in a hypothetical time preference question. Grew export crop last year is an indicator for whether the farmer grew one of a set of export crops last year including beans, coffee, bananas and tomatoes. $^{*}p < 0.1$; $^{**}p < 0.05$.

There are S states of the world, with each state $s \in S$ leading to yield $y(s)$ for the modern crop. An insurance contract is a mapping $I : S \rightarrow \mathbb{R}$ that defines a (possibly negative) payment $I(s)$ from an insurance company or lender as a function of the state of the world. The distribution of states of the world is ambiguous and the utility from adopting the modern crop for an ambiguity averse or MEU farmer is

$$V^M(u, \Pi, I) = \min_{\pi \in \Pi} \sum_{s \in S} \pi(s) u(y(s) + I(s)),$$

where Π is a set of distributions over S and u is a standard strictly concave utility function. Denote $\hat{\pi}(I, \Pi)$ the belief in Π that minimizes expected utility conditional on insurance contract I and $\hat{\pi}(\cdot, \Pi)$ the minimizing belief with no insurance. These are the worst case beliefs with and without insurance respectively.

I compare the behaviour of an MEU farmer to that of an ambiguity neutral or subjective expected utility (SEU) farmer. I assume that an SEU farmer has beliefs $\pi^{SEU} \in \Pi$. An SEU farmer therefore receives utility $V^M(u, \pi^{SEU}, I)$.[26] In comparing the behaviour of SEU and MEU famers, the min operator implies that, all things being equal, an ambiguity averse farmer perceives a lower utility from a modern crop that is subject to ambiguity, although this may be difficult to test empirically if ambiguity averse farmers differ in other ways, for example having lower quality land.

The traditional crop is also subject to both risk and ambiguity. In the empirical settings insurance was provided *conditional* on adoption of the new technology.[27] Hence, although insurance for the modern crop differs across treatment and control, any insurance available for the traditional crop is consistently available across the two groups. This implies that the treatment (insurance provision) does not alter the utility received from growing the traditional crop. I therefore adopt a very simple model of the traditional crop, assuming that the utility from adoption is given by

$$V^T = \alpha + A + \varepsilon_i,$$

where α is the average expected utility from producing the traditional crop, A a fixed effect for ambiguity aversion that may be non-zero (and possibly negative) if the farmer is ambiguity averse, and ε_i is a farmer specific error term, assumed to be uniformly

26. Empirically, my measure of ambiguity aversion does not let me distinguish between SEU and MEU decision makers, but rather to categorise decision makers into two groups with one group being, on average, more ambiguity averse. A natural way to capture this would be to allow one group to entertain a smaller set of beliefs than the other. I do not pursue this approach as it leads to the same results, but is less transparent in how MEU differs from the usual assumption of SEU. Related, it would be in keeping with the existing literature on ambiguity to assume that the SEU decision maker has a belief over the set Π. I comment on the impact of this alternative assumption in the appendix when proving the main results. In general, all results are robust to this alternative. A short coming of the MEU approach is that it is not possible to model ambiguity loving behaviour. As noted previously, some portion of those choosing the ambiguous urn may fit this description. I comment in the footnotes in what follows on the possible theoretical implications. An alternative would be to formally use the α-MEU model axiomatized, for example, in Ghirardato et al. (2004). Using this model does not alter the main results of the paper, but does add a layer of complexity.

27. In the case of the limited liability credit supplied by Drumnet in Kenya, the loan was only available to those who took the Drumnet offer.

distributed and to have zero mean in the population. The term A captures any difference in returns due to ambiguity aversion. For example, the traditional crop may be subject to ambiguity and, as discussed previously, an ambiguity averse farmer would receive a lower expected utility from farming it. Alternatively, ambiguity averse farmers may have different land quality that may favour the traditional crop relative to the modern crop.[28] An MEU farmer will adopt the new crop if $V^M(u, \Pi, I) \geq V^T$.

The key theoretical observation of this paper is that when the insurance contract I is partial (that is $y(s) + I(s) < y(s') + I(s')$ for some $s, s' \in S$) then worst case beliefs with insurance ($\hat{\pi}(I, \Pi)$) are not necessarily the same as those without insurance ($\hat{\pi}(\cdot, \Pi)$).[29] This change in worst case beliefs occurs if $y(s) \geq y(s')$ but $y(s) + I(s) < y(s') + I(s')$ for some $s, s' \in S$, and if there exists $\pi, \pi' \in \Pi$ such that $\pi(s) < \pi'(s)$ and $\pi(s') > \pi'(s')$. That is, if the partial insurance changes the ordering of the states of the world in terms of yield.[30] Hence, relative to the case in which beliefs are fixed at $\hat{\pi}(\cdot, \Pi)$, insurance leads to a lower increase in utility (or potentially a larger decrease in utility if insurance is mandatory) for those whose worst case beliefs change. To the extent that new technologies are subject to a great deal of ambiguity, this observation tends to imply that insurance will be less effective in encouraging adoption of a new technology.

The empirical goal of this paper is to test whether this basic story holds in the data. The aim is to make use of the behaviour of the ambiguity neutral farmers as a reference group for whom $\hat{\pi}$ does not change. In the next two sections I specialize the simple model of this section to the specific empirical settings: rainfall insurance and limited liability credit. This allows me to draw clear empirical predictions about comparative statics, but in each case the general model of this section nests the specialized models.

3.2. Rainfall Insurance

To capture the impact of rainfall insurance in the simplest way I assume there are four states of the world $S \equiv \{(y_H, R_H); (y_H, R_L); (y_L, R_H); (y_L, R_L)\}$ where $y_H > y_L$ are high and low yields respectively and R_H and R_L are high and low rainfall states. I assume that the insurance contract pays I in state R_L and costs a premium P in state R_H. I assume throughout that $y_L + I < y_H - P$.

Given these assumptions, $\pi \in \Pi$ can be derived from a joint distribution over yield and rainfall. Figure 1 displays a joint distribution with λ_H denoting the probability of high yield, p_H the probability of high rainfall and q the probability that rainfall is high, but that yield is low (that is the state (y_L, R_H)). The model is an extension of the work of

28. Differences in land quality may also affect yield of the modern crop. The empirical part of the paper considers differences in crop adoption between ambiguity averse and non-ambiguity averse farmers. Hence, a fixed effect for ambiguity aversion will also absorb both A and any linear impact of ambiguity aversion on expected yield of the modern crop.

29. When insurance is complete, income is the same in any state of the world and hence $\hat{\pi}(I, \Pi)$ can take on any value. In this case we can assume $\hat{\pi}(I, \Pi) = \hat{\pi}(\cdot, \Pi)$.

30. If the rankings of the states remain constant across insurance regimes, then so do worst case beliefs.

	y_H	y_L
R_L	$\lambda_H - p_H + q$	$1 - \lambda_H - q$
R_H	$p_H - q$	q

FIGURE 1. The joint distribution of rainfall and crop yield states.

Clarke (2016) and following Clarke I note that q parameterizes the extent of perceived basis risk. It is important to note that because q is a fact about the joint distribution of rainfall and yield, it is crop specific. Hence, a farmer making insurance decisions for a new crop must form a new belief about q, even if she has been farming a different crop for many years, and we would expect a farmer to learn about the modern-crop specific q over time.

Farmers in the study areas have been engaged in rain fed agriculture for many years, I therefore assume that p_H is known. For simplicity of exposition, I also assume that λ_H is known. This second assumption is not without loss of generality, and I comment in what follows on how relaxing this assumption would change the results. Basis risk (as measured by q) is therefore the only domain of ambiguity in this restricted model and I assume $q \in [\underline{q}, \bar{q}]$. The key implication of this way of specifying the insurance technology is that index insurance may in fact be risk increasing, and that increasing q leads to a mean preserving spread in the yield distribution of the modern crop.

From these assumptions MEU and SEU farmers do not differ in their behaviour in the absence of insurance with both receiving utility $V^M(u, \cdot)$. With insurance,

$$V^M(u, q, I) \equiv qu(y_L - P) + (1 - \lambda_H - q)u(y_L + I)$$
$$+ (p_H - q)u(y_H - P) + (\lambda_H - p_H + q)u(y_H + I).$$

Because increasing q is a mean preserving spread, and u is assumed to be strictly concave $V^M(u, q, I)$ is decreasing in q. An SEU farmer adopts the modern crop if

$$V^M(u, q^{SEU}, I) \geq \alpha + \varepsilon,$$

whereas an MEU farmer adopts if

$$V^M(u, \bar{q}, I) \geq \alpha + A + \varepsilon$$

with a $A \geq 0$ being a sufficient condition for the MEU farmer to be less likely to adopt when insurance is available.[31]

31. As noted previously, several papers try to test this implication and receive mixed results. See, for example, Barham et al. (2014) who find that ambiguity aversion increases adoption. They are not able to control for the fact that ambiguity averse farmers have different yields with the traditional crop, which may drive their results. I am able to control for this because I am not interested in the main effect of ambiguity aversion on adoption, which will capture A in the regressions presented in what follows.

A key object of interest is the impact of the provision of insurance on the probability of adoption, which I denote $\Delta(MEU, u)$ for an MEU farmer and $\Delta(SEU, u)$ for an SEU farmer.[32] Given the assumptions so far we have

$$\Delta(MEU, u) = \begin{cases} Pr\left(\varepsilon \in [V^M(u, \cdot), V^M(u, \bar{q}, I)]\right) & \text{if } V^M(u, \bar{q}, I) > V^M(u, \cdot), \\ -Pr(\varepsilon \in [V^M(u, \bar{q}, I), V^M(u, \cdot)]) & \text{if } V^M(u, \bar{q}, I) \leq V^M(u, \cdot), \end{cases}$$

and

$$\Delta(SEU, u) = \begin{cases} Pr(\varepsilon \in [V^M(u, \cdot), V^M(u, q^{SEU}, I)]) & \text{if } V^M(u, q^{SEU}, I) > V^M(u, \cdot), \\ -Pr(\varepsilon \in [V^M(u, q^{SEU}, I), V^M(u, \cdot)]) & \text{if } V^M(u, q^{SEU}, I) \leq V^M(u, \cdot), \end{cases}$$

where both α and A drop out because of the uniformity assumption. Consequently

$$\Delta(SEU, u) - \Delta(MEU, u) = Pr\Big(\varepsilon \in [V^M(u, \bar{q}, I), V^M(u, q^{SEU}, I)]\Big).$$

As noted previously, this will always be a positive number, because $V^M(u, \bar{q}, I) \leq V^M(u, q^{SEU}, I)$. The main implications of the model are summarised in the following set of predictions.

