Ambiguity and Insurance

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1 Ambiguity Aversion and Missing Insurance Markets

1.1 Introduction

Household incomes in the developing world are highly variable and often close to subsistence. If insurance markets were complete this income variability would not affect consumption and would be of little concern. Insurance markets are, however, far from complete. Formal insurance against variation in crop yield, the bulk of income in many countries, is rarely available and existing evidence shows that informal insurance mechanisms leave consumption susceptible to idiosyncratic shocks (e.g. Townsend 1994). This uninsured risk directly reduces the welfare of risk averse households and may have more dramatic impacts. At the extreme, missing insurance may lead to death (e.g. witch killing as in Miguel 2005) and cause poverty traps (e.g. Dercon and Christiaensen 2010).

This paper studies one possible explanation for missing insurance markets: household income is ambiguous and households are ambiguity averse. I show theoretically and empirically that these two factors combine to reduce demand for insurance, leading to missing markets. The main intuition can be garnered from a simple example. Consider an individual (Maggie) thinking about purchasing rainfall insurance. Suppose that Maggie's income is jointly dependent on rainfall and locusts. Her income is known to be increasing in rainfall and decreasing in locusts, but the joint distribution of income and locusts is unknown. The relation between rainfall and income is therefore ambiguous. What little information she has leads Maggie to believe that after accounting for locusts her income could be increasing or decreasing in rainfall. How should she assess a rainfall insurance contract? If the contract pays out when it's dry she will worry that her income is low when it's wet. On the other hand, if the contract pays out when it's wet she will worry that her income is low when it's dry. In such a situation Maggie may well avoid making the decision, preferring to stay with her endowment – better the devil you know. This choice, however, implies that Maggie is uninsurable – she will not accept any rainfall insurance, no matter its structure.

I formalize this intuition with a particular set of preferences which I refer to as Variational Endowment Anchored (VEA) preferences. VEA households entertain a *set* of priors and assess uncertain prospects using the prior that minimizes the gain from leaving the endowment or status-quo.[1] These assumptions mean that VEA households display what I refer to as choice dependent caution (CDC). Beliefs depend on the prospect under consideration (choice dependence) and are chosen to minimize the gain from the prospect (caution). In the example above, choice dependence means Maggie's beliefs depend on the structure of the contract and caution leads her to stay with her endowment.

I study the implications of VEA preferences and CDC for two different types of insurance, one formal and one informal. I first study the demand for index insurance. Index insurance is a formal insurance contract that pays out based on the realization of an aggregate index. Prominent examples include rainfall insurance based on a village rain gauge, crop insurance based on a region average yield and home equity insurance based on an index of local home prices (Shiller and Weiss 1999). Proponents of index insurance claim that it is not subject to moral hazard and adverse selection and enables firms to supply insurance in areas that are subject to information asymmetries. Recent trials of index insurance, however, garnered little demand (Cole et al. 2010 and Goetzmann et al. 2003). As Maggie's example shows above, ambiguity aversion provides a potential explanation for this low demand.

I formalize the implications of VEA preferences for index insurance in a setting where insurance is used to encourage the adoption of a new technology. Technology adoption is a particularly interesting setting to study index insurance and ambiguity. First, the fact that th technology is new means that there is likely to be ambiguity regarding the production technology. Second, caution implies that a household with VEA preferences can simultaneously not adopt a new technology because it is risky, and also not take out insurance to cover that risk. I use the model to formalize the claim that ambiguity averse (AA) households are uninsurable if there is sufficient ambiguity regarding the production function of the new technology. I also derive three testable implications of the model. First, if the new production technology is sufficiently ambiguous, AA households will gain less from insurance. Second, this differential impact of insurance will be increasing in risk aversion and third the differential impact will be decreasing in experience with the new crop. The second observation follows because, like Maggie, VEA households are concerned that insurance will be risk increasing. The third implication follows from the simple intuition that ambiguity should decrease with experience.

[1] The preferences are closely related to two classic treatments of ambiguity: the Maximin Expected Utility (MEU) preferences of Gilboa and Schmeidler (1989) and the unanimity preferences of Bewley (1986). Agents with VEA preferences have a set of priors as in both these treatments. Similar to MEU agents VEA agents evaluate prospects using a minimizing prior, but unlike MEU the prior is chosen to minimize the gain from departing from the status-quo. Similar to Bewley preferences VEA agents do not depart the status-quo or endowment unless they can find an option which is preferred to the status-quo for all priors. Unlike Bewley's agents, however, VEA agents have complete preferences and compare prospects which dominate the endowment using the minimizing prior.

I test these implications using two data sets that contain experimental variation in the provision of insurance. In both cases the insurance was provided with the aim of encouraging the adoption of a new crop. The first data set comes from a crop insurance experiment documented in Giné and Yang (2009) and the second from a credit experiment documented in Ashraf et al. (2009). I argue that the credit contract embodies an implicit limited liability condition implying that it has an insurance element. Both these data sets have experimental measures of ambiguity aversion and risk aversion in addition to variation in the years of experience households have with new crop. All three testable implications find support in the data. Perhaps the most interesting finding is that if a researcher does not account for ambiguity aversion, risk aversion implies a lower demand for insurance. Controlling for ambiguity aversion this result is reversed. Among ambiguity neutral households the value of insurance is increasing in risk aversion. Among AA households, however, the converse is true.[2]

As a second application, I study the implications of VEA preferences for optimal informal risk sharing. The starting point for the literature on risk sharing is Townsend's (1994) finding that, after controlling for household fixed effects and village aggregate income, consumption is correlated with income. This finding is not consistent with Pareto optimal risk sharing when households have the same preferences and beliefs. I show that the correlation is, however, consistent with a Pareto optimal risk sharing contract when households have identical VEA preferences.

A simple example provides the main intuition. Consider a VEA household (the Jones's) contemplating a risk sharing contract. The contract will specify a set of states in which the Jones's make a transfer, and a set of states in which they receive a transfer. These transfers will move the Jones's away from their endowment and they will tend to believe that states in which they receive a transfer are relatively unlikely, while states in which they make a transfer are relatively likely. The Jones's will therefore be willing to accept a little less when receiving a transfer in return for a little more when they are making a transfer. Hence, the optimal allocation lies closer to the endowment point than in the absence of ambiguity aversion, implying that consumption will be correlated with income even after controlling for individual fixed effects and the aggregate endowment.

I first formalize this intuition and ask whether the theory has testable implications for panel data containing household income and consumption. The full risk sharing test of Townsend (1994) uses the fact that households with the same beliefs will trade to the same point (after

[2]These results hold for the Giné and Yang (2009) data. The theory does not imply this result for the Ashraf et al. (2009) data and it is not true in that context.

controlling for Pareto weights).[3] With VEA preferences, not all households have the same beliefs and formulating a test requires the researcher to be able to infer beliefs from a data set that does not include all households or all states of the world. The intuition in the example above, however, suggests that households making transfers and households receiving transfers will have similar beliefs. I show that if a symmetry condition is satisfied – roughly symmetry requires that all households believe that ambiguity and income are evenly distributed around their entitlement as given by their Pareto weight – then all households making (receiving) transfers will have the same beliefs, implying that they trade to the same point. I also show that the differences in beliefs between giving and receiving households creates a wedge between their consumption levels. Symmetry then implies that households whose incomes fall inside this wedge do not trade, instead consuming their own income.

Empirically, these observations imply that in any state, households with income sufficiently above (below) their entitlement point will share risk fully. Among these households consumption should not be correlated with income. For those households whose income falls in the "wedge" between these two consumption levels, however, consumption moves one for one with income. I propose a test for these properties using a non-linear least squares routine which allows for estimation of households fixed effects, village fixed effects and the "wedge" created by ambiguity. I implement the test on two panel data sets. The famous ICRISAT data from India which formed the basis for Townsend's (1994) paper and Townsend's Thai monthly survey data, a 10 year panel data set recently completed. I do not reject the model in either of these settings.

The remainder of the paper is structure as follows. Section 1.2 provides some discussion of ambiguity aversion. It can easily be skipped by readers familiar with the Ellsberg paradox and the notion of ambiguity. Section 1.3 formally defines VEA preferences and discusses their relation to other preferences in the literature. Section 2 contains my study of index insurance including a discussion of the policy relevance of ambiguity. Section 3 discusses optimal risk sharing with VEA preferences.

1.2 Ambiguity Aversion

The literature on ambiguity aversion distinguishes between two types of uncertainty. A situation is risky if it is uncertain and the probabilities of different states of the world are known, it

[3]With equal Pareto weights optimality requires that $p^i_s u'(c^i_s) = p^j_s u'(c^j_s)$ for all pairs i, j and in all states s. If $p^i_s = p^j_s$, this equation can only hold if $c^i_s = c^j_s$.

is ambiguous if it is uncertain and the probabilities are unknown. According to the Subjective Expected Utility (SEU) theory of Savage (1972) this distinction has no interesting implications – decision makers should assign a subjective prior to all events and act so as to maximizes their expected utility using that prior. Ellsberg (1961), however, showed that decision makers do tend to differentiate between risky and ambiguous situations. The Ellsberg Paradox demonstrates:

Example 1 (Ellbserg's Paradox)**.** *There are two urns, a risky urn and an ambiguous urn. The risky urn contains 5 white and 5 black balls. The ambiguous urn contains 10 white or black balls with the ratio unknown. A decision maker is asked to choose a color and an urn. A ball will then be drawn from the chosen urn and if it is the chosen color the decision maker will win \$1.*

Ellsberg (1961) observed that faced with the above choice many individuals strictly prefer the risky urn. Ellsberg's observation cannot be reconciled with Subjective Expected Utility maximization. An SEU maximizer assigns a probability p to the event that a black ball will be chosen from the ambiguous urn. If $p > 0.5$ she should choose the ambiguous urn and the black ball. If $p < 0.5$ she should choose the ambiguous urn and the white ball and if $p = 0.5$ she should be indifferent. Therefore there does not exist a p such that she strictly prefers the risky urn.

The Ellsberg paradox can, however, be rationalized by beliefs that exhibit choice dependent caution. An agent displays CDC if the probability distribution she uses depends on the choice that she is considering and is chosen so as to make that choice unfavorable. In the choice above the paradox is avoided if probability p depends on the color chosen. For example, the behavior can be explained if $p = 0.4$ when black is chosen and $p = 0.6$ when white is chosen.

1.3 VEA Preferences

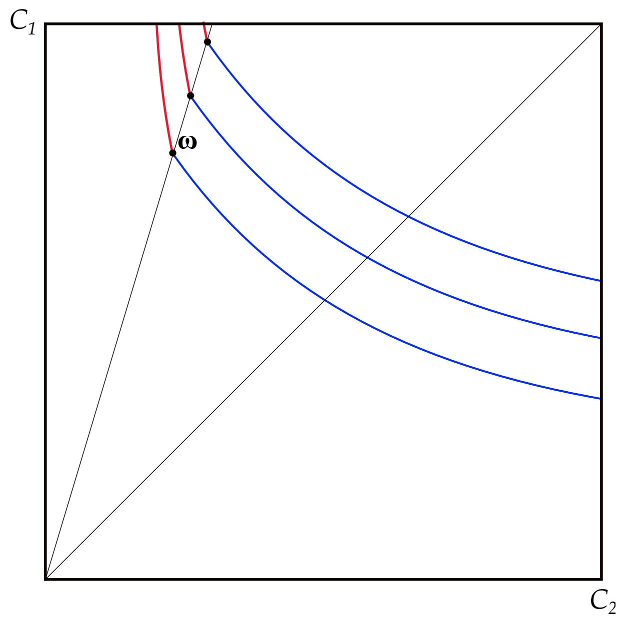
I assume that households make use of a production technology leading to an endowment (or status-quo) ω_i that specifies an element of $\mathbb{R}$ for each state s in some state space S. Households have preferences $\succeq_i$ over consumption bundles c_i that specify an element of $\mathbb{R}_+$ for each $s \in S$. I assume that these preferences can be represented by

$$U(c) = \min_{\pi \in \Pi} \sum_{s \in S} \pi_s \Big(u(c_s) - u(\omega_s) \Big), \tag{1.1}$$

where u is a strictly concave, twice continuously differentiable, real valued function and Π is some closed convex set of priors in Δ, the set of possible priors over S.[4] Figure 3.1 shows the

[4]The interpretation is that $c \succeq c'$ iff $U(c) \geq U(c')$.