PREDICTION 1. *If $q^{SEU} \in [\underline{q}, \bar{q}]$, then*

(1) *Mandatory rainfall insurance causes a smaller increase (or larger decrease) in adoption rates for MEU farmers than for SEU farmers. That is,*

$$\Delta(SEU, u) - \Delta(MEU, u) \geq 0.$$

(2) *Comparing MEU and SEU farmers, the difference in the impact of rainfall insurance on adoption of the modern crop is increasing in risk aversion. That is,*

$$\Delta(SEU, \varphi \cdot u) - \Delta(MEU, \varphi \cdot u) \geq \Delta(SEU, u) - \Delta(MEU, u),$$

for all concave transformations φ and strictly concave utility functions u.

(3) *Comparing MEU and SEU farmers, the difference in the increase in adoption rates caused by provision of mandatory rainfall insurance is zero for farmers that have sufficient experience with the modern crop. That is*

$$\Delta(SEU, u) - \Delta(MEU, u) \to 0,$$

as the number of observations of rainfall and yield from the modern crop increase.

The predictions relate to the provision of mandatory insurance because the treatment group in Malawi were required to purchase insurance if they wanted to adopt the HYV groundnut. I provide a more formal derivation of the predictions in Appendix A and also a more complete model of learning in which to formalise Part 3 of the prediction. Part 1 is discussed previously. Intuition for part 2 can be gained by noting that it is possible that an MEU farmer perceives the insurance to be

32. This is the object identified by the experiments described previously.

risk increasing, whereas an SEU farmer perceives it to be risk decreasing. Standard comparative statics then imply that $\Delta(SEU, u)$ is increasing in risk aversion, whereas $\Delta(MEU, u)$ is decreasing in risk aversion and hence their difference increases with risk aversion. In Appendix A, I show that this intuition carries over to the more general case in which both MEU and SEU farmers see the insurance in the same way—as risk increasing or risk decreasing. Finally, Part 3 follows because we expect that as farmers gain more experience with the crop, they will come to better understand the relationship between rainfall and yield of the modern crop. This suggests that the set $[\underline{q}, \bar{q}]$ will decrease in size as experience with the modern crop increases. Basis risk may remain, but MEU and SEU farmers will agree on how much basis risk there is. In the appendix, I use a result from Marinacci (2002) to show that, as the number of observations of yield goes to infinity, MEU and SEU farmers behave in the same way.[33]

Prediction 1 forms the basis of the empirical analysis of rainfall insurance. Evaluating the empirical relevance of ambiguity aversion as a concept separate from risk aversion is difficult because ambiguity aversion can often be thought of as a higher degree of risk aversion when considering different sources of risk. In the Ellsberg two urn experiment there is no paradox if the decision maker displays more risk aversion when choosing the ambiguous urn. Prediction 1, part 2 suggests that when considering index insurance risk aversion and ambiguity aversion behave in different ways, and provides a way to separate ambiguity averse behaviour from degrees of risk aversion.

As noted previously, a more general model would also allow ambiguity about the distribution of yields (e.g., $\lambda_H \in [\underline{\lambda}_H, \bar{\lambda}_H]$). A model along these lines was explored in an earlier working paper Bryan (2010). In that paper I argue that it is still the case that an MEU farmer *may* value insurance less and that if that is the case then the other parts of Prediction 1 continue to hold. The key complication is that ambiguity in λ implies that an ambiguity averse farmer may believe that the modern crop is more risky even without insurance. The effect of changing beliefs highlighted previously implies that insurance will be less valuable for the ambiguity averse, but there is also a countervailing effect because the ambiguity averse value insurance more because they believe the crop to be more risky—that is, MEU farmers have more to gain from insurance. If the first effect is large enough to overcome the second effect, then ambiguity averse farmers will gain less from insurance.

33. Although not modelled explicitly, the possibility that some of the farmers categorized as ambiguity neutral are in fact ambiguity loving will likely reinforce these results. First, we can conceptualize an ambiguity seeking individual as believing that ambiguity will be resolved in his favour. If the extent of basis risk is ambiguous, then an ambiguity loving individual will act as if q is very low, leading to larger adoption in response to the provision of insurance. This same argument suggests that this ambiguity loving individual will tend to act as if the insurance is very effective, demanding more insurance as risk aversion increases. This ambiguity loving effect, like the ambiguity averse effect will dissipate as experience grows and $[\underline{q}, \bar{q}]$ shrinks. Consequently, the key parts of the prediction are likely to go through.

3.3. Limited Liability

I assume that limited liability implies that a loan will not have to be repaid if crop yield is low enough. To explore the implications of this assumption I limit the state space to three crop yield levels: $S \equiv \{\hat{y}_L, \hat{y}_M, \hat{y}_H\}$. An MEU farmer entertains a set of beliefs Π over S. Based on anecdotal evidence that extension workers are good at communicating expected yields, but not good at describing risk, I assume that

$$\sum_{s \in S} \pi(s) y(s) = \kappa \quad \forall \pi \in \Pi, \tag{1}$$

so that all beliefs have the same expected yield and differ only in the variability of the yield. This is a key assumption that drastically simplifies the task of deriving comparative statics. I discuss the implications of relaxing this assumption in what follows.

To model limited liability I assume that a loan amount of L is given, which requires repayment $\widehat{P}$. I assume that the lender observes the state of the world (i.e., the farmer's yield) and whether the loan is repaid. Allowing the lender to observe a signal of yields would not alter the results. The lender can choose to chase the borrower at a cost $C < \widehat{P}$. If the lender chases and the borrower does not pay the borrower suffers a utility cost F, for example, the lender may seize a bicycle or deny future loans. There is no cost to failed repayment if the lender does not chase. If the lender chases, the borrower will repay the loan if

$$u(y + L - \widehat{P}) \geq u(y + L) - F. \tag{2}$$

Two points should be noted. First, F is independent of the state of the world. I make this assumption as F should be seen as a long run cost of, for example, being excluded from future lending. Second, I am assuming that a farmer either repays, or does not repay—there is no partial payment. This could be thought of as reflecting the inability of a lender to engage in partial punishment.

This way of modelling limited liability implies that there exists a crop yield $\tilde{y}$ above which the loan will be repaid when the lender chases and below which it will not. This, coupled with the cost of chasing and the fact that the lender observes yield, implies that the lender will only chase if $y > \tilde{y}$. I assume that $\hat{y}_L < \tilde{y} < \hat{y}_M < \hat{y}_H$.[34] In a richer model with more states this would amount to assuming that some crop yield falls below $\tilde{y}$. To map this model of limited liability to the general description of insurance given previously, define $I(s)$ such that $I(\hat{y}_L) = L$ and $I(\hat{y}_M) = I(\hat{y}_H) = L - \widehat{P}$. A key implication is that state $\hat{y}_L$ improves relative to state $\hat{y}_M$ and may even become preferable. In terms of the discussion in Section 3.1 this means that worst case beliefs with limited liability may differ from those without limited liability. There are two

34. As noted previously, DrumNet loans had a group loan component. The model here seems equally appropriate to that setting, with group members even more likely to observe yield. A richer model of group lending would include the strategic element, but is likely to lead to similar outcomes (e.g., Besley and Coate 1995).

possibilities. First, in the extreme case that state $\hat{y}_L$ becomes preferable to state $\hat{y}_M$ then it is clear the ordering of the states has changed and so beliefs will change to put more weight on state $\hat{y}_M$. Second, if $\hat{y}_L$ improves relative to $\hat{y}_M$ then beliefs that put high weight on $\hat{y}_L$ will lead to higher expected utility and so beliefs may change. With this as background, a simple example will clarify how ambiguity aversion interacts with limited liability.[35]

EXAMPLE 1. *Let $\hat{y}_L = 10$, $\hat{y}_M = 20$ and $\hat{y}_H = 30$ and assume that the expected yield is a constant equal to 20 ($\kappa = 20$ in terms of equation (1)). Π is restricted only to ensure that expected yield is constant. With no insurance $\hat{\pi}_H = \hat{\pi}_L = 0.5$ as this maximizes risk. Consider first a setting in which $L = 10$ and $\widehat{P} = 12$, so that $\hat{y}_M + L - \widehat{P} < \hat{y}_L + L$. With insurance, $\hat{\pi}_M = 1$ as state y_M is now the worst outcome, beliefs switch in response to insurance. If instead $\widehat{P} = 9$ then beliefs $\hat{\pi}_H = \hat{\pi}_L = 0.5$ lead to an expected income of 25.5 whereas belief $\pi_M = 1$ leads to expected income 21. $\pi_M = 1$ can be shown to be the expected earning minimizing belief given (1) Hence, if farmers are not too risk averse, beliefs will switch to $\pi_M = 1$.*

Relative to the case in which beliefs do not change (i.e., stay constant at $\hat{\pi}_H = \hat{\pi}_L = 0.5$), there are two effects. First, π_L is lower, so the farmer perceives it as less likely that he will receive the benefits of limited liability. Second, the farmer now perceives that the production technology is less risky. Together these effects imply that limited liability leads to a smaller increase in utility than in the case with fixed beliefs, and that the impact of limited liability is most positive for those that are more risk averse. This second results follows because the certainty equivalent of a mean preserving reduction in risk is increasing in risk aversion. ■

This example shows why ambiguity aversion tends to reduce the impact of limited liability credit. Without credit the farmer tends to believe that the crop is very risky. When credit is given, the farmer instead believes the yield will not be so bad that he could take advantage of the limited liability. How does he hold this belief but at the same time continue to believe that expected yield remains constant? The only way to do this is to believe that the crop is in fact not risky enough to lead the limited liability to kick in.