Figure 1.1: Indifference Curves for VEAP Preferences



indifference curves generated by 1.1 when there are two possible states and $u = \ln$. The key observation is that the indifference curves are kinked along a ray through the origin and the endowment point.

The preferences represented by Equation (1.1) belong to the class of variational preferences axiomatized by Maccheroni et al. (2006).[5] They are also related to the classic treatments of ambiguity by Gilboa and Schmeidler (1989) and Bewley (1986). In particular, if there is no ambiguity regarding the endowment – in this case if ω is constant in S – then (1.1) collapses to the maxmin model of Gilboa and Schmeidler. On the other hand (1.1) represents one way of choosing among alternatives which dominate the status-quo but would be incomparable in Bewley's model of incomplete preferences.

As with all examples of variational preferences, the preferences in (1.1) can be given a simple psychological interpretation. When considering making a decision with only limited information, the agent behaves as if she is playing a game against a malevolent agent (nature) who is

[5]To the best of my knowledge, these preferences appear only one other time in the literature. Dana and Riedel (2010) use these preferences to provide an easy proof for the existence of equilibrium in a dynamic economy where agents have Bewley (1986) preferences. Dana and Riedel refer to the preferences in (1.1) as "variational utility anchored at ω."

able to alter π.[6] In the case of (1.1), the malevolent nature chooses π from within the set Π with the aim of making the decision to depart from the endowment as bad as possible. Given the relation to variation preferences and the role played by the endowment I refer to the preferences in (1.1) as Variational Endowment Anchored (VEA) preferences.

VEA households display Choice Dependent Caution (CDC). In considering a move to a new allocation c a VEA household uses a prior in $\pi(c) \in \Pi$ that depends on c – hence choice dependent. Further, $\pi(c)$ is chosen in a manner that is cautious – favoring the endowment over c. It is this choice dependence that leads to interesting implications with respect for insurance. At its most simple level, the claim of this paper is that households that exhibit CDC will be hard to insure because whatever an insurance contract specifies, a VEA household will tend to believe that it is unlikely to payout.

Choice dependence also allows VEA preferences to rationalize the Ellsberg Paradox presented in Example 1 above. Specifically, when considering choosing the ambiguous urn and the white ball VEA households will worry that black balls are relatively common. On the other hand, when considering choosing the ambiguous urn and the black ball the same household will worry that red balls are relatively common. Formally let $\pi \in \Pi$ be the perceived probability of drawing a white ball. If the status-quo is not subject to uncertainty, or the risky urn is the status quo then so long as $\Pi \supset \{0.5\}$ a VEA household will choose the risky urn over the ambiguous urn.

The choice of VEA preferences, rather than some other model of ambiguity, is largely driven by the application to risk sharing in Part 3 of the paper. It is well known that the MEU preferences of Gilboa and Schmeidler (1989) tend to increase the benefit to mutual insurance, while the preferences of Bewley (1986) reduce the likelihood of trade in a Edgeworth box economy (see Bewley 1989 and Rigotti and Shannon 2005). VEA preferences capture this implication of Bewley preferences, but make more specific predictions regarding optimal contracts. This specificity is required to give empirical content to the model. When I consider index insurance in Part 2 of the paper I assume that there is a modern and a traditional crop that the household must choose from. The traditional crop is the status-quo, but is not subject to ambiguity. Following the discussion above this implies that VEA preferences have the same implications as the MEU model of Gilboa and Schmeidler (1989). With this as background I now turn to the two applications.

[6] For some neuroscientific evidence consistent with this interpretation see Hsu et al. (2005).

2 Index Insurance and Ambiguity

2.1 Outline of Argument

In this part of the paper I argue that choice dependent caution has important implications for the design of index insurance contracts. Index insurance makes payments conditional on a measure (the index) that is not specific to an individual and is not influenced by the actions of the insured. For example, a typical contract for rainfall insurance pays out if a village rain gauge measures less than a pre-specified amount of precipitation. These two features of index insurance imply that it is not subject to moral hazard or adverse selection and, proponents argue, is therefore able to mitigate many risks for which insurance markets are currently missing (see for example Gine et al. 2008 and Shiller and Weiss 1999).

Index insurance, however, has one key feature that implies it is unlikely to be demanded by those who exhibit CDC. The payout from index insurance is not perfectly correlated with income. Even if the index itself is not ambiguous, which may be the case for rainfall, there is likely ambiguity surrounding the production technology (i.e. the mapping from the index to income). When considering whether to acquire insurance, household that exhibit CDC will concentrate their beliefs on technologies that imply the household is wealthy when the insurance pays out and poor when the insurance requires payment (just as in Maggie's example in the introduction). Therefore, for households that are both risk averse and ambiguity averse, the insurance will not be valuable.

It is important to note that this implication is not specific to a particular insurance contract, but applies to all insurance contracts so long as the set of beliefs entertained by the AA agent is sufficiently large. It is, therefore, not simply a matter of offering a different contract. AA agents are to an extent uninsurable (this claim is formalized in Proposition 1 Part 3 below).

I study the implications of CDC in a setting where insurance is used to encourage the take-up of new technologies. It has been argued that uninsured risk leads the poor to use low risk but low return technologies (Rosenzweig and Binswanger 1993) and delay the take-up of newer high return but potentially high risk technologies (Feder et al. 1985). In such a setting CDC operates as a double edged sword, implying that an agent can simultaneously avoid take-up *because* of risk, but be unwilling to accept insurance that mitigates the risk. Example 2 starkly illustrates this possibility.

Example 2 (A Double Edged Sword)**.** *An AA agent must decide between two technologies. The traditional technology gives a certain return of* \$$(1-\epsilon)$ *while the modern technology is risky and ambiguous. There are two possible states of the world L (for low rain) and H (for high rain) and it is assumed that both are known to be equally likely. The agent believes there are two possible mappings from the state of the world to income: θ_1 which gives* \$0 *in state L and* \$2 *in state H and θ_2 which gives a certain income of* \$1*. Thus the AA agent believes that the new technology has a higher return. In the absence of insurance, pessimism (along with risk aversion) implies that the AA individual believes that θ_1 is the true mapping and (for suitable $\epsilon > 0$) will not adopt the new technology despite its having a higher expected return.*[1]

Now consider an actuarially fair insurance contract which pays out \$1 in state L and costs \$1 in state H. Pessimism implies that when considering the insurance contract the agent will believe that θ_2 is the true mapping and that the insurance contract is actually risk increasing. Insurance will therefore not encourage adoption. Thus risk constrains the choice of the new technology but it cannot be mitigated by the provision of a (generous) insurance contract which mitigates the risk.[2]

This section of the paper has two broad aims. First, I provide a simple model of technology adoption among households with VEA preferences and derive the theoretical implications of CDC. I place particular emphasis on the possibility that VEA households are uninsurable. Second, I test the theory using data from two randomized control trials designed to study the take-up of new technologies. The first data set is from Malawi and documents demand for a rainfall insurance product and the second is from Kenya and studies the provision of credit. Section 3.5 discusses the settings in detail and particularly addresses why credit can be thought of as a partial insurance product subject to low demand by AA households. Importantly, in both cases, the technology had been available for some time and therefore some farmers had experience with it. Further, both data sets have measures of risk aversion and ambiguity aversion.[3] The experimental nature of the data sets implies that the impact of insurance on demand for the new crop is well identified. I use changes in demand for the new crop as a natural measure of the value of insurance.

Beyond uninsurability, the main implication of the theory for insurance demand is that relative to an ambiguity neutral (AN) household, an AA household that has similar beliefs in the

[1] I formalize these preferences below in Section 3.3, but for now the meaning of pessimism is sufficiently clear.

[2] It is also possible to show that the impact of insurance is limited regardless of the specifics of the contract. Suppose that the contract provides \$$x$ in state L and costs \$$x$ in state H. The optimal contract for the ambiguity averse agent is $x = 0.5$, while for an ambiguity neutral agent who is concerned by risk the optimal contract is $x = 1$. Thus regardless of the insurance contract it is less effective for the AA agent.

[3] I discuss the measures in more detail in Section 2.4.3.

absence of insurance will gain less from insurance (Proposition 1 Part 2). Beliefs are, however, not observable and consequently this implication is not directly testable. My empirical strategy is therefore to look for the stronger implication that AA agents benefit less from insurance than AN agents (Proposition 3.3 Part 1 shows that this will be the case if the situation is sufficiently ambiguous). Assuming that caution in the absence of insurance implies that insurance is valuable (in the sense that it will increase demand for the new crop), observing that AA agents benefit less from insurance implies CDC (Proposition 3.3 Part 2).

Having documented that AA individuals do indeed benefit less from insurance, the theory has two further testable implications. First, the beliefs of AA and AN agents will tend to converge as the agents learn about the new technology (Marinacci 2002 & Epstein and Schneider 2007). Consequently if learning is fastest when the farmer grows the crop himself, the disparity in demand for insurance between AA and AN agents will tend to decrease as experience with the new technology increases. I show that this implication holds for both data sets. Second, for index insurance (but not limited liability credit), the theory implies that the negative effect of CDC on take-up is stronger for agents who are also risk averse. An increase in risk aversion implies that insurance is more valuable for AN households, but increases the fear that the insurance is risk increasing for AA households. This surprising implication also holds in the data. Interestingly, if this second implication is ignored it appears that risk aversion is not correlated with demand for insurance. After accounting for this effect, however, measures of risk aversion behave as theory predicts – demand for insurance is increasing in risk aversion among AN households and decreasing among AA households.[4]

The model has several policy implications. First, index insurance is more likely to be valuable in situations where production techniques and the index are well understood. For example, rainfall insurance is more likely to be successful in areas where the main crop has been cultivated for some time. Further, index insurance is not well suited to encouraging the take-up of new crops. Second, it may be possible to encourage take-up of new crops through short term subsidies for use and long term provision of insurance. Third, because ambiguity is likely to persist even in the long run (Bewley 1988, Epstein and Schneider 2007 & Al-Najjar 2009) index insurance should not be seen as a complete solution to the non-existence of insurance markets.

The remainder of the discussion on index insurance proceeds as follows. Section 2.2 discusses the data in more detail. Section 2.3 outlines a formal model of ambiguity aversion and its consequences for index insurance. Empirical implications are derived in Section 2.4 and Section 2.5 discusses policy implications. Section 2.6 presents the empirical results and section 2.7

[4]This is particularly interesting given the often poor predictive power of risk aversion measures. See for example, Giné et al. (2007).

discusses other possible explanation of the data. Finally, section 2.8 offers some conclusions.

2.2 Data

2.2.1 Kenya

The first data set is from a Kenyan experiment that aimed to understand what prevents farmers from growing export crops. The details of the experiment are reported in Ashraf et al. (2009). The authors worked with DrumNet, a project of Pride Africa. Drumnet provides 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. The experiment consisted of several treatments, but only one is relevant for the current study: a subset of the farmers were randomly chosen to receive credit from DrumNet as well as the usual services. The data set provides information on the take-up decision, past use of the export crops and measures of risk aversion and ambiguity aversion. Ambiguity aversion and risk aversion measures are only available for 409 of 450 farmers and I restrict my analysis to these subjects.[5] These measures as well as the exogenous variation in credit provision make the data ideal for this study.

Of course, one may wonder why data documenting the impact of a credit intervention is relevant to a paper on insurance? I argue that if the situation is characterized by limited liability then a credit contract also provides a form of insurance. The issue is discussed in depth in the next section, but here I give some intuition. Suppose there are three states of the world $(1, 2, 3)$ that are equally likely and provide income $-1, 2$ and 4 respectively. A simple credit contract provides 1 unit of income and has an interest rate cost of $r < 2$. If income cannot fall below 0 (the limited liability constraint) then in state 1 the loan is not repaid. Therefore, this simple credit contract could be thought of one which provides a payment 1 in state 1 but $1 - r < 0$ in states 2 and 3, and is thus an insurance contract.[6] All that is required for the interpretation is that farmers perceive that there is a level of yield below which the credit company cannot claim repayment.[7]

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

[6] That credit contracts with limited liability provide insurance is essential to the literature on moral hazard (see, for example Stiglitz and Weiss 1981).

[7] That is the limited liability can be implicit.

2.2.2 Malawi

The second data set comes from an experiment in Malawi which was designed to test the efficacy of index insurance in promoting the take-up of HYV seeds – in this case groundnut seeds. The details of the experiment can be found 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 provided with the opportunity to purchase a package of HYV groundnut seeds.[8] 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. Details of the insurance product can be found in Giné and Yang (2009), but the essential ingredient is that it is an index insurance product paying out an amount which depends on rainfall measured at a village rainfall gauge. The insurance was also intended to be actuarially fair with the calculation based on historic 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, experience with groundnut and measures of ambiguity aversion and risk aversion for 731 of the farmers. I concentrate my analysis on these 731 farmers.[9] It is worth noting that the groundnut seeds offered as part of the experiment were a new HYV variety that had not previously been available. The previous seasons planting of groundnut, however, consisted almost entirely of a slightly older HYV strain. There are therefore two potential sources of ambiguity: ambiguity surrounding groundnut in general and ambiguity surrounding the new HYV seeds. Because no farmers reported using the new HYV seeds before the experiment it is not possible to assess the impact of learning with respect to the second form of ambiguity. However, a measure of experience with groundnut captures learning with respect to the former. It is unclear whether ambiguity regarding each new HYV strain is important or whether farmers tend to treat strains as similar. Either way, the model presented below suggests that both factors should be relevant and that learning with respect to groundnut in general should lead to diminished impact of ambiguity aversion.

2.2.3 Summary Statistics

Tables 2.1 and 2.2 provides some basic summary statistics for the two data sets. The columns present the means of each variable within the AN and AA groups. Orthogonality with respect to the treatment is established in each of the respective papers. The main take-away point from Tables 2.1 and 2.2 is that measured ambiguity aversion is not correlated with many household

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

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

characteristics, making the strong correlation between ambiguity aversion and insurance demand more surprising. The variable definitions are given in Appendix E.

2.3 A Model of Technology Adoption with VEA Preferenes

In this section I introduce a simple model of technology adoption when households have VEA preferences. I use the model to analyze the impact of insurance on demand for the new technology. The analysis in this section applies to index insurance contracts such as the rainfall insurance introduced in Malawi by Giné and Yang (2009). Section 2.4 derives testable implications of the theory and in that section I indicate how the model can be adapted to apply to limited liability credit.

The model has implications for the probability that a household will adopt the new technology, and the impact of insurance on that probability. Regarding adoption, the model implies that among otherwise identical households, AA households are less likely than AN households to adopt. This implication holds with or without insurance and follows from the assumption that AA households are cautious.

The model also implies that AA households benefit less from insurance. I show two specific implications. First, given pre-insurance beliefs,[10] adoption rates for AA households increase less in response to insurance. Second, households that are sufficiently ambiguity averse are uninsurable in the sense that no actuarially fair insurance contract increases the rate of adoption. This implication holds even in a context where AA households perceive the new technology to be risky. When insurance is compulsory, uninsurability implies that actuarially fair insurance has a negative value, an implication that is particularly relevant given the finding in Giné and Yang (2009) that compulsory rainfall insurance decreased adoption rates.

The uninsurability result has important implications for the ability of insurance to help encourage technology adoption. In particular it implies that an AA household can *simultaneously* not adopt a new technology *because* of risk, and not demand insurance that would mitigate that risk. The result, however, also applies to the more general question of demand for insurance when there is no new technology under consideration. In that context, so long as the crop under production has an ambiguous technology, households that are sufficiently ambiguity averse will not benefit from index insurance.

[10] As discussed above pre-insurance are the beliefs in the set Π which minimize the benefit of adopting the new technology when insurance is not available.

Table 2.1: Summary Statistics: Malawi

	AN	*AA*	*p-Value*
Respondent Age	40.377	40.492	0.904
	(13.100)	(12.467)	
Head Female	0.119	0.121	0.949
	(0.325)	(0.327)	
Years Schooling Head	5.107	5.450	0.198
	(3.427)	(3.678)	
House Quality	-0.050	0.015	0.495
	(1.247)	(1.293)	
Land Holding	7.345	7.114	0.709
	(8.235)	(8.374)	
Total Income	36.860	30.108	0.563
	(215.910)	(85.823)	
Saving Account	0.195	0.237	0.171
	(0.397)	(0.426)	
Ever Committee Member	0.472	0.419	0.154
	(0.500)	(0.494)	
Experience Gnut	9.110	8.074	0.101
	(8.743)	(8.168)	
Correct Insurance	0.437	0.414	0.532
	(0.497)	(0.493)	
Risk Tolerance	3.808	3.554	0.092*
	(1.926)	(2.083)	
Trust Insurance	0.003	0.002	0.853
	(0.056)	(0.049)	
Trust Finance	5.963	5.909	0.775
	(2.440)	(2.555)	
Trust Gauge	5.770	5.660	0.685
	(3.530)	(3.379)	
Trust General	0.346	0.305	0.101
	(0.338)	(0.329)	
N	318	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	

$^{***} \Rightarrow p < 0.01$, $^{**} \Rightarrow p < 0.05$, $^{*} \Rightarrow p < 0.1$. Standard deviations in parentheses. p-values are for a ttest of the hypothesis that the mean value does not depend on measured ambiguity.

Table 2.2: 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)	
years 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	2.650	2.355	0.059*
	(1.635)	(1.497)	
Impatient	0.160	0.146	0.700
	(0.367)	(0.354)	
N	169	240	

$^{***} \Rightarrow p < 0.01$, $^{**} \Rightarrow p < 0.05$, $^{*} \Rightarrow p < 0.1$. Standard deviations in parentheses. p-values are for a ttest of the hypothesis that the mean value does not depend on measured ambiguity. Member refers to the household member of NASFAM.

2.3.1 Preference, Technology Adoption and the Value of Insurance

Consider a sample of households choosing between two technologies, a modern crop M and a traditional crop T. The output of the two technologies is dependent on the level of rainfall $r \in R$ and all households agree that the probability of rainfall level r is $p(r)$.[11]

The traditional technology is the status-quo and I assume that households receive expected utility from the traditional technology

$$Eu^T = \alpha + \eta,$$

where α is the mean expected utility from the crop and $\eta \sim U[-\bar{\eta}, \bar{\eta}]$ is a household specific characteristic that determines the profitability of the traditional crop. This formulation of the return to the traditional crop allows for it to be dependent on rainfall, but not ambiguous.

The modern crop is characterized by ambiguity. The production function for the modern crop is a map $\theta : R \to \mathbb{R}_+$ and households believe that this map is chosen from some set Θ. I assume that households have limited information regarding which θ is most likely and therefore have a *set* of priors $\mathcal{C}$ over Θ. A single prior $\mu \in \mathcal{C}$ assigns a probability $\mu(\theta) \in [0, 1]$ to each possible production function in Θ. I denote $\mathcal{C}^A$ the set of priors of a household measured to be ambiguity averse and $\mathcal{C}^N$ the set of priors of a household measured to be ambiguity neutral. I assume throughout that $\mathcal{C}^N$ is a strict subset of $\mathcal{C}^A$. This model captures a situation where the rainfall distribution is not ambiguous, but the mapping from rainfall to output is ambiguous for the modern crop.[12]

An insurance contract is a mapping $\gamma : R \to \mathbb{R}$ which assigns to each rainfall state a (not necessarily positive) transfer from the insurance company to the household. An insurance contract is actuarially fair if $\sum_{r \in R} p(r)\gamma(r) = 0$.

With insurance available, a household with $\mu = \hat{\mu}$ adopts the new crop if

$$\min_{\mu \in \mathcal{C}} \sum_{\theta \in \Theta} \mu(\theta) \sum_{r \in R} p(r) u(\theta(r) + I\gamma(r)) \geq \alpha + \hat{\mu}, \tag{2.1}$$

for $I = 0$ or $I = 1$. If insurance is not available the households adopts if (2.1) holds with $I = 0$ and if insurance is compulsory the household adopts if (2.1) holds for $I = 1$.

In the absence of heterogeneity other than η, equation (2.1) defines $\tilde{\eta}^A$ and $\tilde{\eta}^N$, cutoff points below which AA and AN households adopt the new technology. I denote $\tilde{\eta}(NI)$, $\tilde{\eta}(CI)$ and $\tilde{\eta}(I)$ as the cutoff values of η in the case of no-insurance, compulsory insurance and optional

[11] All sets referred to in the model are assumed discrete and finite.

[12] See Giné et al. (2007) for evidence that farmers are well informed regarding the rainfall distribution.

insurance respectively.

With this notation I define the value of optional insurance to AA households to be the density of AA households motivated to adopt the new crop because of the insurance:

$$V^A(I) = \frac{\eta^A(NI) - \eta^A(I)}{2\bar{\eta}}. \tag{2.2}$$

The value of insurance in other cases and to other groups, $V^N(I), V^A(CI)$ and $V^N(CI)$ are defined analogously.

2.3.2 A Two State Example

I illustrate the main implications of the model in a very simple setting with two rainfall states. Appendix A shows that the results of this section also apply in the more general setting. I make the following assumptions for the purposes of the example:

1. There are two rainfall states r_l and r_h;
2. All production functions, $\theta \in \Theta$, have the same expected yield;[13]
3. All priors are degenerate placing a probability of 1 on a particular θ and zero on all others; and
4. Ambiguity neutral households have a single prior $\mu^N \in \mathcal{C}^A$.