Changing beliefs as highlighted in Example 1 will lead to a decrease in the value of limited liability relative to the case in which beliefs stay constant. In the empirical work, however, I will compare the behaviour of an MEU farmer to an SEU farmer, rather than the behaviour of two MEU farmers, one of whose beliefs do not change. The SEU farmer does not necessarily behave the same as an MEU farmer that does not change beliefs, because he will potentially start with different beliefs. Without limited liability, worst case beliefs for the MEU farmer must place weakly more weight on state $\hat{y}_L$ than SEU beliefs ($\pi_L^{SEU} \leq \hat{\pi}_L(\cdot, \Pi)$) and so if $A = 0$ adoption without limited

35. Unlike rainfall insurance, moral hazard may be a concern in the limited liability setting: farmers with limited liability will face reduced incentives to avoid the state $\hat{y}_L$. If the ambiguity averse are differential effected by moral hazard with the ambiguity averse shirking particularly when they are more risk tolerant then that could drive the empirical results.

liability is more likely for the SEU farmer. With unchanging beliefs an MEU farmer will, therefore, gain *more* from limited liability. Hence, whether or not MEU farmers gain less from limited liability depends on whether MEU and SEU farmers beliefs are, in the absence of insurance, sufficiently similar.[36]

Formally the differences in the change in adoption rates is given by

$$\Delta(SEU, u) - \Delta(MEU, u) = Pr\Big(\varepsilon \in [V^M(u, \Pi, I), V^M(u, \pi^{SEU}, I)]\Big) \\ - Pr\Big(\varepsilon \in [V^M(u, \Pi, \cdot), V^M(u, \pi^{SEU}, \cdot)]\Big),$$

with the second term capturing the lower adoption rate without insurance for MEU farmers. The following set of predictions summarizes the empirical implications of the model.

PREDICTION 2. *If* $\sum_{s\in\{L,M,H\}} \pi_s \hat{y}_s = \kappa \ \ \forall\, \pi \in \Pi$ *and* $\hat{y}_L < \tilde{y}$ then

(1) *There exist beliefs* $\pi^{SEU} \in \Pi$ *such that limited liability credit causes a smaller increase*[37] *in adoption rates for MEU farmers than for SEU farmers. That is,*

$$\Delta(SEU, u) - \Delta(MEU, u) \geq 0.$$

The inequality will be strict if, either $\hat{y}_M - \widehat{P} < \hat{y}_L$*, or if the farmers are not too risk averse.*

(2) *If* $\Delta(SEU, u) - \Delta(MEU, u) > 0$ *then comparing across MEU and SEU farmers, the difference in the impact of limited liability on adoption of the modern crop is decreasing in risk aversion. That is,*

$$\Delta(SEU, \varphi \cdot u) - \Delta(MEU, \varphi \cdot u) \leq \Delta(SEU, u) - \Delta(MEU, u),$$

for all concave transformations φ *and strictly concave utility functions* u*.*

(3) *Comparing MEU and SEU farmers, the difference in the increase in adoption rates caused by provision of limited liability credit is zero for farmers that have sufficient experience with the modern crop. That is,*

$$\Delta(SEU, u) - \Delta(MEU, u) \to 0,$$

as the number of observations of rainfall and yield from the modern crop increase.

Intuition for the first two parts of the prediction comes from Example 1 and the discussion there. Intuition for part 3 follows the same logic as the discussion in the previous section.[38] A more formal proof is given in the appendix.

36. The complications is reflected in the conditions in Prediction 2, part 1.

37. Although the rainfall insurance contract in the previous section could lead to a reduction in adoption rates, that is not the case for the credit contract considered in this section.

38. Again, the possibility that some of the farmers categorised as ambiguity neutral may be ambiguity loving likely strengthens the prediction. In Example 1 we can think of an ambiguity loving individual acting as if $\hat{\pi}_M = 1$ without limited liability. With insurance he will act as though $\hat{\pi}_H = \hat{\pi}_L = 0.5$. The consequence is that he will see limited liability as an increase in risk, plus a transfer.

Prediction 2 forms the basis of the empirical analysis of limited liability. In many settings trust and ambiguity aversion have similar implications. In the Ellsberg two urn experiment one explanation for subjects avoiding the ambiguous urn is that they do not trust the experimenter, fearing he or she has rigged the ambiguous urn in some way. Farmers who do not trust an experimenter may also not trust an insurance company to make payments. This would lead to a correlation between measured ambiguity aversion and insurance uptake, but one that is driven not by aversion to ambiguity, but rather a lack of trust. Limited liability credit does not have this feature. First, limited liability occurs when the borrower chooses not to pay. Hence trust in the bank is not directly relevant. Second, a trust explanation would likely imply that the most risk averse would value limited liability most.[39] Instead, in the limited liability context ambiguity predicts the opposite comparative static. Hence, evidence from index insurance is useful in ruling out risk aversion as an alternative explanation and limited liability is useful for ruling out trust as an alternative explanation.

Given the specific nature of the assumptions made, both in the analysis of limited liability and index insurance, one may wonder about the robustness of the comparative statics, especially those with respect to risk aversion. I believe that in both cases the comparative statics capture a robust feature of the setting. One of the hallmarks of index insurance is that it creates basis risk. As argued persuasively by Clarke (2016) basis risk means that index insurance may increase risk. Concern about this possibility is likely to drive the choices of those who are ambiguity averse, with the natural implication that index insurance will be least valuable for those who are both ambiguity averse and risk averse. In the case of limited liability, although it is possible to think of many models, all will entail a reduction in downside risk. The only way this could be less beneficial for an ambiguity averse farmer is if it leads some low yield states to become preferable to some higher yield states and hence a change in worst case beliefs. Changing beliefs to place less weight on low yield states either involves believing the crop is less risky (as discussed previously) or that the crop has a higher average yield. The risk decrease will give the comparative static in Prediction 2, part 2, whereas increasing crop yield will have no implications for risk aversion. Further, believing that the crop is less risky seems more in line with the "pessimistic" nature of MEU preferences. Hence, both predictions seem to identify robust intuitions for comparative statics.

3.4. *The Interaction of Limited Liability and Rainfall Insurance*

As noted previously, the Malawi experiment layered rainfall insurance on top of limited liability credit. Adopting the new crop required taking a credit contract in both treatment and control groups, with the treatment group also required to take rainfall insurance. The insurance paid a portion of the principal and interest on the loan. In cases where the farmer did not intend to pay the loan, this insurance contract made a payment only to the lender, but in cases where the farmer intended to pay back the

39. See Dercon et al. (2011) for a derivation.

loan, the insurance would effectively increase the income of the farmer who no longer has to make full payment on the loan. In this section I briefly argue that the interaction between limited liability (modelled as in Section 2.3) and rainfall insurance (modelled as in Section 2.2) does not alter the comparative statics for rainfall insurance recorded in Prediction 1.

As in Section 3.3, suppose that there are three different yield states $\{\hat{y}_L, \hat{y}_M, \hat{y}_H\}$, and a loan that requires payment of $\widehat{P}$. As discussed previously, in state $\hat{y}_L$ no payment is made by the borrower, and no punishment exacted by the lender. In this state of the world the rainfall insurance will make a payment to the credit company if there is low rainfall, but this payment is irrelevant to the farmer. From the farmer's perspective when determining the value of the rainfall insurance, the only states that matter are $\hat{y}_M$ and $\hat{y}_H$. In these states the farmer intends to make payment on the loan, which will be reduced by the value of the rainfall insurance. We can then relabel the states so that the low state from Section 3.2 becomes $y_L = \hat{y}_M + L - \widehat{P}$ and the high state becomes $y_H = \hat{y}_H + L - \widehat{P}$. The discussion in Section 3.2 then applies directly, and Prediction 1 is not changed, so long $\hat{y}_M - P > \tilde{y}$ so that the farmer wishes to repay the loan in state $\tilde{y}_M$ even if there is no insurance payout but the premium has to be paid. If $\hat{y}_M - P < \tilde{y}$ then the farmer will not want to repay the loan in state $\{y_L, R_H\}$, meaning that there would be no basis risk left in the contract. Under this condition the model in Section 3.2 would predict no difference in the impact of treatment between ambiguity averse and ambiguity neutral farmers. As discussed below, this is inconsistent with the primary empirical result that farmers measured to be ambiguity averse gain less from the rainfall insurance.

It is important to note that although state $\hat{y}_L$ is not relevant to the farmer's assessment of insurance value, it will be used when calculating the actuarially fair price. For example, if state $\hat{y}_L$ occurs with probability $\hat{\pi}_L$ and only occurs if there is low rainfall, then the actuarially fair price of one unit of rainfall insurance will be increased by $\hat{\pi}_L I$, the expected payout. This payout, however, will not be made to the farmer, but to the credit company, and so the insurance will be less than actuarially fair when viewed from the farmer's perspective. Gine and Yang (2009) assign this mechanism a primary place in explaining why the insurance contract they studied leads to an average *reduction* in crop adoption. A more formal analysis of the links between credit and index insurance contracts can be found in Carter et al. (2016), who study the competitive supply of loans, with and without interlinked insurance. They show that once the competitive response is taken in to account, interlinking of insurance contracts may have positive impacts on technology adoption.

4. Results

4.1. Empirical Specification

In this section I present empirical tests of the comparative statics contained in Predictions 1 and 2. Using the Malawi data I estimate regressions of the form

$$
\begin{aligned}
Takeup_i = {} & \beta^0 + \beta^1 AA_i + \beta^2 RT_i + \beta^3 Treat_i + \beta^4 AA_i \cdot Treat_i \\
& + \beta^5 AA_i \cdot RT_i + \beta^6 RT_i \cdot Treat_i + \beta^7 AA_i \cdot RT_i \cdot Treat_i \\
& + \beta^8 Exp_i + \beta^9 Exp_i \cdot Treat_i + \beta^{10} AA_i \cdot Exp_i \\
& + \beta^{11} AA_i \cdot Exp_i \cdot Treat_i + X_i' \beta^{12} + \eta_i, \qquad (3)
\end{aligned}
$$

where $Takeup_i$ is an indicator for whether farmer i adopted the new crop, AA_i is an indicator taking on value 1 if farmer i was measured to be ambiguity averse, $Treat_i$ is an indicator for whether the farmer was in the treatment group (receiving insurance), RT_i is a measure of the farmer i's risk tolerance, Exp_i is a measure of how much experience farmer i has with similar crops and X_i' is a vector of controls. I run the same regressions in the Kenyan data with *RT* replaced by *RA*—a measure of risk aversion.[40] The different specifications for the two data sets corresponds to the different expectations for the effect of risk aversion.[41]

The measure of experience requires some discussion. The Kenyan data includes a measure of how many years' experience the farmer has growing French beans. These were not the same French beans offered by DrumNet, which were an organic crop, but experience with a similar crop is likely to lead to a reduction in ambiguity. In the Malawian data I have measures of how many years' experience the farmer has with growing groundnuts in general. Again, these were not the same crop as offered through the experiment, which was a new HYV variety, but it seems reasonable to assume that experience with groundnut reduces the ambiguity associated with a new variety of groundnut.