Assumption 3 implies that all priors can be associated with a specific production function θ. I denote Θ^A to be those $\theta \in \Theta$ for which $\mu(\theta) > 0$ for some $\mu \in \mathcal{C}^A$. Similarly θ^N is the θ for which $\mu^N = 1$. In this example equation (2.1), which determines adoption, can be rewritten

$$\min_{\theta \in \Theta^A} \sum_{r \in R} p(r) u(\theta(r) + I\gamma(r)) \geq \alpha + \hat{\mu},$$

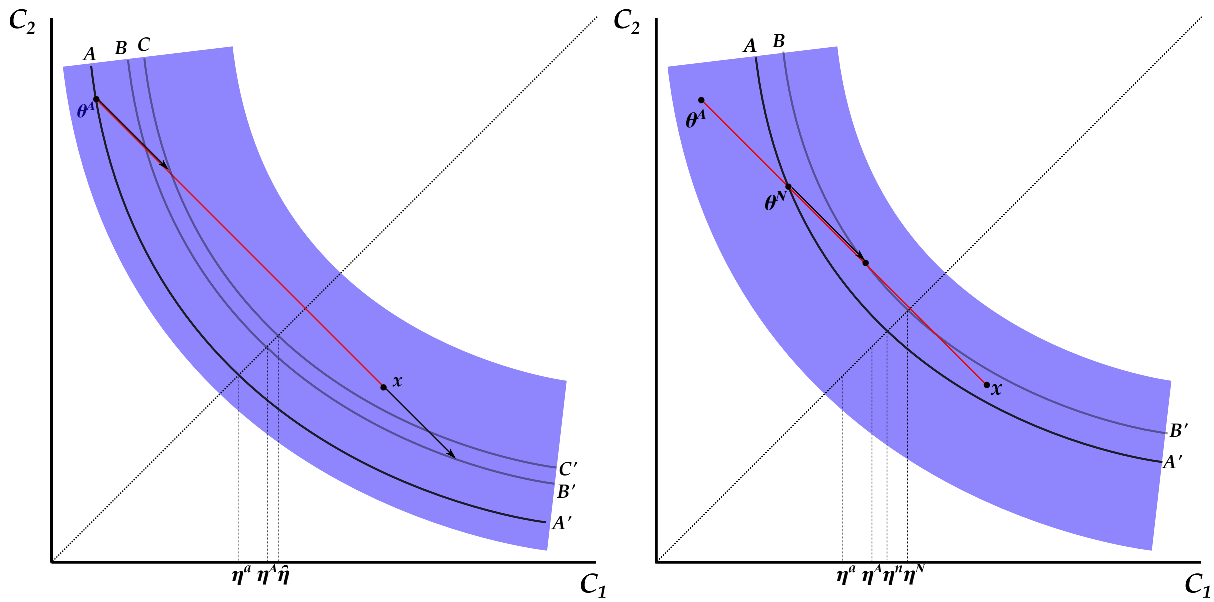
for the AA households and

$$\sum_{r \in R} p(r) u(\theta^N(r) + I\gamma(r)) \geq \alpha + \hat{\mu},$$

for the AN households.

[13] That is $p(r_l)\theta(r_l) + p(r_h)\theta(r_h) = K$ for all θ and some constant K.

Figure 2.1: Takeup for Ambiguity Averse and Ambiguity Neutral Households



Figures 2.1 and 2.2 illustrate the main theoretical implications of the model. In the diagrams the x and y axes show consumption in the low rain state and consumption in the high rain state respectively.

I first show that ambiguity averse households are less likely to adopt, either with or without insurance. Consider first Figure 2.1. In both panels the red line $\theta^A x$ represents the set Θ^A and the black arrows represents an actuarially fair insurance contract. Assumption 2 implies that an actuarially fair insurance contract is collinear with the set Θ^A. The left panel shows the choice for ambiguity averse households. Throughout the analysis I use θ^A to denote the solution to

$$\underset{\theta \in \Theta^A}{\text{argmin}} \sum_{r \in R} p(r) u(\theta(r)), \tag{2.3}$$

and I refer to the belief θ^A as the "beliefs without insurance" or "pre-insurance beliefs". For AN households pre-insurance beliefs and beliefs are obviously the same.

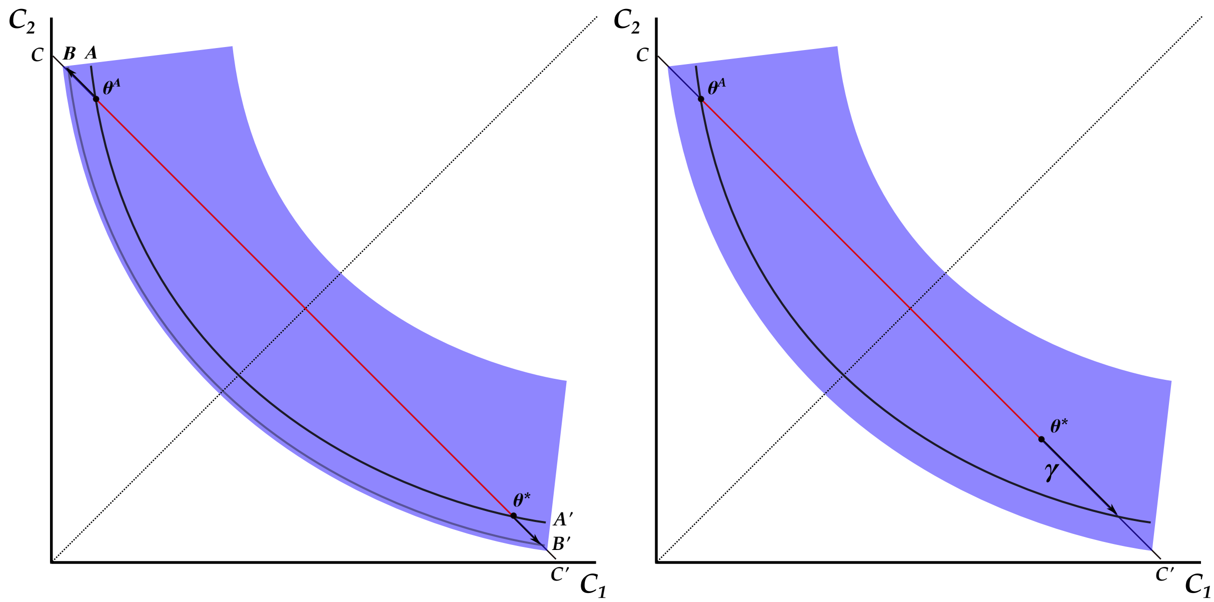
Indifference curve AA' shows expected utility in the absence of insurance and indifference curve BB' expected utility with optional insurance. AA households with $\eta < \eta^a$ adopt the new technology in the absence of insurance, and households with $\eta < \eta^A$ adopt with insurance. The indifference curves are similarly labeled in the right panel for the AN households. Households with $\eta < \eta^n$ will adopt without insurance and $\eta < \eta^N$ with insurance. The assumption that $\theta^N \in \Theta^A$ immediately implies that $\eta^A \leq \eta^N$ and $\eta^a \leq \eta^n$ implying that AA households are less likely to adopt the new technology either with or without insurance.

The left panel of Figure 2.1 also shows that conditional on pre-insurance beliefs, insurance is less valuable to the AA households. In particular suppose that in addition to being the solution to (2.3), θ^A is the singleton belief of the AN households. In the diagram the value of the insurance for the AA household is $(\eta^A - \eta^a)/2\bar{\eta}$, while the value for the AN household is $(\hat{\eta} - \eta^a)/2\bar{\eta}$ implying that the value of the insurance to the AA household is weakly less than for the AN household. This implication follows more generally because if indifference curve CC' is to the left of indifference curve BB', then the minimizing beliefs with insurance will be θ^A and both AN and AA households will benefit equally. On the other hand, if indifference curve BB' is to the left of CC' (as it is in the diagram) then the AA households will change beliefs when considering the insurance and the propensity to benefit from insurance will be lower.

Figure 2.2 illustrates the results on uninsurability. Consider first the left panel. In that diagram, all actuarially fair insurance contracts can be represented as arrows moving along the line CC'. The definition of θ^A is as above. Suppose that in addition to θ^A the set Θ^A also includes θ^*, then all actuarially fair insurance contracts will have zero value to the ambiguity averse household (insurance contracts that move north-west along CC' are risk increasing when beliefs are θ^A, implying that minimal utility is given by indifference curve BB' and insurance contracts that move south-east are risk increasing when beliefs are θ^* with a similar implication). The simple point is that if the set of beliefs Θ^A is such that the household cannot rule out the possibility that a given contract is risk increasing, then that contract will have zero value.

Four points should be noted about the uninsurability result. First, the result holds despite the fact that the AA households perceive the modern crop to be risky. This is illustrated by the fact that θ^A is not on the certainty line. As discussed above, this implies that AA households can simultaneously be deterred from adopting because of risk, but also not demand insurance to mitigate that risk. Second, the majority of insurance contracts require some kind of minimum purchase. In the diagram this is a minimum length of the insurance arrow. The size of the set Θ^A required for a household to be uninsurable is decreasing in the minimum purchase requirement. This fact is illustrated in the right panel of Figure 2.2 where once again θ^A is the minimum of the set Θ^A. Suppose that the minimum insurance level is indicated by the length of the arrow γ. If this is the case then uninsurability requires that θ^* be in the set Θ^A. It is easy to see that as γ increases θ^* moves north-west and the set Θ^A shrinks.

Figure 2.2: Ambiguity Averse Households May be Uninsurable



Third, with only two rainfall states the uninsurability result seems unsurprising. With more rainfall states, however, the result is more surprising. One common explanation for low demand for rainfall insurance is basis risk. Because rainfall on a particular plot is not perfectly correlated with rainfall measurement at the gauge there may be some states of the world in which rainfall insurance is risk increasing. This risk is termed basis risk and it implies that it is always be possible to write a valuable insurance contract with a gauge that is centered on a households particular plot.[14] The uninsurability result for ambiguity averse households implies that this will not be the case if there is sufficient ambiguity. Fourth, the left panel of Figure 2.2 illustrates that if the insurance is compulsory, in the sense that it is not possible to adopt the new crop without it, then insurance may have a negative value. Again this is true despite the fact that the ambiguity averse household is risk averse and believes that the new crop is risky.

I show in Appendix A that the four points made in this section hold in the more general case with multiple rainfall states and non-degenerate priors. Proposition 1 states the results formally.

Proposition 1 (Theoretical Implications of VEA)**.** *If* $\mathcal{C}^N \subset \mathcal{C}^A$ *then*

1. *Ambiguity averse households are less likely than ambiguity neutral households to adopt the new*

[14] See Doherty and Schlesinger (1990) for a related analysis.

technology. This result holds either with or without insurance.

2. *Holding constant beliefs without insurance, ambiguity averse households gain less from insurance.*

3. *There exist Θ and $\mathcal{C}^A$ such that all actuarially fair insurance contracts have no value (i.e. $V^A(I) = 0$). Moreover this result holds when AA households perceive the modern crop to be risky.*

4. *There exist Θ and $\mathcal{C}^A$ such that all compulsory actuarially fair insurance contracts have negative value (i.e. $V^A(CI) < 0$). Again this result holds when AA households perceive the modern crop to be risky.*

2.4 Empirical Implications

Proposition 1 provides the main theoretical implications of the model. None of those implications are, however, directly testable. In particular, testing Part 1 requires controlling for all other characteristics of the households that might be correlated with ambiguity aversion and testing Part 2 would require knowledge of households beliefs. A direct test of Parts 3 and 4 seems to require offering a multitude of insurance contracts and observing demand.

Parts 2 and 3 of Proposition 1 however suggest an empirical strategy. If the set $\mathcal{C}^A$ is sufficiently larger than $\mathcal{C}^N$, AA households will gain less from any insurance contract ($V^A < V^N$). This implication is particularly easy to test in a setting where insurance is experimentally provided. Equation (2.2) defines the value of insurance, V^A and V^N, in terms of the increase in demand for the new crop induced by the provision of insurance. This is simply the effect of an insurance treatment on the probability of adopting the new crop. The claim that $V^A < V^N$ can then be assessed as a heterogeneous treatment effect. Testing for heterogeneous treatment effects means that variables which are correlated with measured ambiguity aversion and overall demand for the new crop are controlled for (i.e. α can be correlated with AA) significantly reducing the identification problem that would be encountered if one were to test Part 1 of Proposition 1.

Further, if $V^A < V^N$ the theory has two more testable implications, both of which can be formulated as heterogeneous treatment effects. First, if the insurance contract is valuable to household with beliefs θ^A (defined in equation (2.3)) then finding that insurance is less valuable for those who are ambiguity averse is evidence of CDC – it must be the case that the minimizing prior is different when insurance is offered. This in turn implies that AA households believe that the insurance is more than sufficient to overcome all risk and implies that the difference between the two treatment effects $V^N - V^A$ should be increasing in risk aversion. Because the data I use has measures of risk aversion, this implication is testable. Finally, if the set $\mathcal{C}^A$ converges to the set $\mathcal{C}^N$ as households learn and households learn more from their own experience than the experience of others, then the differences $V^N(CI) - V^A(CI)$ should be decreasing with experience.[15]

These are the simple implications that are tested in the empirical section of this paper. The remainder of this section is broken in to two parts. First, I demonstrate more formally the empirical implications continuing with the example from section 2.3.2. Second, I consider a slight variation of the model to accommodate the limited liability credit contract offered in Kenya. I show that in that context we should expect that $V^A < V^N$ and that this heterogeneous treatment effect should be decreasing in experience. In the context of limited liability credit, however, it is no longer the case that the heterogeneous treatment effect should be increasing in risk aversion and there is some reason to believe that it will be decreasing in risk aversion.

2.4.1 Empirical Implications: Malawi

I first argue that if Θ^A is large enough, AA households will gain less from insurance ($V^A < V^N$). Consider an AN household that has a prior θ^N as in the left panel of Figure 2.3. Insurance moves this households from indifference curve CC' to DD' and the distance V^N measures the gain. Next, consider an AA household that has beliefs without insurance given by θ^A. If θ^* is included in the set Θ^A, then the gain from insurance for the ambiguity averse household is given by $V^A = V^N$. Now consider moving θ^* south-east. This will decrease V^A and implies that for any θ^N and θ^A there exists a large enough Θ^A such that the value of insurance to the AA households is smaller than for the AN households. As a consequence, if there is "sufficient" ambiguity, AA households will have a lower value for insurance than AN households.

Second, I show that if insurance is valuable given pre-insurance beliefs then $V^A < V^N$ implies CDC.[16] Formally I assume:

Assumption 1 (Insurance is Valuable Given Pre-Insurance Beliefs)**.**

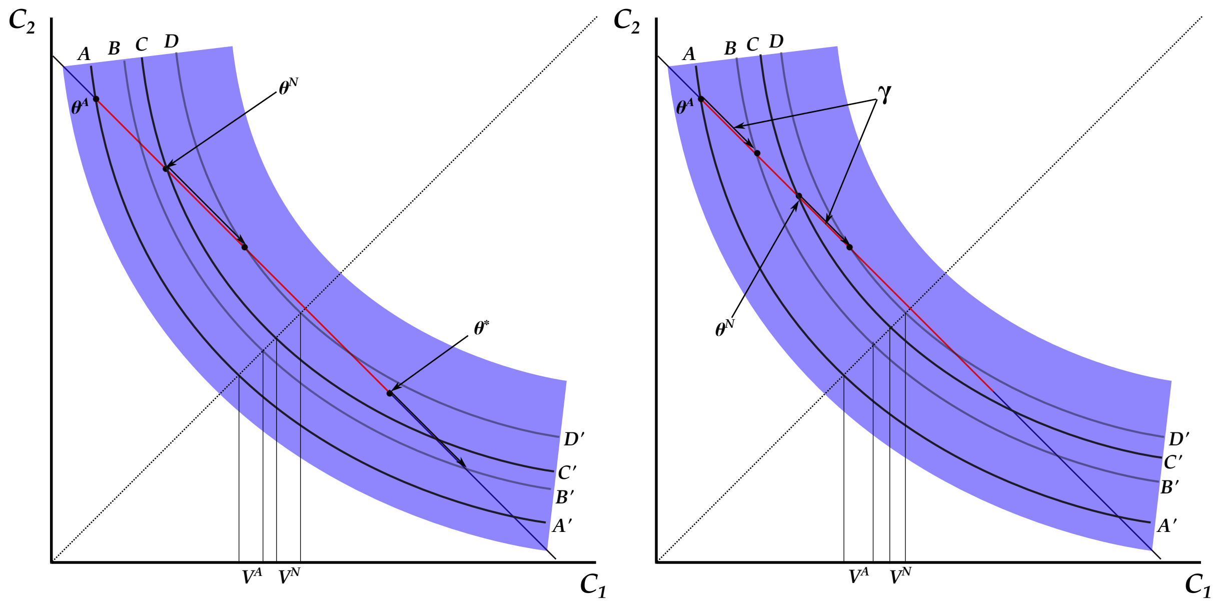
$$\sum_{r \in R} p(r)u(\theta^A(r) + \gamma(r)) > \sum_{r \in R} p(r)u(\theta^A(r)),$$

where γ is the insurance contract offered in the data.

As shown in the right panel of Figure 2.3, this assumption coupled with the assumption that $\theta^N \in \Theta^A$ implies that θ^A lies to the north-west of θ^N when insurance moves money from state

[15]See Foster and Rosenzweig (1995) for evidence that learning is faster from own experience than from peers.
[16]I discuss the empirical relevance of this assumption below.

Figure 2.3: A Lower Value of Insurance for AA Households Implies CDC



r_h to r_l. Given this, if households are prudent ($u''' > 0$) the value of insurance when beliefs are θ^A is greater than when beliefs are θ^N.[17] Therefore, if $V^A < V^N$ it must be because the set Θ^A is large and, as depicted in the left panel of Figure 2.3, the belief of the AA households changes in response to the insurance.

Third, I consider the impact of risk aversion. It is definitional of risk aversion that more risk averse households benefit more from actuarially fair insurance. Therefore, if the rainfall insurance considered is of value to AN households, the benefit of the insurance will be increasing in risk aversion. Consider AA households on the other hand. The argument above establishes that for $V^A < V^N$ to hold it must be the case that the minimizing belief with insurance (θ^* in the left panel of Figure 2.3) lies to the right of the certainty line. As a consequence the insurance contract is seen as risk increasing relative to certainty. This implies that for the AA households the cost of the insurance is increasing in risk aversion. Therefore, the benefit for the AN households (V^N) is increasing in risk aversion, while the cost ($-V^A$) is increasing for AA households

[17]To see this consider an example in which $p(r_l) = p(r_h) = \frac{1}{2}$. The value of actuarially fair insurance of size γ is then $u(y_l - x + \gamma) + u(y_h + x - \gamma) - (u(y_l - x + \gamma) + u(y_h + x - \gamma))$. Taking the derivative and setting $x = 0$ we find that the value is increasing in x if $u'(y_l) - u'(y_l + \gamma) > u'(y_h) - u'(y_h - \gamma)$. Finally taking a first order Taylor approximation around y_l on the left hand side and $y_h - \gamma$ on the right hand side gives $u''(y_l) < u''(y_h - \gamma)$ and assuming that $y_h - \gamma > y_l$ which it must be if the insurance is not complete, this last condition holds if $u''' > 0$.

implying that $V^N - V^A$ must be increasing in risk aversion.

Fourth, I argue that experience decreases the difference between AA and AN households. Intuitively the size of the set Θ^A will decreases as information about the production function is revealed. If households learn more from their own experiences than from the experience of others then Θ^A is decreasing in experience and we would expect the behavior of AA and AN households to converge with experience. Formally assume that learning only occurs from own experience. In the context of the example, only one period of experience is required to determine the the "true" θ. It then follows that so long as θ^N is the truth, the behavior of AA and AN households will converge after one observation of the new technology. More generally if the set Θ^A is two dimensional complete learning requires an observation of both r_l and r_h and the number of periods of experience required for convergence is increasing in the number of rainfall states. Appendix A shows that a result of Marinacci (2002) implies that behavior of AA and AN households also converges when the priors $\mu \in \mathcal{C}$ are not degenerate. This result holds so long as all priors place positive probability on the truth and updating is according to Bayes rule.

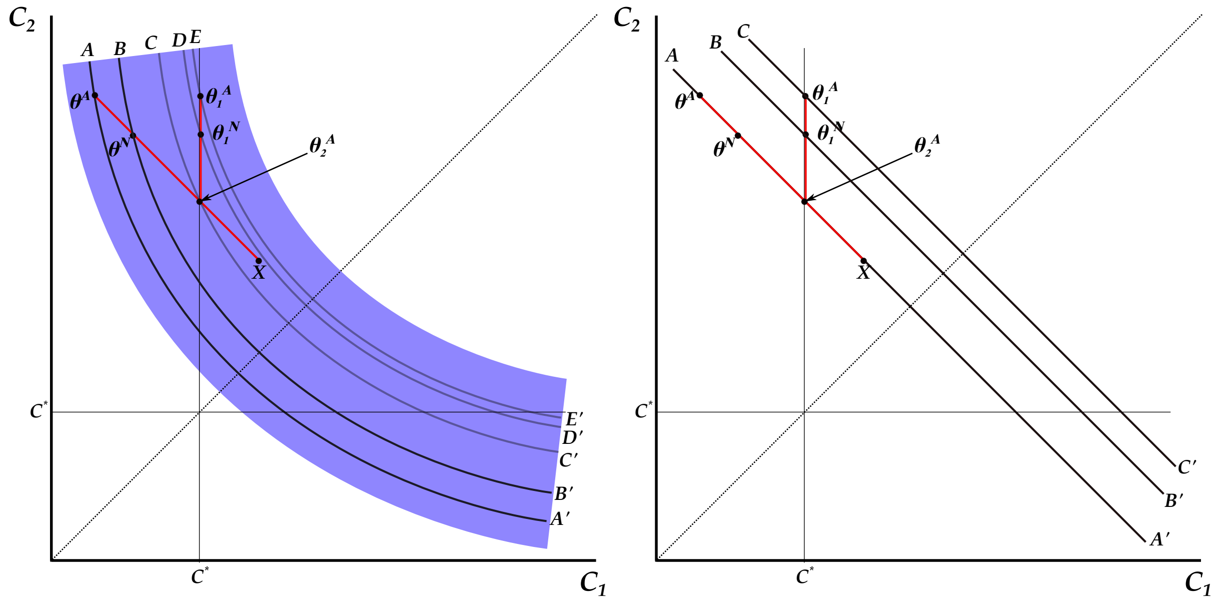
I collect the four observations of this section as Proposition 3.3:

Proposition 2 (Empirical Implications of VEA preferences)**.** *If $\mathcal{C}^N \subset \mathcal{C}^A$ then*

1. *For any $\mathcal{C}^N$ there exists $\mathcal{C}^A$ such that $V^N - V^A > 0$.*
2. *If insurance is valuable given pre-insurance beliefs and $u''' > 0$ then $V^N - V^A > 0$ implies CDC.*
3. *If insurance is valuable given pre-insurance beliefs, $u''' > 0$ and $V^N - V^A > 0$ then $V^N - V^A$ is increasing in risk aversion.*
4. *If $V^N(CI) - V^A(CI) < 0$ and learning is faster from own experience then $V^N(CI) - V^A(CI)$ is decreasing in experience.*

I conclude this section by discussing the empirical relevance of Assumption 1. Assumption 1 is a joint assumption regarding the insurance offered in the experiment of Giné and Yang (2009) and the beliefs of AA households. It essentially implies that in the environment under study caution without insurance would lead a household to favor beliefs in which the modern crop would be sensitive to drought. Two facts suggest that this is a plausible assumption. First, when asked the majority of households in the sample cited drought risk as the most important risk to their income. Second, a great deal of research has gone in to producing new varieties of seeds for this area. Most of this work goes in to producing drought resistant varieties. Both of these observations suggest that drought is among the main concerns and therefore that a significant

Figure 2.4: The Impact of Limited Liability on Takeup



concern about the modern crop would be that it is not drought resistant. I discuss the impact of relaxing this assumption in Section 2.7.