I discuss the interpretation of the regression coefficients for the Malawi data. The case for the Kenyan data is analogous, but with risk tolerance replaced with risk aversion. I wish to test three things. First, $\hat{\beta}^4 < 0$ implies that the impact of insurance is smaller for farmers who are ambiguity averse, among those who are risk averse and inexperienced. This is what is implied by Prediction 1, part 1. Second, $\hat{\beta}^7 > 0$ implies that that the difference in the impact of insurance is decreasing in risk tolerance, as implied by Prediction 1, part 2. Finally, $\hat{\beta}^{11} > 0$ implies that the difference in the impact of insurance is decreasing in experience, as implied by Prediction 1, part 3.[42]

40. Because the regression is close to being saturated I run it as OLS. A probit specification does not alter the qualitative conclusions.

41. The difference is merely expositional, the two specifications are equivalent. If I estimate (3) in Kenya, testing the comparative static in Prediction 2, part 2 requires adding coefficients and performing *F*-tests.

42. One might wonder whether it is appropriate to test whether the reduced difference in insurance values caused by a decrease in risk aversion decreases in experience. In addition to being a mouthful, the theory does not necessarily support this hypothesis. Specifically, the theory does not imply that increasing risk aversion will monotonically decrease the effect of experience on the difference in values. For example, amongst very risk averse farmers, experience may have no impact as no ambiguity averse farmers are adopting. As a consequence, although it is true that if the data contained people who were risk neutral I would expect experience to have no effect, the theory does not imply that the effect of experience will

The main concern with interpreting these regressions is that the measures of ambiguity aversion, risk aversion and experience are correlated with other characteristics that are driving the results. The main argument of the paper is that the comparative statics are sufficiently unlikely that it is hard to reconcile the results with other obvious explanations. I discuss alternative explanations further in Section 5.

4.2. Results

Table 4 shows the main results for Malawi. Odd columns have no controls and even columns include controls. Controls include a dummy for the region and a control for the distance to the rainfall gauge as well as other demographic factors.[43] Standard errors are clustered at the level of randomisation. The columns also differ in how risk tolerance is treated. Columns (1) and (2) use the raw risk tolerance categories in the data. There are 6 categories. The interpretation of the marginal effect is difficult with this measure. In columns (3) and (4), I convert the raw measures to percentiles. In these columns coefficients on *RT* measure the impact of a 10 percentile increase in how risk tolerant the farmer is. Columns (5) and (6) use a discrete measure of risk tolerance. Farmers with above median risk tolerance are coded as 1 and those with below median risk tolerance are coded as 0.

Overall the comparative statics in Prediction 1 find support in the data. The coefficient on *AA.Treat* is always negative and strongly significant. Comparing the coefficient on *Treat* and *AA.Treat* in columns (2) and (4) implies that among risk averse and inexperienced ambiguity neutral farmers, insurance increases take-up by about 15 percentage points. In contrast, ambiguity averse farmers decrease take-up by around 30 percentage points when offered insurance. These are large numbers given that the mean take-up among ambiguity neutral farmers in the control group is roughly 30%. It should be noted that the mean take-up rate is higher for the ambiguity averse. This is not formally inconsistent with the theory and may simply reflect the fact that ambiguity averse farmers are using older crops or have better land. It may also reflect the fact that the new HYV seeds were designed to be less "risky" than the traditional variety. Table 3 shows that once controls are included it is no longer the case that the

decrease with risk tolerance. Therefore, although it is necessary to control for risk aversion while testing the impact of experience (and vice versa) as is done in (3), it is not necessarily appropriate to test the sign of the quadruple interaction. I have run the relevant regressions and find that a decrease in risk aversion significantly decreases the difference in values when experience is less than the mean and does not significantly affect the difference in values when experience is greater than the mean. The difference between the two estimates is, however, not significant.

43. I discuss distance to the rainfall gauge and its importance in more detail below. The regressions also include a control for growth of groundnut in the past period and its interaction with ambiguity aversion and risk aversion. This is to control for the possibility that α is correlated with *AA* because ambiguity averse farmers become "stuck" using old crop technologies. This effect should only be apparent for those who are ambiguity averse and risk averse. Leaving out this control does not affect the size or significance of the coefficients of interest. Further, the treatment effects are identified even if this control is correlated with the error. See the table notes for details of other controls.

TABLE 4. The impact of ambiguity aversion on adoption in malawi. Dep Var Takeup. OLS.

Risk measure	Raw		Percentile		Above median	
	(1)	(2)	(3)	(4)	(5)	(6)
Ambiguity Averse	0.269**	0.0757	0.312**	0.0847	0.112*	0.00342
(AA)	(0.105)	(0.107)	(0.127)	(0.127)	(0.0603)	(0.0676)
Risk Tolerance	0.0377**	0.0298	0.0268**	0.0268**	0.149*	0.0678
(RT)	(0.0163)	(0.0183)	(0.0126)	(0.0126)	(0.0777)	(0.0802)
Treated	0.0437	0.114	0.0934	0.172	−0.0314	0.0108
(Treat)	(0.140)	(0.148)	(0.153)	(0.163)	(0.133)	(0.135)
AA.Treat	−0.345**	−0.418***	−0.400**	−0.480***	−0.207**	−0.247***
	(0.127)	(0.126)	(0.151)	(0.150)	(0.0779)	(0.0817)
AA.RT	−0.0621**	−0.0261	−0.0432**	−0.0432**	−0.229*	−0.0659
	(0.0239)	(0.0271)	(0.0181)	(0.0181)	(0.114)	(0.116)
RT.Treat	−0.0367*	−0.0443**	−0.0295*	−0.0295*	−0.214**	−0.236**
	(0.0205)	(0.0206)	(0.0160)	(0.0160)	(0.103)	(0.108)
AA.RT.Treat	0.0567*	0.0642**	0.0418*	0.0418*	0.251*	0.267*
	(0.0290)	(0.0267)	(0.0215)	(0.0215)	(0.135)	(0.133)
Years' Experience	0.000	−0.00117	7.00e-05	−0.00107	0.000594	−0.000491
with Gnut (Exp)	(0.00331)	(0.00360)	(0.00330)	(0.00362)	(0.00341)	(0.00378)
Exp.Treat	−0.00176	−0.00322	−0.00190	−0.00326	−0.00238	−0.00365
	(0.00508)	(0.00533)	(0.00507)	(0.00528)	(0.00514)	(0.00531)
AA.Exp	−0.00182	−0.00113	−0.00194	−0.00116	−0.00225	−0.00141
	(0.00300)	(0.00310)	(0.00305)	(0.00319)	(0.00330)	(0.00355)
AA.Exp.Treat	0.00812*	0.0103**	0.00821*	0.0102**	0.00835*	0.00990*
	(0.00470)	(0.00473)	(0.00473)	(0.00480)	(0.00490)	(0.00512)
Controls	N	Y	N	Y	N	Y
Mean DV	0.305	0.305	0.305	0.305	0.305	0.305
Treat = 0 AA = 0	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
N	730	730	730	730	730	730
R^2	0.145	0.173	0.145	0.173	0.143	0.173

Notes: Standard errors clustered at the level of randomisation. Controls: Region, age, female, female household head, years of schooling, house quality, land owned, income at baseline, saving account, committee member, distance to rainfall gauge, past year growth of groundnut and a set of interactions between growing groundnut, ambiguity aversion and risk tolerance. Risk measure refers to how the risk tolerance measure is coded. Raw uses the raw data from the risk aversion assessment question on a scale of 1–6, percentile converts these into percentiles of the population and the coefficient reported is for a 10 percentile change. Above median divides the sample into two groups, those with above median risk tolerance and those with below median risk tolerance. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

ambiguity averse are more likely to adopt, suggesting some support for the claim that the difference in the regressions without controls is driven by omitted variables.[44]

All regressions also show a large and statistically significant decrease in the difference in impact of treatment in response to an increase in risk tolerance. Column (4) is the easiest to interpret. It says that a 10 percentile increase in risk tolerance decreases the difference in the impact of insurance by about 5 percentage points. The

44. The reduction in the coefficient on AA is largely driven by inclusions for whether or not the farmer was previously growing ground nut, again suggesting support for the notion that the AA households are further from the frontier and so would gain more from adoption of the seeds.

same column estimates the difference in the impact of insurance on adoption to be 48 percentage points, indicating that a move from the 0 percentile of risk tolerance to the 100th percentile completely removes the differential impact of ambiguity aversion. This is what would be expected from the theory. It is also interesting to note that all regressions show the intuitive comparative static that, among ambiguity neutral farmers, an increase in risk tolerance (decrease in risk aversion) leads to a decrease in the impact of insurance. In contrast, when ambiguity aversion is not accounted for, this data suggests that an increase in risk tolerance leads to higher insurance demand (see Giné and Yang 2009).

The regressions also show large and statistically significant coefficients on the interaction *AA.Exp.Treat*, indicating that the difference in insurance impacts attributable to ambiguity is decreasing in experience. The results suggest that 1 year of additional experience with groundnut decreases the difference between ambiguity averse and ambiguity neutral farmers by 1 percentage point. At the median level of risk aversion, column (6) indicates that the differential is equal to approximately 25 percentage points suggesting that 20 years' experience is required for the behaviour of ambiguity averse and ambiguity neutral farmers to converge, although this calculation may take the linearity assumption in (3) too seriously.