2.4.2 Application to Limited Liability Credit

In this section I show that with the exception of the risk aversion results, the same empirical predictions apply to a model with limited liability credit rather than rainfall insurance. The model is identical apart from the definition of the states and the definition of insurance. Assume there are two c states of the world $S = \{1, 2\}$ the probability of which is known and equal to $p(1)$ and $p(2)$. With this exception, the basic setup is as above. A production function θ is a mapping from S to $\mathbb{R}$ and $\theta^N \in \Theta^A$. In this setting, I model a limited liability constraint as a minimum consumption level c^* in each state of the world.

Figure 2.4 illustrates the main empirical implications. In the left panel of the figure, θ^N is the belief of the ambiguity neutral households. The effect of the limited liability clause is to move the ambiguity neutral households consumption bundle to θ_1^N. The value of the limited liability clause is therefore measured by the difference between indifference curves DD' and BB'. The red line $\theta^A X$ is the set Θ^A, while the kinked red line $\theta^A \theta_2^A X$ is the set of possible consumption bundles with limited liability. Each consumption bundle corresponds to a belief $\theta \in \Theta^A$. Once again, denote θ^A the minimizing prior in the set Θ^A when there is no limited liability. For a household with constant belief θ^A the value of insurance is given by the difference between indifference curves AA' and EE' which is clearly larger than the benefit to a household with beliefs θ^N. Therefore, if $V^A < V^N$ it must be the case that beliefs of the AA household have changed. In particular the minimizing prior with limited liability lies at the point θ_2^A and the kink in the set $\theta^A\theta_2^A X$ provides a positive explanation for AA households not valuing limited liability. As a consequence, if it is observed that $V^A < V^N$ then under the assumption that $\theta^N \in \Theta^A$ it is possible to infer that there has been a change in beliefs, implying CDC.

The right hand panel of Figure 2.4 shows that risk aversion is not necessary for this argument. In that diagram all households are risk neutral and the limited liability constraint is beneficial to the AN households but not the AA households. In fact, there is some reason to believe that $V^N - V^A$ should be decreasing in risk aversion. For an AN household, Figure 2.4 shows that the effect of limited liability is a transfer in the state in which income is low. The benefit of this is related to the marginal utility of wealth and need not be related to risk aversion. On the other hand, for an AA household the effect of the limited liability is similar to insurance, moving beliefs from θ^A to θ_2^A. As discussed above, the benefit of this "insurance" is increasing in risk aversion. Therefore V^A is increasing in risk aversion while V^N is likely to be constant in risk aversion implying that $V^N - V^A$ is decreasing in risk aversion. Finally, the same argument made above with respect to learning applies to the limited liability case.

2.4.3 Measuring Ambiguity and Risk Aversion

Testing these implications requires measures of both risk aversion and ambiguity aversion. In this section I discuss the measures available in the two data sets. Ambiguity aversion is measured by the following question:

Question 1 (Measuring Ambiguity)**.** *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" color, 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 color ball wins. You must then pick this color ball to win.*

Which bag would you like to choose from?[18]

Decision makers were also given a visual aid which is shown in the Appendix B. The question was not incentivized. Those who prefer bag one are treated as being AA and those who choose bag two are identified as AN. Because the probability of winning from the risky urn 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 urn when the probability of winning is 0.5 is consistent with indifference between the two urns. In terms of the representation (**??**) and Example 1, individuals identified as AA have $\Pi \supseteq [0.4, 0.6]$. This implies that while those who chose bag 1 are labelled as AN, some portion of them may in fact be ambiguity averse.

For this measure of ambiguity aversion to be useful in a more applied setting, there must be a link between the response to Question 1 and behavior in the real world setting. With VEA prefereces, the degree of ambiguity aversion and the amount of perceived ambiguity are jointly measured by the "size" of the set Π. I do not have access to a measure of how ambiguous each agent perceives the crop decision, nor the urn choice problem in Question 1. Indeed it seems difficult to measure perception of ambiguity in an applied setting.[19] I, therefore, assume that when faced with the same choice and the same information about that choice, all agents perceive the choice as equally ambiguous. Differences in the set Π can, therefore, be ascribed to ambiguity attitude. More formally, let a choice problem be a complete description of all possible acts, states of the world and available information. I assume the following regarding the size of the sets Π:

Assumption 2 (Ambiguity Aversion is a Fixed Characteristic)**.** *Let $\mathcal{P}$ be the set of all choice problems. Define $\Pi_i(l)$ as the set of priors for agent i in choice problem l. Then*

$$\Pi_i(a) \subset \Pi_j(a) \Rightarrow \Pi_i(b) \subseteq \Pi_j(b) \tag{2.4}$$

for all choice problems $a, b \in \mathcal{P}$. If (2.4) holds j is identified as more ambiguity averse than agent i.

Assumption 2 coupled with the assumption that all agents have VEA preferences implies that those who are identified as AA by question 1 will be more ambiguity averse in real world choice problems including the insurance choice problems motivating this paper.

[18] In Malawi the ratio of balls differed. There were 5 balls in each bag and 3 were yellow and 2 were red.

[19] Several papers propose models which allow for a separation of ambiguity attitude and ambiguity perception. See for example Klibanoff et al. (2005) & Ghirardato et al. (2004) as well as the discussion in Epstein (2010).

Risk aversion is also a key measure. Both surveys include a measure of risk aversion based on that of Binswanger (1980). As this is a standard question I do not discuss it in detail, although it is worth noting that an assumption similar to Assumption 2.4 is required in all applied uses of this measure. The exact question can be found in Appendix C.

2.5 Policy Implications of the Model

In this section I briefly discuss policy implications based on the model. Of course, while a static model is appropriate for analyzing a once off offer of insurance as occurred in both experiments, a real world insurance product would be offered on an ongoing basis and requires a dynamic model. Unfortunately, the dynamic extension of ambiguity averse preferences is the subject of a large and unsettled literature (see, for example, Gilboa and Schmeidler 1993, Epstein and Schneider 2003, Hanany and Klibanoff 2007 & Siniscalchi 2006). In the current setting there are two issues which arise when considering dynamic choice. First, the major emphasis of the literature on dynamic ambiguity averse preference is the possibility that AA preferences are dynamically inconsistent. In the setting of this paper, requiring dynamic consistency would allow a household to effectively hedge their choices over time, choosing a sequence $\{insure, don't\ insure, \ldots\}$.

Second, when studying technology adoption in a situation of uncertainty there is a tradeoff between current payoffs and learning. This tradeoff is usually captured by the multi-armed bandit model (see Bergemann and Valimaki 2008 for a review). While I am unaware of any literature on ambiguity aversion and bandit problems, intuition suggests that the provision of the ongoing opportunity to purchase insurance may have different impacts on AA and AN agents in a bandit model. Incorporating strategic learning in to the model may therefore have implications for policy analysis. Appendix D discusses these issues in more detail and provides plausible assumptions under which the static model is appropriate for analyzing the behavior of AA households in response to insurance. The remainder of this discussion assumes that the implication of the static model will hold in a richer dynamic setting.

The (static) model has several important policy implications. The discussion of learning implies that index insurance is more likely to find success when the production function is well known and not open to ambiguity. A corollary is that index insurance is unlikely to be successful in promoting the use of new technologies. A policy which combines subsidies for short term use of a crop with long term insurance may overcome this difficulty by encouraging AA households to gain experience with the new crop.

The model also casts some doubt on the ability of index insurance to be useful even when the production technology is old. Several recent papers (Bewley 1988, Epstein and Schneider 2007 & Al-Najjar 2009) study formal learning models and show that under plausible assumptions ambiguity can persist in the long run. If these results apply, then index insurance will continue to suffer from low demand even if the production technology has been available for some time.

Third, while Proposition 1 shows that AA agents may not respond to any kind of index insurance, there is a potential role for marketing. There are two reasons for this belief. First, it can be argued from a theoretical perspective that being subject to the Ellsberg paradox is a mistake.[20] This raises the possibility that clever marketing could convince households of this mistake. Second, recent lab experimental work has shown that the effects of ambiguity aversion can be overcome by simple treatments which alter the status-quo (Roca et al. 2006). There may be other simple treatments that would have a similar effect.

Finally, the discussion of dynamic decision making under ambiguity in Appendix D suggests that AA households who are strategic with respect to learning will benefit more from insurance when they are certain that it will be provided on an ongoing basis. Thus insurance contracts should, as far as possible, be provided by trusted and permanent members of the community. From a project evaluation perspective these observations also highlight the importance ofstudies that assess ongoing, rather than temporary, insurance products.

2.6 Tests of the Model

2.6.1 Empirical Specification and Test

In this section I present empirical tests of the model. To recap, the empirical strategy is to show that $V^A < V^N$, a fact which is consistent with a high degree of ambiguity aversion and implies CDC. If this is found, the model then implies that $V^N - V^A$ must be increasing in risk aversion and decreasing in experience. That is I wish to test three hypotheses:

1. $V^A < V^N$;
2. $V^N - V^A$ decreases as risk tolerance increases (in Malawi only); and
3. $V^N - V^A$ decreases as experience increases.

[20]See for example Rustichini (2005).

To document these three facts I estimate:

$$\begin{aligned} Takeup_i = \beta^0 + \beta^1 AA_i + \beta^2 RT_i + \beta^3 Treat_i + \beta^4 AA_i \cdot Treat_i + \\ \beta^5 AA_i \cdot RT_i + \beta^6 RT_i \cdot Treat_i + \beta^7 AA_i \cdot RT_i \cdot Treat_i + \beta^8 Exp_i + \\ \beta^9 Exp_i \cdot Treat_i + \beta^{10} AA_i \cdot Exp_i + \beta^{11} AA_i \cdot Exp_i \cdot Treat_i + X_i' \beta^{12} + \eta_i, \end{aligned} \tag{2.5}$$

in Malawi and

$$\begin{aligned} Takeup_i = \beta^0 + \beta^1 AA_i + \beta^2 RA_i + \beta^3 Treat_i + \beta^4 AA_i \cdot Treat_i + \\ \beta^5 AA_i \cdot RA_i + \beta^6 RA_i \cdot Treat_i + \beta^7 AA_i \cdot RA_i \cdot Treat_i + \beta^8 Exp_i + \\ \beta^9 Exp_i \cdot Treat_i + \beta^{10} AA_i \cdot Exp_i + \beta^{11} AA_i \cdot Exp_i \cdot Treat_i + X_i' \beta^{12} + \eta_i, \end{aligned} \tag{2.6}$$

in Kenya. In these regressions:

1. $Takeup_i$ is an indicator taking on value 1 if household i adopted the modern crop;
2. AA_i is an indicator variable taking on value 1 if household 1 was measured to be ambiguity averse;
3. Exp_i is a measure of how many years experience household i has with the modern crop;
4. RL_i is a measure of how risk tolerant household i is. It takes on value 1 for the most risk averse households and 6 for the least risk averse households;
5. RA_i is a measure of how risk averse household i is. It takes on value 1 for the most risk loving households and 10 for the least risk loving households;
6. $Treat_i$ is an indicator taking on value 1 if household i was in the treatment group that was offered insurance (credit) and zero otherwise;
7. X_i is a vector of control variables; and
8. η_i is a mean zero error term.

The different specifications for the two data sets corresponds to the different expectations for the effect of risk aversion.

I first discuss the interpretation for the Malawi data. The specification (2.5) allows me to test each of the three implications while controlling for the other two. The tests are particularly simple because, as discussed above, V^A and V^N are simply measures of the impact of insurance on the probability of adopting the new crop.

First, specification (2.5) allows me to test whether $V^A < V^N$ among those who are risk averse and inexperienced. The coefficient on $Treat_i$ (i.e. β^3) measures the impact of the treatment on households that are measured to be ambiguity neutral and who are the least experienced and most risk averse. The effect of the treatment on those who are ambiguity averse is the sum of the coefficient on $Treat_i$ and $AA_i \cdot Treat_i$ (i.e. $\beta_3 + \beta_4$). Consequently testing whether $V^A < V^N$ implies testing whether the coefficient on $AA_i \cdot Treat_i$ is less than zero (i.e. $\beta_4 < 0$).

Second, 2.5 allows for a test of whether $V^N - V^A$ is decreasing in risk tolerance. The coefficient on $RT_i \cdot Treat_i$ (i.e. β^6), measures how the effect of the treatment on AN households changes as risk tolerance increases. The sum of the coefficients on $AA_i \cdot RT_i \cdot Treat_i$ and $RT_i \cdot Treat_i$ (i.e. $\beta^6 + \beta^7$) measures the effect for AA households. Consequently testing the claim that $V^N - V^A$ decreases in risk tolerance is equivalent to testing whether the coefficient on $AA_i \cdot RT_i \cdot Treat_i$ is positive (i.e. $\beta^7 > 0$). Importantly, this test controls for the impact of experience and consequently tests whether risk aversion has the predicted impact *independent* of the effect of experience.

Third, specification (2.5) allows me to test whether $V^N - V^A$ is decreasing in experience. The same logic as above implies that testing this fact is equivalent to testing whether the coefficient on $AA_i \cdot Exp_i \cdot Treat_i$ is positive (i.e. $\beta^{11} > 0$).

Similar arguments apply to specification (2.6) when assessing the impact of limited liability credit. Hypothesis 1 implies $\beta^4 < 0$ and Hypothesis 3 implies $\beta^{11} > 0$. Finally, if $V^N - V^A$ is decreasing in risk aversion we expect to see $\beta^7 > 0$.

Before turning to the results of these tests one might wonder whether it is appropriate to test the combination of Hypotheses 2 and 3. That is, that the reduction in $V^N - V^A$ 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 experience will monotonically decrease the effect of risk aversion on $V^N - V^A$. As a consequence, while it is true that if the data contained people who were "completely experienced" we would expect risk aversion to have no effect, it is not the case that we expect the effect of risk aversion to decease with experience. Therefore, while it is necessary to control for hypothesis 2 while testing 3 (and vice-versa) as is done in (2.5), it is not appropriate to test their conjunction.[21]

[21] I have tested the conjunction and find that a decrease in risk aversion significantly decreases $V^N - V^A$ when experience is less than the mean and does not significantly affect $V^N - V^A$ when experience is greater than the mean. The difference between the two estimates is, however, not significant.

2.6.2 Results

Table 2.3 shows the main results. Columns 1 - 3 show the results of regression (2.5) for the Malawi data. The columns differ in how risk tolerance is treated. Column 1 uses the raw risk tolerance categories based on Question 2. The interpretation of the marginal effect is difficult with this measure. In Column 2 I convert the raw measures to percentiles. In this column coefficients on RT measure the impact of a 10 percentile increase in how risk tolerant the household is. Column 3 uses a discrete measure of RT. Households with above median risk tolerance are coded as 1 and those with below median risk tolerance are coded as 0. All three columns include controls for household characteristics (sex, age and years of schooling of the head, house quality, total income, land holdings and whether the household has ever been a member of the SHG committee), a dummy for the region and a control for the distance to the rainfall gauge.[22]

All three columns support the three hypotheses. Consider first Hypothesis 1 (that $V^A < V^N$). The coefficient on $AA.Treat$ is always negative and strongly significant. Comparing the coefficient on *Treat* and $AA.Treat$ in Columns 1 and 2 implies that among risk averse and inexperienced AN households, insurance increase takeup by 10 to 15%. In contrast AA households decrease takeup by around 25% when offered insurance. These are large numbers given that the mean takeup among AN households in the control group group is roughly 30%.

Second, consider Hypothesis 2 (that $V^N - V^A$ is increasing in risk aversion). Columns 1 - 3 all show a large and statistically significant decrease in $V^N - V^A$ in response to an increase in risk tolerance. Column 2 is the easiest to interpret. It says that a 10 percentile increase in RT decreases $V^N - V^A$ by 4 percentage points. The same column estimates $V^N - V^A$ to be 40% indicating that a move from the 0 percentile of RT to the 100th percentile completely removes the differential impact of ambiguity aversion. It is also interesting to note that columns 1 - 3 all show the intuitive comparative static that among AN households, an increase in RT (decrease in risk aversion) leads to a decrease in the value of insurance. In contrast, when AA is not accounted for this data suggests that risk tolerance leads to higher insurance demand (see Giné and Yang 2009).

Third, the data strongly supports Hypothesis 3 (that $V^N - V^A$ is deceasing in experience). Columns 1 - 3 all show a large and statistically significant coefficient on the interaction $AA.Exp.Treat$ indicating that $V^N - V^A$ is decreasing in experience. The results suggest that 1 year of additional experience with groundnut decreases the difference between AA and AN households by percentage point. At the median level of risk aversion, column 3 indicates that $V^N - V^A$ is equal to approximately 25% suggesting that 20 years experience is required for the behavior of AA

[22] I discuss distance to the rainfall gauge and its important in more detail below.

Table 2.3: The Impact of Ambiguity Aversion on Adoption. Dep Var Takeup. OLS

	Malawi			*Kenya*		
	1	2	3	4	5	6
Risk Measure	*Raw*	*Percentile*	*Discrete*	*Raw*	*Percentile*	*Discrete*
AA	0.273**	0.320**	0.116*	0.160*	0.190	0.178**
	(0.100)	(0.122)	(0.059)	(0.084)	(0.118)	(0.078)
RT	0.040**	0.029**	0.160**	0.014	0.017	0.144
(RA Kenya)	(0.016)	(0.013)	(0.076)	(0.010)	(0.013)	(0.084)
Treat	0.092	0.148	0.003	0.472***	0.530***	0.427***
	-0.139	(0.154)	(0.136)	(0.109)	(0.154)	(0.102)
AA.Treat	**-0.388*****	**-0.449*****	**-0.234*****	**-0.412****	**-0.490****	**-0.376****
	(0.118)	**(0.142)**	**(0.076)**	**(0.162)**	**(0.227)**	**(0.143)**
AA.RT	-0.063**	-0.044**	-0.239**	-0.019	-0.021	-0.231
(AA.RA Kenya)	(0.023)	(0.018)	(0.112)	(0.015)	(0.020)	(0.135)
RT.Treat	-0.042**	-0.034**	-0.237**	-0.023	-0.029	-0.160
(RA.Treat Kenya)	(0.020)	(0.016)	(0.107)	(0.018)	(0.025)	(0.153)
AA.RT.Treat	**0.063****	**0.046****	**0.275****	**0.037**	**0.045**	**0.327**
(AA.RA.Treat Kenya	**(0.027)**	**(0.020)**	**(0.129)**	**(0.024)**	**(0.033)**	**(0.216)**
Exp	-0.001	-0.001	0.000	0.036*	0.035*	0.036*
	(0.004)	(0.003)	(0.004)	(0.019)	(0.019)	(0.019)
Exp.Treat	-0.004	-0.004	-0.004	-0.040*	-0.039	-0.040*
	(0.006)	(0.005)	(0.006)	(0.023)	(0.023)	(0.023)
AA.Exp	-0.002	-0.002	-0.003	-0.034	-0.033	-0.034
	(0.003)	(0.003)	(0.003)	(0.021)	(0.021)	(0.021)
AA.Exp.Treat	**0.010****	**0.010****	**0.010****	**0.054***	**0.054***	**0.054***
	(0.005)	**(0.005)**	**(0.005)**	**(0.028)**	**(0.028)**	**(0.028)**
Mean DV	0.305	0.305	0.305	0.170	0.170	0.170
Treat = 0 AA = 0	(0.036)	(0.036)	(0.036)	(0.039)	(0.039)	(0.270)
Observations	731	731	731	409	409	409
R-squared	0.160	0.160	0.159	0.219	0.218	0.209

*** $\Rightarrow p < 0.01$, ** $\Rightarrow p < 0.05$, * $\Rightarrow p < 0.1$. Standard errors clustered at the level of randomization. Controls Malawi: Region, age, female, female household head, years of schooling, house quality, land owned, income at baseline, saving account and committee member. Controls Kenya: Region, age, female head, head schooling, head literate, house quality, saving account, land owned, officer of SHG, time with SHG .

and AN households to converge, although this calculation may take the linearity assumption inherent in (2.5) too seriously.

Columns 4 – 6 present the results of regression (2.6) using the Kenya data. Again the columns differ in the risk aversion measure used. The regressions include controls for a similar set of demographic variables and dummy variables for region.

All three columns strongly support Hypothesis 1. Among the least experiences and most risk tolerant households, the credit treatment increased adoption by AN households by approximately 35% from a base of 18%. The increase for AA households was, however, significantly less as shown by the strongly negative coefficient on $AA.Treat$. In fact, the estimates imply that AA households do not gain from the credit.

Hypothesis 3 is also supported in the data. All three columns show a positive coefficient on $AA.Exp.Treat$ although the coefficient is only significant at the 10% level ($p \in [0.62, 0.7]$ for all three columns). This may reflect the small number of households with experience with the export crop. Only 98 of the 409 households report having any experience with the export crop. The coefficient on $AA.Exp.Treat$ in Column 6 indicates that it requires around 6-years of experience for the behavior of AA households to converge to that of AN households.

Finally, the data provides some limited support for the proposition that $V^N - V^A$ is decreasing in risk aversion. The theory suggests that this may be the case, although it is not 100% clear. The coefficient on $AA.RA.Treat$ is positive in all three columns columns, although it is never statistically significant at conventional levels ($p \in [1.32, 1.81]$ depending on the column).

2.7 Alternative Explanations

In this section I discuss other models that could explain the results. Because the results are based on experimental data the regressions above accurately identify the heterogeneous treatment effects. For example, the coefficient on the interaction $AA.Treat$ is the impact of insurance on households that are measured to be ambiguity averse. Consequently any confound must come from omitted variables that are correlated with AA, RA or Exp, but are not included in the regressions. Moreover, these omitted variables cannot simply be correlated with demand for the new crop. Because I interpret only coefficients on terms which are interacted with $Treat$, potential confounding variables must cause low demand for insurance. In terms of the model, the results are robust to correlations between RA, AA or Exp and α.

What sort of missing variables should be cause for concern? I make two main policy claims in the paper. First I claim that ambiguity averse households are uninsurable even though they perceive risk and second I claim that experience with the new crop mitigates the impact of ambiguity. The first claim depends crucially on CDC and is not directly demonstrated in the paper as I have access to only one insurance contract in each setting. I use the secondary implications of the model to argue that the data is consistent with a model in which households that are measured to be AA exhibit CDC. If measured ambiguity aversion is correlated with a different characteristic, then we should be concerned that households measured to be AA do not display CDC. Alternative explanations would require that households measured to be AA either A) do not care about risk, B) perceive the insurance to be risk increasing, C) have a land holding such that the insurance actually is risk increasing or D) do not trust the insurance to payout. I discuss each of these possibilities under their own headings below.