Table 4 also adds some interesting nuance to the original results reported in Gine and Yang (2009). Among the risk averse and ambiguity neutral, the insurance has no significant impact on the adoption choice; the negative effect found by Gine and Yang (2009) seems limited to the ambiguity averse, and the risk tolerant among the ambiguity neutral. It is important to note that although the impact of insurance is no longer negative once ambiguity aversion is taken in to account, it is not the positive effect that would be expected from classic theory. As noted previously, the literature provides two potential explanations for the poor performance of the insurance contract. First, basis risk may mean that the rainfall insurance is not valuable, as emphasised by Clarke (2016) and second, the limited liability mechanism discussed in Gine and Yang (2009) and in Section 3.4 may mean that the insurance is incorrectly priced from the perspective of the farmer.

Table 5 presents the results using the Kenyan data. As with the results from Malawi, the columns differ in how the risk aversion measure is treated and whether or not controls are included. The controls are a similar set of demographic variables and dummy variables for region, and again standard errors are clustered at the level of randomisation.[45]

The data tends to support the comparative statics in Prediction 2. The coefficient on *treated* indicates that among the least experienced and most risk tolerant farmers, the credit treatment increased adoption by ambiguity neutral farmers by approximately 45 percentage points from a base of 17%. The increase for ambiguity averse farmers was, however, significantly less as shown by the strongly negative coefficient on *AA.Treat*. In fact, the estimates imply that the data cannot rule out that ambiguity averse farmers

45. See the table notes for details.

TABLE 5. The impact of ambiguity aversion on adoption in Kenya. Dep Var Takeup. OLS.

Risk measure	Raw		Percentile		Above median	
	(1)	(2)	(3)	(4)	(5)	(6)
Ambiguity averse	0.213*	0.103	0.228*	0.108	0.242*	0.151
(AA)	(0.117)	(0.141)	(0.132)	(0.182)	(0.122)	(0.132)
Risk aversion	0.00640	0.0105	0.00810	0.0126	0.0883	0.128
(RA)	(0.00705)	(0.0101)	(0.00895)	(0.0125)	(0.0638)	(0.0875)
Treated	0.330**	0.458***	0.354*	0.511**	0.304**	0.429***
(treat)	(0.140)	(0.147)	(0.179)	(0.180)	(0.138)	(0.151)
AA.Treat	−0.486**	−0.552**	−0.526**	−0.643**	−0.462**	−0.520**
	(0.190)	(0.203)	(0.233)	(0.250)	(0.194)	(0.200)
AA.RA	−0.00984	−0.00873	−0.0109	−0.00837	−0.154	−0.182
	(0.0118)	(0.0196)	(0.0159)	(0.0254)	(0.109)	(0.178)
RA.Treat	−0.00979	−0.0219	−0.0124	−0.0279	−0.0454	−0.158
	(0.0181)	(0.0174)	(0.0251)	(0.0235)	(0.153)	(0.160)
AA.RA.Treat	0.0229	0.0424*	0.0263	0.0513	0.200	0.382*
	(0.0221)	(0.0222)	(0.0310)	(0.0302)	(0.211)	(0.218)
Years' experience	0.0157	0.0178	0.0154	0.0174	0.0164	0.0188
with beans (Exp)	(0.0165)	(0.0170)	(0.0167)	(0.0173)	(0.0166)	(0.0173)
Exp.Treat	−0.0208	−0.0331	−0.0204	−0.0324	−0.0215	−0.0341
	(0.0241)	(0.0217)	(0.0242)	(0.0220)	(0.0243)	(0.0222)
AA.Exp	−0.0327	−0.0250	−0.0326	−0.0249	−0.0333	−0.0263
	(0.0198)	(0.0199)	(0.0203)	(0.0203)	(0.0197)	(0.0202)
AA.Exp.Treat	0.0532*	0.0556*	0.0532*	0.0559*	0.0537*	0.0567*
	(0.0289)	(0.0271)	(0.0292)	(0.0273)	(0.0290)	(0.0275) v
Controls	N	Y	N	Y	N	Y
Mean DV	0.170	0.170	0.170	0.170	0.170	0.170
Treat = 0 AA = 0	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)
N	409	409	409	409	409	409
R^2	0.093	0.253	0.093	0.253	0.096	0.254

Notes: Standard errors clustered at the level of randomisation. Controls: Region, age, female head, female respondent, years of schooling head, head literate, house quality, saving account, land owned, relation to chief, officer of SHG, time with SHG, household size and last year growth of export crop. Risk measure refers to how the risk aversion measure is coded. Raw uses the raw data from the risk aversion assessment question on a scale of 1–6, percentile converts these into percentiles of the population and the coefficient reported is for a 10 percentile change. Above median divides the sample into two groups, those with above median risk tolerance and those with below median risk tolerance. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

do not gain from credit. This is consistent with the idea that much of the value of a credit contract is in the insurance element induced by limited liability.[46] For risk tolerant, ambiguity averse farmers, this insurance has no value.

The hypothesis that the difference in the impact of limited liability is decreasing in risk aversion is also confirmed in the data, although the effect is not as strong as for the other comparative statics. The coefficient on *AA.RA.Treat* is positive in all regressions, and statistically significant in regressions with controls using the discrete measure of

46. See Karlan et al. (2014) for evidence in a similar setting that suggests that, while risk is very important for farmer choices, credit constraints are not.

risk aversion and the raw measure of risk aversion, although only at the 10% level (p-values are 0.071, 0.104, and 0.094 for the three columns).

Finally, all regressions show a positive coefficient on $AA.Exp.Treat$ although the coefficient is only significant at the 10% level ($p \in [0.062, 0.07]$ for all six columns). The coefficient on $AA.Exp.Treat$ in column (6) indicates that, among risk tolerant farmers, it requires around 10-years of experience for the behaviour of ambiguity averse farmers to converge to that of ambiguity neutral farmers.

4.3. Quantitative Importance of the Effects

The Kenyan experiment with Drumnet provides an opportunity to give a direct estimate of the quantitative importance of ambiguity aversion.[47] In addition to the two groups used in the previous analysis, the experiment included a control group that were not offered Drumnet services. Ashraf et al. show that the treatment significantly increases the uptake of Drumnet crops, and that, among farmers that have not previously grown export crops, the treatment leads to a statistically significant 30% increase in household income. This is an intent to treat estimate. To directly quantify the impact of adoption, I use the assignment to treatment (either with or without credit) as an instrument for whether or not a farmer grows Drumnet crops. The regression coefficient implies that, among households induced to adopt Drumnet, adoption lead to an 75% increase in household income.[48] The confidence interval for this estimate, however, is large with the coefficient insignificant at conventional levels ($p = 0.169$). The result is suggestive of a large potential loss associated with ambiguity. One way to interpret the results in Table 4 is as showing that, while credit increases adoption rates by about 40% among those that are ambiguity neutral, among those that are ambiguity averse and risk neutral there is no effect of credit. Conservatively, the data suggests that 25% of the population is risk averse and ambiguity neutral. Taking these facts together implies that about 10% of the population are missing out on an opportunity for a 75% increase in household income. In a sense, these results may be conservative because, as discussed previously, the measure of ambiguity used in this paper may treat some ambiguity averse farmers as being ambiguity neutral.

A limitation of this exercise is that it ignores dynamics. There are several issues that may be important, but likely cannot be determined by the data that I have. First, the results suggest that the impact of ambiguity aversion will decrease as farmers gain experience with the new crop. This observation implies that index insurance may be least effective when crops are new, and hence ineffective at encouraging new technologies. Second, the experience results suggest that ambiguity may have only a temporary effect on insurance demand. In particular, a strategy that subsidises adoption in the short run, and then supplies insurance in the long run may be effective, because

47. I do not have the data to conduct a similar analysis in the Malawian setting.

48. I regress the log of household income on a dummy for adoption of Drumnet instrumented with treatment assignment and controls. The coefficient is 0.755 with (robust) standard error 0.549 giving a p-value of 0.169.

experienced ambiguity averse farmers are predicted to have greater insurance demand. Finally, recent work by Elabed and Carter (2015), drawing on the work of Halevy (2007), argues that demand for index insurance may be limited as farmers do not compound lotteries. Halevy shows that there is a strong correlation between ambiguity aversion and failure to compound objective lotteries. If this behaviour explains the main effects in my setting, then learning will not reduce the impact of ambiguity aversion, and demand for index insurance will be low even for existing crops. The empirical results suggest that there is some truth to the claim that experience reduces ambiguity, but they cannot determine with certainty whether experience is sufficient to remove all the negative impacts.

5. Robustness and Alternative Explanations

The basic empirical claim of this paper is twofold. First, if the data did not support the comparative statics from Predictions 1 and 2, then the theory would have been proven false. Second, it is difficult to think of alternative theories that would lead to the combination of comparative statics seen in the data. I, therefore, hope that readers will update their prior on the importance of ambiguity aversion in explaining real world insurance purchasing decisions. In this section I use the additional data in each of the data sets to show that the results are robust to several other alternative theories.

The basic fact that I have tried to document is that those farmers measured to be ambiguity averse are less positively affected in their choices by the provision of insurance. There seem to be four broad classes of alternative explanations for this basic fact: first, it may be that farmers measured to be ambiguity averse are less risk averse; second, it may be that the insurance is actually less useful for the ambiguity averse, perhaps because their plots differ from those of ambiguity neutral farmers; third it may be that, for some reason other than ambiguity aversion, ambiguity averse farmers *perceive* the insurance to be less likely to pay; and finally it may be that the ambiguity averse are simply less able to afford the insurance.[49]

Tables 6 and 7 provide regressions that attempt to rule out these hypotheses in each of the data sets. The basic approach is to rerun the regression in Tables 4 and 5 including controls that are treated in the same way as measured ambiguity aversion, that is, interacted with treatment, risk tolerance and experience. In the interest of saving space, these tables report only the main coefficients of interest, which are the interactions between treatment, ambiguity aversion, risk aversion or risk tolerance, and experience. Main effects are, however, all included in the regressions. The regressions reported all use the raw measure of risk tolerance, the results are not sensitive to this choice.

To begin the robustness tests, column (0) in each of the tables presents a specification in which experience is not included in the regression. One may be

49. This last explanation cannot explain the credit results in Kenya.

TABLE 6. OLS regressions of takeup including interacted controls: Malawi.

Control variable	Without Exp. (1)	Without risk tolerance (2)	With risk controls (3)	Self-reported risk aversion (4)	Wealth: land value/house quality (5)	Last seasons income (6)	Irrigated land (7)	Distance to rain gauge (8)	Self-reported relevance of rain gauge (9)	Trust finance companies (10)	General trust (11)	Insurance question correct (12)	All (13)
AA.Treat	−0.267**	−0.176**	−0.176**	−0.448***	−0.404***	−0.403***	−0.407***	−0.390***	−0.392***	−0.485***	−0.405***	−0.416***	−0.430***
	(0.117)	(0.0768)	(0.0772)	(0.135)	(0.133)	(0.127)	(0.127)	(0.125)	(0.126)	(0.137)	(0.121)	(0.122)	(0.153)
AA.RT.Treat	0.0540*	–	–	0.0712**	0.0616**	0.0611**	0.0652**	0.0625**	0.0616**	0.0700**	0.0646**	0.0645**	0.0694**
	(0.0291)	–	–	(0.0281)	(0.0282)	(0.0262)	(0.0271)	(0.0263)	(0.0275)	(0.0284)	(0.0254)	(0.0265)	(0.0335)
AA.Exp.Treat	–	0.00969*	0.0107**	0.0102**	0.0100**	0.0105**	0.00858**	0.00750	0.00837	0.0132**	0.00842	0.0109**	0.0101
	–	(0.00494)	(0.00477)	(0.00479)	(0.00480)	(0.00462)	(0.00408)	(0.00463)	(0.00567)	(0.00542)	(0.00504)	(0.00498)	(0.00600)
Var	–	–	–	0.0342*	−0.0106	−0.0006***	0.0745	−0.00382	−0.122	0.0382**	0.138	0.0187	–
	–	–	–	(0.0185)	(0.00767)	(0.000160)	(0.0860)	(0.00852)	(0.149)	(0.0144)	(0.216)	(0.116)	–
Var.Treat	–	–	–	−0.00264	−0.00677	0.00174	−0.0877	−0.00199	0.410**	−0.0215	0.138	0.123	–
	–	–	–	(0.0348)	(0.0121)	(0.00133)	(0.178)	(0.0100)	(0.193)	(0.0182)	(0.216)	(0.155)	–
Var.RT.Treat	–	–	–	−5.28e-05	−0.000102	−0.000118	0.0341	0.00137	−0.0613*	−0.00277	−0.0408	−0.00692	–
	–	–	–	(0.00608)	(0.00244)	(0.000211)	(0.0276)	(0.00183)	(0.0328)	(0.00425)	(0.0440)	(0.0317)	–
Var.Exp.Treat	–	–	–	−0.000587	0.000245	−6.56e-05	0.00328	−0.000190	−0.0112	0.000318	0.00841	−0.0106	–
	–	–	–	(0.00173)	(0.000373)	(0.000109)	(0.0101)	(0.000378)	(0.00977)	(0.00131)	(0.00946)	(0.00757)	–
Var2	–	–	–	–	0.00909	–	–	–	–	–	–	–	
	–	–	–	–	(0.0359)	–	–	–	–	–	–	–	
Var2.Treat	–	–	–	–	−0.0214	–	–	–	–	–	–	–	–
	–	–	–	–	(0.0494)	–	–	–	–	–	–	–	–
Var2.RT.Treat	–	–	–	–	0.00535	–	–	–	–	–	–	–	–
	–	–	–	–	(0.0102)	–	–	–	–	–	–	–	–
Var2.Exp.Treat	–	–	–	–	0.000713	–	–	–	–	–	–	–	–
	–	–	–	–	(0.00282)	–	–	–	–	–	–	–	–
Additional Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	730	730	730	730	730	730	730	730	730	730	730	730	730
R^2	0.142	0.171	0.176	0.202	0.184	0.194	0.180	0.199	0.195	0.211	0.183	0.181	0.308

Notes: Standard errors clustered at the level of randomisation. *Var.Treat* refers to the interaction of the variable in the column heading interacted with treatment. For example, in column (3) this is self-reported risk aversion interacted with treatment. Controls in all regressions: Region, age, female, female household head, years of schooling, house quality, land owned, income at baseline, saving account, committee member, distance to rainfall gauge and past year growth of groundnut. Self-reported risk aversion is on a scale 1–10. House quality is an index of housing quality defined in Gine and Yang (2009). Trust measures are of the form "on a scale of 1–10 how much do you trust ...". Missing rain gauge data may imply that the distance is unknown. General trust measure is an index from General Social Survey style questions. Insurance question is a simple example of when an insurance product would payoff. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE 7. OLS regressions of takeup including interacted controls: Kenya.

Control variable	Without exp. (1)	Without risk aversion (2)	With risk controls (3)	Wealth: land value/house quality (4)	Last seasons income (5)	Irrigated land (6)	Flat land (7)	Black soil (8)	Previous years yield (9)	Literate (10)	Years as SHG member (11)	Optimistic (12)	All (13)
AA.Treat	−0.398**	−0.291*	−0.299*	−0.580***	−0.514**	−0.540**	−0.456**	−0.501**	−0.558**	−0.596**	−0.605***	−0.543**	−0.621**
	(0.150)	(0.155)	(0.151)	(0.196)	(0.224)	(0.208)	(0.201)	(0.218)	(0.221)	(0.216)	(0.207)	(0.201)	(0.250)
AA.RA.Treat	0.0425*	–	–	0.0504**	0.0391	0.0376*	0.0335	0.0424*	0.0424*	0.0439*	0.0529**	0.0457*	0.0566*
	(0.021)	–	–	(0.0210)	(0.0233)	(0.0210)	(0.0210)	(0.0210)	(0.0236)	(0.0228)	(0.0229)	(0.0225)	(0.0302)
AA.Exp.Treat	–	0.0534*	0.0544*	0.0530*	0.0591*	0.0735**	0.0610*	0.0604**	0.0583**	0.0693**	0.0591**	0.0602**	0.0804
	–	(0.0273)	(0.0283)	(0.0301)	(0.0291)	(0.0292)	(0.0297)	(0.0250)	(0.0258)	(0.0292)	(0.0265)	(0.0271)	(0.0478)
Var	–	–	–	−0.00216	−0.00111*	−0.0349	−0.201***	0.0587	−0.00376	0.0231	−0.00782	−0.00967	–
	–	–	–	(0.00222)	(0.000545)	(0.0645)	(0.0682)	(0.115)	(0.0139)	(0.0478)	(0.00877)	(0.00869)	–
Var.Treat	–	–	–	0.00283	0.000773	−0.0423	0.181	−0.0267	−0.0241	0.200	0.00107	0.000421	–
	–	–	–	(0.00933)	(0.000597)	(0.141)	(0.128)	(0.251)	(0.0193)	(0.231)	(0.00233)	(0.0111)	–
Var.RA.Treat	–	–	–	−0.00135	−0.000203*	−0.0296	0.000207	0.0110	0.00371*	0.00289	0.000487***	0.000766	–
	–	–	–	(0.00114)	(0.000109)	(0.0224)	(0.0147)	(0.0259)	(0.00194)	(0.0208)	(0.000166)	(0.00232)	–
Var.Exp.Treat	–	–	–	0.00327	0.000	0.191***	−0.0597**	0.0173	−0.00187	−0.0363	0.000	−0.00809	–
	–	–	–	(0.00333)	(0.000222)	(0.0589)	(0.0259)	(0.0194)	(0.00569)	(0.0385)	(0.000259)	(0.00483)	–
Var2	–	–	–	0.0452	–	–	–	–	–	–	–	–	–
	–	–	–	(0.0290)	–	–	–	–	–	–	–	–	–
Var2.Treat	–	–	–	−0.0844	–	–	–	–	–	–	–	–	–
	–	–	–	(0.0693)	–	–	–	–	–	–	–	–	–
Var2.RA.Treat	–	–	–	0.00789	–	–	–	–	–	–	–	–	–
	–	–	–	(0.0124)	–	–	–	–	–	–	–	–	–
Var2.Exp.Treat	–	–	–	0.0204*	–	–	–	–	–	–	–	–	–
	–	–	–	(0.0114)	–	–	–	–	–	–	–	–	–
Additional controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	409	409	409	409	409	409	409	409	409	409	409	409	409
R^2	0.239	0.242	0.244	0.328	0.268	0.309	0.303	0.294	0.264	0.263	0.275	0.266	0.426

Notes: Standard errors clustered at the level of randomisation. *Var.Treat* refers to the interaction of the variable in the column heading interacted with treatment. For example, in column (4) this is land holdings interacted with treatment. Controls: region, age, female head, female respondent, years of schooling head, head literate, house quality, saving account, land owned, relation to chief, officer of SHG, time with SHG, household size, and last year growth of export crop. Optimism is a self-reported measure of optimism. Impatient is an indicator for having above median discount rate in a hypothetical time preference question. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

concerned that this variables is measured with error. The table shows that the main results are robust to this concern: evaluated at the mean of experience, the ambiguity averse gain less from insurance or limited liability. Next, to address the question of whether ambiguity averse farmers are simply more risk averse, column (1) in each of the tables repeats the main regressions from above, but leaves out risk tolerance/aversion and its interactions. Column (2) then adds in controls for risk aversion/tolerance and its interaction with experience and the treatment, but not ambiguity aversion. If a correlation between risk tolerance and measured ambiguity aversion explains the results, and if the measure of risk tolerance is correlated with true risk tolerance, then we would expect the inclusion of the control to alter the coefficients in a meaningful way. The tables show that adding the risk controls leads to only very small changes in the coefficients of interest, suggesting that risk tolerance is not the main driver of the results.[50]

For the Malawi data, I also have self-reported measures of risk aversion. These are answers to questions of the form "on a scale of 1–10 how averse are you to taking new risks".[51] There is a large amount of variation in this measure, with answers spread throughout the distribution.[52] Column (3) shows that adding this control does not affect the coefficients of interests in a significant way. We may worry, however, that the variable is not an excellent measure of risk aversion. Although the main effect shows that those self-reported to be risk tolerant are more likely to adopt the new crop, the interaction with treatment reveals that the risk tolerant do not have a significantly different demand for insurance.

If preferences display decreasing absolute risk aversion (DARA), then actual risk aversion should be correlated with measures of wealth and income. If risk aversion is driving the main results of interest, a correlation between ambiguity aversion and income or wealth could be the cause. Column (4) in Table 6 and column (3) in Table 7 include controls for land holdings and house quality as proxies for wealth. Column (5) in Table 6 and column (4) in Table 7 include controls for last year's household income. The main results of interest are robust to these controls, again suggesting that a correlation between risk aversion and ambiguity aversion is not driving the results. These results also suggest that the main results cannot easily be explained by a correlation between measured ambiguity aversion and famer's ability to afford insurance.

I also have several pieces of data that help to understand whether the results are driven by actual differences in the usefulness of the insurance. One hypothesis would be that ambiguity averse farmers have different land, and that this land either has

50. This sort of argument is recently formalised by Oster (2013).

51. Data is available for a general measure as well as aversion to risk taking with respect to new crops and health. I use the average response to these three questions. Results are similar if each measure is entered individually.

52. In all the regressions in Tables 6 and 7 I dummy out missing observations. The qualitative conclusions of the exercise are the same if I simply restrict the sample to those that have a measure of the relevant control.

different risk characteristics or differs in how it is impacted by rainfall or the new crop. I have limited data on land type in Malawi, but I do have a dummy for whether or not any of the farmer's land is irrigated. Irrigation is likely an important factor in determining the relevance of rainfall insurance. In Kenya I have the same measure of irrigation as well as an indicator for whether or not any of the farmer's plots have a higher yielding black solid type, rather than lower yielding red soil. I also have a measure of the portion of the farmer's land that is flat, as opposed to sloped. All three of these indicators potentially determine the risk characteristics of the plots. Column (6) in Table 6 and columns (5)–(7) in Table 7 show results when these measures of land type are included. Again the ambiguity aversion results are not affected by inclusion of the controls.

A second plot characteristic that may drive the results is the extent of basis risk. As discussed previously, basis risk can be thought of as the possibility that the insurance does not pay out when it is needed. The model that I present in Section 3.2 is essentially an extension of Clarke (2016) arguing that ambiguity regarding the extent of basis risk is likely with new technologies and that the ambiguity averse will, therefore, find index insurance less useful. There is no obvious measure of basis risk in the Kenyan data, but for Malawi I have a measure of the (self-reported) distance of the farmer's house from the rain gauge, as well as a self-reported assessment of how closely the farmer thinks readings at the gauge reflect rainfall on his plots. The distance measure is a measure of basis risk on the assumption that a farmer's plots are close to his house, and that distance is an important determinant of the correlation between rain conditions on the plot and at the gauge.[53] Table 6, columns (7) and (8) show the results of including these controls. First, distance to the rainfall gauge does not behave as theory would suggest—those that are further from the gauge are not less affected by the treatment. The self-reported relevance of the rainfall gauge does, however, behave as theory would suggest. Those that claim the rainfall gauge is relevant for their plot are more positively affected by the treatment. Further, the difference between those that have high basis risk and those that have low basis risk is decreasing in risk tolerance.[54] This suggests that the self-reported measure of basis risk is a useful measure. Importantly, the inclusion of these measures does not substantially affect the coefficients of interest with respect to ambiguity aversion. The coefficient on *AA.treat* remains largely unchanged and statistically significant, as does the coefficient on *AA.RT.Treat*. The coefficient on *AA.Expt.Treat* falls marginally in both columns and drops below conventional levels of significance. When additional controls are added along with the basis risk measures in column (12), the coefficient returns to significance.

The data also provides several measure that deal with the farmers' perceptions, which may determine the demand for insurance and be correlated with ambiguity aversion. First, the Malawi data contains a large number of self-reported measures of trust. Most of the questions are of the form "on a scale of 1–10 how much do you

53. See Mobarak and Rosenzweig (2012) for evidence in favour of the second assumption.

54. This follows from the theory presented in Section 3.2.

trust *X*" where *X* is insurance companies in general, the credit provider, NASFAM or rainfall measurement. There are also generalised trust questions similar to those in the GSS and Glaeser et al. (2000).[55] I aggregate the specific trust questions, taking the average of the responses to the questions involving the main institutions involved in the contract—NASFAM and the credit providers. Including these measures of trust in the financial companies, or generalised trust as controls does not alter the main coefficients of interest. Caution is required in interpreting these results. One would expect that effective measures of trust would imply the interaction between the trust measure and the treatment enter the regression positively. For the specific trust measure this coefficient is close to zero and while it is positive for the general trust measure, it is far from statistically significant. Perhaps the best evidence, then, against the trust interpretation is simply that it is very hard to give a trust interpretation of the Kenya results.

Second, if farmers are not able to understand the contract they are signing, they may be unwilling to purchase it. This lack of understanding may be correlated with measured ambiguity aversion. Subjects in the Malawi study were asked a simple question about when an example insurance contract would make a payment—nearly 60% of farmers got the question wrong meaning there is variation in measured understanding of the insurance contract. In the Kenya data I have a measure of whether the farmer is literate. Inclusion of these measures as controls in the regressions does not meaningfully alter the main coefficients of interest. For the Kenya data I also have a measure of how long the farmer has been a member of the self-help group that was the focal point for Drumnet's activities.[56] Long term membership may suggest better understanding of the processes involved. Including this as a control has almost no effect. Finally, the Kenya data set also has an individual level measure of optimism that may be relevant to how the farmer perceives their need for insurance. The measure is an index based on answers to questions like: "in uncertain times I expect the best". and "if something can go wrong it will". Column (11) of Table 7 shows that including this as a regressor has little effect.

Overall, the tables show that the main results are robust to a range of controls. Under the assumption that the controls provide good proxy variables for the real characteristics of interest, and that other unobservable characteristics are proportional to those I have measures of, this suggests that the results are robust to the four main alternative theories. As a final check, column (12) in each of the tables provides results from a regression including all control variables, again interacted with treatment, risk aversion and experience. Once again, it seems that the main results of interest remain robust. Of course, there are still a range of other omitted variables that could be driving the results and for which I am not able to control. Further, my approach in this

55. The exact question is "Generally speaking, would you say that most people can be trusted or that you should be careful in dealing with people?" There is some evidence that these questions do not capture trust well. See Glaeser et al. (2000).

56. In the Malawi data I have a measure of whether or not the farmer has been a committee member in the group through which the insurance was distributed. Including this control also has no effect.

section is only useful if the control variables do not have too much measurement error. Many of the controls do not enter the regressions significantly, and so this is a real concern. Perhaps the most compelling evidence then is a consistent set of results across settings that are compatible with comparative statics derived from theory. Ultimately, a theory is relevant because it allows us to predict how people will behave in response to changes in exogenous variables: that is, because we can sign comparative statics. The main results of the paper show that at least 3 comparative statics implied by the theory are confirmed in the data. Further research would be needed to determine whether other important comparative statics are confirmed. One obvious possibility is to subsidize crop adoption, therefore creating exogenous variation in experience and hence perception of ambiguity.

6. Conclusion

I provided a theory that implies ambiguity may decrease the adoption of novel technologies by limiting the value of insurance. The theoretical argument finds support in data taken from two experiments in Africa. The theory suggests that insurance will be more effective in areas where the production technology is well known and will be ineffective in promoting take-up of novel technologies among the ambiguity averse. Because the effects of ambiguity aversion decrease with experience with a particular crop type, a policy of short-term subsidisation and long-term insurance may help to alleviate low demand for insurance and encourage take-up at the same time.

Appendix A: Proof of Prediction 1

Part 1. Follows from the text.

REMARK A.1. Because this statement holds for all $q^{SEU} \in [\underline{q}, \bar{q}]$ it also holds when the SEU decision maker instead has a prior over the set $[\underline{q}, \bar{q}]$.

Part 2. We want to show that

$$V^M(\varphi \cdot u, \bar{q}, I) - V^M(\varphi \cdot u, q^{SEU}, I) \geq V^M(u, \bar{q}, I) - V^M(u, q^{SEU}, I)$$

for concave φ. Define $\xi(u)$ so that

$$\begin{aligned} V^M(\varphi \cdot u, \bar{q}, I) = \; & q^{SEU} u(y_L - P - \xi(u)) + (1 - \lambda_H - q^{SEU}) u(y_L + I - \xi(u)) \\ & + (p_H - q^{SEU}) u(y_H - P - \xi(u)) \\ & + (\lambda_H - p_H + q^{SEU}) u(y_H + I - \xi(u)). \end{aligned}$$

$\xi(u)$ is the risk premium for the move from the lottery perceived by an SEU farmer to the lottery perceived by an MEU farmer. Denote $\widehat{F}$ to be the lottery

$$\{y_L - P, 1^{SEU}; y_L + I, 1 - \lambda_H - q^{SEU}; y_H - P, p_H - q^{SEU}, y_H + I, \lambda_H - p_H + q^{SEU}\}.$$

This is the lottery perceived by the *SEU* farmer. Denote F to be the lottery

$$\{y_L - P, \bar{q}; y_L + I, 1 - \lambda_H - \bar{q}; y_H - P, p_H - \bar{q}, y_H + I, \lambda_H - p_H + \bar{q}\}.$$

This is the lottery perceived by the MEU farmer with insurance. Following Jewitt (1989), if F is location independent riskier than $\widehat{F}$, then $\xi(u)$ is increasing in risk aversion, and by implication so is $V^M(u, \bar{q}, I) - V^M(u, q^{SEU}, I)$. A straightforward calculation shows that F is location independent riskier than $\widehat{F}$, which proves the result.

REMARK A.2. If the SEU decision maker instead has a prior over the set $[\underline{r}, \bar{r}]$ it is possible to show that the distribution perceived by the MEU farmer continues to be location independent riskier than that of the SEU farmer.

Part 3. To provide a formal proof of this Prediction I relate the model in the text to the setting of Marinacci (2002). Let Θ be a finite set of parameters, P_θ a probability measure describing the likelihood of observing each of the four states

$$\{(y_H, R_H); (y_H, R_L); (y_L, R_H); (y_L, R_L)\}$$

conditional on the state being $\theta \in \Theta$, and $\mathcal{C} = \{\mu : \mu([\alpha, \beta]) = 1\}$ be a set of priors $\mu : 2^\Theta \to [0, 1]$ all of which imply that $\theta \in [\alpha, \beta]$. Marinacci proves that, if the realisation of the state in

$$\{(y_H, R_H); (y_H, R_L); (y_L, R_H); (y_L, R_L)\}$$

is drawn repeatedly from the distribution $P_{\hat{\theta}}$ where $\hat{\theta}$ is the truth and $\hat{\theta} \in \Theta$, and the decision maker updates each prior in $\mathcal{C}$ individually using Bayes' rule, then as the number of draws from the distribution $P_{\hat{\theta}}$ goes to infinity, the behaviour of an MEU decision maker, almost surely, converges to that of a Bayesian SEU decision maker with a single prior over Θ. To translate this observation to our setting, let each $\theta \in \Theta$ correspond to a possible value of q and P_θ be the joint distribution over the four states implied by that q. The model differs slightly from that in the text as the set of possible q's must be finite. The result then implies that the behaviour of the SEU and MEU decision maker converge if the truth lies in $[\underline{q}, \bar{q}]$ and, either q^{SEU} is correct, or the SEU farmer has a single prior belief over the set $[\underline{q}, \bar{q}]$.

REMARK A.3. The result here applies to the general case in which the SEU decision maker has a prior over the set $[\underline{q}, \bar{q}]$.

Appendix B: Proof of Prediction 2

Part 1. Follows from the text, in particular let $\pi^{SEU} = \hat{\pi}(\cdot, \Pi)$.

REMARK B.1. If instead the SEU farmer had a prior over the set Π the logic still implies the *possibility* that the MEU farmers benefit less from insurance.

Part 2. I want to show that

$$\Gamma(u) \equiv V^M(u, \Pi, I) - V^M(u, \pi^{SEU}, I) - \left(V^M(u, \Pi, \cdot) - V^M(u, \pi^{SEU}, \cdot)\right)$$

is decreasing in risk aversion. We can multiply by a positive constant without affecting anything. Therefore, this is equivalent to showing

$$\frac{1}{2}\left(V^M(u, \Pi, I) + V^M(u, \pi^{SEU}, \cdot)\right) - \frac{1}{2}\left(V^M(u, \pi^{SEU}, I) + V^M(u, \Pi, \cdot)\right)$$

is decreasing in risk aversion. Both terms are expected utility for well-defined lotteries. Denote $\widehat{F}$ the lottery for the first term and F the lottery for the second term. Define $\xi(u)$ as the risk premium that, when subtracted from lottery $\widehat{F}$ would make a decision maker with utility function u indifferent between $\widehat{F}$ and F. If $\widehat{F}$ is location independent riskier than F, Jewitt (1989) implies that $\xi(u)$ and hence $\Gamma(u)$ is increasing in risk aversion. Lottery $\widehat{F}$ is

$$\left\{ y_L, \frac{\pi_L^{SEU}}{2}; y_M + L - P, \frac{\underline{\pi}_M}{2}; y_M, \frac{\pi_M^{SEU}}{2}, y_L + L, \frac{\underline{\pi}_L}{2}, \right.$$
$$\left. y_H + L - P, \frac{\underline{\pi}_H}{2}, y_H, \frac{\pi_H^{SEU}}{2} \right\},$$

F is

$$\left\{ y_L, \frac{\bar{\pi}_L}{2}; y_M + L - P, \frac{\pi_M^{SEU}}{2}; y_M, \frac{\bar{\pi}_M}{2}, y_L + L, \frac{\pi_L^{SEU}}{2}, \right.$$
$$\left. y_H + L - P, \frac{\pi_H^{SEU}}{2}, y_H, \frac{\bar{\pi}_H}{2} \right\},$$

where $\bar{\pi}_S$ and $\underline{\pi}_S$ denote the riskiest and least risky distributions in Π respectively. Straightforward, but tedious, algebra shows that if

$$\sum_{s \in \{L,M,H\}} \pi_s Y_s = \kappa \ \ \forall\, \pi \in \Pi,$$

then $\widehat{F}$ is location independent riskier than F, completing the proof.

REMARK B.2. It is again possible to show that this logic extends to the case in which the SEU decision maker has a prior belief over the set Π, simply by applying the definition of location independent risk to a newly defined lottery F.

Part 3. As in the proof of Prediction 1, Part 3.

Appendix C: Description of Experiments

C.1. Malawi

This section provides a description of the Malawi rainfall insurance experiment. The description draws heavily on the original report Giné and Yang (2009).

The experimental sample were current National Smallholder Farmers Association of Malawi (NASFAM) members. NASFAM is an NGO that provides technical assistance and marketing services to nearly 100,000 farmers in Malawi. NASFAM contacted clubs in June and July 2006 and offered them the opportunity to be included in the study. The study sample consists of 159 clubs from four different regions of central Malawi: Lilongwe North, Mchinji, Kasungu, and Nkhotakota. To minimize concerns about fairness if farmers discovered that other farmers in the study were being treated differently, the treatments were randomized at the level of 32 localities. Each locality has roughly 5 clubs from neighbouring villages. Localities were randomized into two equal sized groups: 16 uninsured (control) localities and 16 insured.

Through a microfinance organization, all farmers were offered loans for the purchase of hybrid seeds. These were group liability contracts for clubs of 10–20 farmers. Take-up of the loan was an individual decision, but the subset of farmers who took up the loan was told that they were jointly liable for each other's loans.

The 394 farmers from uninsured localities were simply offered a loan (standard debt contract) for the hybrid seeds, whereas the 393 farmers from insured localities were not only offered the loan for the hybrid seeds (identical to the uninsured one) but they also received a rainfall insurance policy with an approximately actuarially fair premium. In this insured loan group, farmers were required to take the insurance if they wanted the loan package.

Farmers were given the option to purchase improved groundnut only or improved groundnut and a hybrid maize seed and fertilizer package. In order to obtain either package, a deposit of 12.5% of the package amount was required in advance. The uninsured groundnut loan package provided enough seed (32 kg) of an improved variety (ICGV-SM 90704) for planting on 1 acre of land, with a total of MK 4692.00 to be repaid at harvest time 10 months later (roughly US$33.51). Of this total repayment, MK 3680 was the cost of seed and MK 1012.00 was interest. Farmers offered the insured groundnut package were in addition charged for the insurance premium, which ranged from MK 297.98 in Nkhotahota to MK 529.77 in Lilongwe (about 6 to 10% of the uninsured principal) so that the total repayment due at harvest time was between MK 5130.07 and MK 5367.45 (roughly US$36.23–US$38.34).

Corresponding costs for the hybrid maize package (which provided inputs sufficient for 1/2 acre of land) were as follows: MK 3900 for seeds and fertilizer for a total uninsured package of MK 4972.50 (US$35.52) and an insurance premium that ranged from MK647.16 to MK 1082.29, depending on the reference weather station. In practice there was very little demand for the maize package.

The insurance policy bundled with the loan paid out a proportion (or the totality) of the principal and interest depending on the level of rainfall. The insured loan was in essence a contingent loan whose repayment amount depends on the realization of rainfall at the nearest weather station. The coverage for both maize and groundnut policies was for the rainy season, which is the prime cropping season, running from September to March. The contract divided the cropping season into three phases (sowing, podding/flowering, and harvest) and paid out if rainfall levels fell below particular threshold or "trigger" values during each phase. An upper and lower threshold was specified for each of the three phases. If accumulated rainfall exceeded the upper threshold, the policy paid zero for that phase. Otherwise, the policy paid a fixed amount for each millimeter of rainfall below the threshold, until the lower threshold was reached. If rainfall fell below the lower threshold, the policy paid a fixed, higher payout. The total payout for the cropping season was then simply the sum of payouts across the three phases. The maximum payout corresponded to the total loan amount plus the premium and the interest payment.

C.2. Kenya

This section provides a description of the Kenyan credit experiment. The description draws heavily on the original report Ashraf et al. (2009).

The evaluation was conducted in the Gichugu division of the Kirinyaga district of Kenya. The sample of farmers was selected from 36 self-help groups (SHGs). The thirty-six SHGs were divided into three experimental groups of twelve SHGs each: (a) treatment credit: all Drum-Net services, totalling 373 individuals; (b) treatment no credit: all DrumNet services except credit, totalling 377 individuals; and (c) control: no DrumNet services, totalling 367 individuals. For the purposes of this paper I use only groups (a) and (b).

The DrumNet Program is designed by Pride Africa. A farmer that wants to be a member of DrumNet has to satisfy the following requirements: (a) be a member of a registered farmer group (also known as a self-help group) with the Department of Social Services; (b) express an interest, through the SHG, in growing crops marketed by DrumNet, namely French beans, baby corn, or passion fruit; (c) have irrigated land; and (d) be able to meet the first Transaction Insurance Fund (TIF) commitment (roughly US$10 or the equivalent of a week's labourer wages). DrumNet clients first receive a four-week orientation course in which the process is explained. During this course, farmers learn about the need to employ Good Agricultural Practices on their farms to ensure the quality and safety of their produce. After the course, participants open a personal savings account with a local commercial bank and, for those in the credit treatment group, they make a first cash contribution to the TIF that will serve as partial collateral for their initial line of credit. They also decide on the TIF percentage that DrumNet will automatically deduct from each future marketing transaction. Maximum loan size is four times their balance in the TIF. The initial TIF amount depends on the specific crop the farmer wants to grow and the area under cultivation.

To ensure repayment, DrumNet organizes farmers into groups of five members each who are jointly liable for the individual loans taken out. The seeds and other inputs are distributed and the planting is monitored by DrumNet staff. At harvest time, DrumNet negotiates price with the exporter and arranges the produce pickup at prespecified collection points.

In the credit treatment group, DrumNet also worked with local agricultural retail stores to coordinate the in-kind loans. The retailers are trained in basic DrumNet record keeping and submit receipts to DrumNet to receive payment. Once the produce is delivered to the exporter at the collection points, the exporter pays DrumNet who in turn will deduct any loan repayment, pre-specified TIF percentage, and credits the remainder to individual bank savings accounts that each farmer opened when they registered. Defaults occur in this system when farmers choose to sell their produce through another provider or do not have a high enough yield to cover their loan expenses.

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Supplementary Data

Supplementary data are available at *JEEA* online.