The second policy claim is that the the implications of AA can be ameliorated through experience with the new crop. To support this claim I show that the difference in insurance demand between AA and AN households is decreasing in experience. In my model the differences in experience would be driven by differences in α. Other household characteristics, however, might cause households to become experienced and also be correlated with insurance demand. If this is the case then it is not possible to put a causal interpretation on the impact of experience. The main reason to believe that the effect is causal is that it is hard to think why an omitted variable that causes experience should have differential impacts on the insurance demand for AA and AN households, as shown in Table 2.3. Nevertheless, the following sections consider the possibility that trust and risk tolerance are jointly correlated with measured ambiguity aversion and experience. The evidence tends to suggest that these potential confounds do not drive the results.

2.7.1 Households Measured to be AA are Risk Tolerant

If measured ambiguity aversion is correlated with risk tolerance, this could drive the main implication that AA households demand less insurance. There are, however, several reasons to believe this is not the case. First, Table 2.3 shows that households measured to be AA increase demand for insurance as risk tolerance increases while the opposite is true of those measured to be ambiguity neutral. This result is difficult to explain with a model in which AA households are merely more risk tolerant. Second, an explanation based entirely on risk tolerance cannot easily explain the differential impact of experience on the value of insurance. Third, as discussed in Section 2.4.2 the simple model of limited liability insurance does not support the idea that the value of limited liability should be increasing in risk aversion. Explaining the results from both Kenya and Malawi, therefore, requires more than just a correlation between measured AA and risk tolerance.

Finally, suppose that the modeling of ambiguity aversion based on VEA preferences is completely wrong and all the data can be explained by a correlation between measured AA and risk tolerance. Then, consider estimating

$$\begin{aligned} Takeup_i = \beta^0 + \beta^1 AA_i + \beta^2 Exp_i + \beta^3 Treat_i + \beta^4 AA_i \cdot Treat_i + \\ \beta^5 AA_i \cdot Exp_i + \beta^6 Exp_i \cdot Treat_i + \beta^7 AA_i \cdot Exp_i \cdot Treat_i + \\ \beta^7 RT_i + \beta^8 RT_i \cdot Treat_i + \beta^9 RT_i \cdot Exp_i + \beta^{10} RT_i \cdot Exp_i \cdot Treat_i + \eta_i. \end{aligned} \tag{2.7}$$

Suppose that RT is an imperfect measure of risk tolerance, but that it is correlated with a single dimensional behaviorally relevant measure of risk aversion. Under these assumptions, if risk tolerance is driving the results, estimating (2.7) with and without the controls for RT will lead to a change in the estimates of β^4 and β^7. Table 2.4 shows the results of doing this for both data sets. Columns 1 and 2 show the results for Malawi and 3 and 4 for Kenya. In both cases the odd column shows the coefficients without risk tolerance controls and the even columns show the results with the controls. The table shows that the estimates do not change substantially, and if anything move in the opposite direction required for risk tolerance to explain the results.[23] The only way in which a correlation between risk tolerance and measured AA can explain all the results is if the measure of risk tolerance in the data is uncorrelated with true risk aversion.

2.7.2 Households Measured to be AA Perceive Insurance to be Risk Increasing

To derive the implication that $V^N - V^A > 0$ implies CDC I use assumption 1 – that insurance is valuable given pre-insurance beliefs. This assumption coupled with the assumption that $\mathcal{C}^N \subset \mathcal{C}^A$ rules out the possibility that AA households simply perceive the new crop to be less risky. There are several reasons to believe that this possibility does not explain the results. First, in Malawi this explanation would require that households measured to be AA believe that the new crop is more drought resistant. Given the weather patterns in the area this is a particularly optimistic view of the crop. It seems unlikely that this optimistic view would be correlated with a question designed to measure some sort of pessimism. There is some evidence that this is not the case. Households in Malawi were asked whether they believe the new crop is more of less drought resistant than an older version of the crop. There is no statistically significant differences between their responses and if anything AA households were less likely

[23] Note that the results in Table 2.4 differ from those in Table 2.3 as equation 2.7 does not allow for RT to have a differential impact on those who are AA. This is consistent with the counterfactual that there is in fact nothing different about AA households except for the correlation between measured AA and risk tolerance.

Table 2.4: The Impact of Ambiguity Aversion On Take-up – With and Without Risk Aversion Controls

	Malawi		*Kenya*	
	1	2	3	4
Risk Control	*N*	*Y*	*N*	*Y*
AA	0.042	0.043	0.053	0.057
	(0.053)	(0.051)	(0.061)	(0.059)
Treat	-0.061	-0.016	0.333***	0.360***
	(0.136)	(0.177)	(0.088)	(0.086)
Exp	0.000	-0.011	0.034	0.034
	(0.004)	(0.007)	(0.020)	(0.026)
AA.Treat	**-0.156****	**-0.158****	**-0.188****	**-0.193****
	(0.071)	**(0.067)**	**(0.086)**	**(0.082)**
AA.Exp	-0.002	-0.001	-0.032	-0.034
	(0.003)	(0.003)	(0.021)	(0.021)
Exp.Treat	-0.004	-0.004	-0.037	-0.042
	(0.006)	(0.010)	(0.024)	(0.029)
AA.Exp.Treat	**0.010****	**0.010****	**0.051***	**0.053***
	(0.005)	**(0.004)**	**(0.028)**	**(0.028)**
Mean DV	0.305	0.305	0.170	0.170
Treat = 0 AA = 0	(0.036)	(0.036)	(0.039)	(0.039)
Observations	731	731	409	409
R-squared	0.153	0.162	0.211	0.212

$^{***} \Rightarrow p < 0.01$, $^{**} \Rightarrow p < 0.05$, $^{*} \Rightarrow p < 0.1$. Standard errors clustered at the level of randomization. Controls Malawi: Region, age, female, female household head, years of schooling, house quality, land owned, income at baseline, saving account and committee member. Controls Kenya: Region, age, female head, head schooling, head literate, house quality, saving account, land owned, officer of SHG, time with SHG .

to believe that the new crop is drought resistant. Second, in the context of limited liability credit, explaining the results would require that AA households believe that their income is less likely to fall below the limited liability constraint. Again, this belief seems unlikely to be correlated with a question designed to measure pessimism and there is again some evidence against the interpretation. Households in the Kenya survey were asked a series of questions regarding how optimistic they are. An index was created from these questions and as shown in Table 2.2 households measured to be AA self reported as being less optimistic.

2.7.3 Insurance is Risk Increasing for Households Measured to be AA

Explaining the Malawi results in Table 2.3 requires both that AA households have less need of insurance *and* that the insurance is risk increasing for them. An alternative explanation for low demand for index insurance, which can deliver both these implications, is basis risk. The simple idea is that rainfall on a farmers plot will not be perfectly correlated with the rainfall measure. There may, therefore be states in which the insurance is costly, but the rainfall on the actual plot was very low. It can be shown that even if the correlation between actual rainfall and measured rainfall is quite high it is possible for risk averse farmers to believe that rainfall insurance is risk increasing. There are two reasons to believe that this is not driving the results. First, it seems unlikely that basis risk is correlated with whether a household was measured to be AA. Second, the Malawi data contains a measure of distance from the household to the rainfall gauge. So long as plot location is correlated with household location this measure will be correlated with basis risk. Table 2.1 shows that this measure is not correlated with measured AA, although AA households were more likely not to know the location of the rainfall gauge. In order to verify that distance to the gauge does not drive the results I undertook a similar analysis to that in Section 2.7.1 estimating (2.5) with and without controls for distance to gauge (or the fact that it is missing) and its interaction with Exp, $Treat$ and RT. The inclusion of the controls has almost no impact on the coefficients of interest implying that basis risk can only explain the results if measured distance to gauge is uncorrelated with true basis risk.

2.7.4 Households Measured to be AA are Low Trust

It is possible that households that are low trust avoided the ambiguous urn in Question 1 as they did not trust the experimenter not to alter the composition of the urn. Indeed, Table 2.1 suggests that this may be the case – AA households are less trusting according to a series of generalized trust questions.

This correlation between AA and trust may drive the results. A low trust household may not trust the insurance company to pay out. Further, this possibility could also drive the risk tolerance and experience results. Concern about non-payment is likely increasing in risk aversion and experience with the new crop may increase trust in sellers of the seeds and NGOs. There are, however, several reasons why trust is unlikely to explain the results. First, Question 1 was not incentivized. As such, it is more of a conceptual question and there is need for the respondent to trust the experimenter. Second, it seems hard to explain the Kenya results as based on trust. The Kenyan experiment involves giving credit and there is no real need for the household to trust the credit company in order to benefit from credit. The argument would have to be that the household does not trust the company not to collect it even when it has income below the limited liability constraint. This seems like a stretch.

Third, the Malawi data set contains a large number of trust questions, both specific to the NGO selling the seeds and providing the insurance and also general trust questions. I conduct a similar analysis to that in Table 2.4 presenting results both with and without controls for measured trust and its interactions. Table 2.5 shows the results. The first column reports the regression coefficients from Column 2 of Table 2.3 (I use the percentile measure of risk tolerance as it is easiest to interpret. The results are not sensitive to this choice). Columns 2 - 5 have controls for trust measures designed to measure trust in the rain gauge, the insurance company, the finance companies providing the seeds and general trust. The questions in columns 2 - 4 are of the form "On a scale of 1 - 10 how much do you trust ... " while the generalized trust questions are similar to those in the GSS and Glaeser et al. (2000).[24] The Table shows that the inclusion of the trust controls do not substantially change the coefficients of interest. Consequently, for trust to explain the results, it would have to be the case that these 4 trust measures are not correlated with the true value of a households trust.

While these arguments suggest that trust does not drive the results, it is also not clear that we should be too concerned if the results are driven by trust. A model of trust which gives the experience and risk aversion results reported in Table 2.3 has very similar implications to the ambiguity aversion model presented in Section 3.3. The major difference would appear to be the methods through which marketing could be used to increase the demand for insurance. For example, trust may be increased by changing the person selling the insurance contract, while ambiguity may be avoided by marketing aimed to alter the status-quo. Much more research is required to determine which, if any, of these suggestions are effective whether trust or ambiguity is the relevant behavioral notion.

[24] There is some evidence that these questions do not capture trust well. See Glaeser et al. (2000).

Table 2.5: The Impact of Ambiguity Aversion On Take-up – With and Without Risk Aversion Controls

	Malawi				
	1	2	3	4	5
Trust Control	*None*	*Rain Gauge*	*Insurance*	*Finance*	*General*
AA	0.320**	0.306**	0.308**	0.363**	0.301**
	(0.122)	(0.118)	(0.121)	(0.134)	(0.124)
RT	0.029**	0.022	0.0267**	0.024	0.0238*
(RA Kenya)	(0.013)	(0.013)	(0.012)	(0.016)	(0.012)
Treat	0.148	0.062	0.154	0.376*	0.118
	(0.154)	(0.155)	(0.158)	(0.210)	(0.145)
AA.Treat	**-0.449*** **	**-0.478*** **	**-0.458*** **	**-0.517*** **	**-0.433*** **
	(0.142)	**(0.154)**	**(0.144)**	**(0.156)**	**(0.141)**
AA.RT	-0.044**	-0.045**	-0.042**	-0.044**	-0.042**
(AA.RA Kenya)	(0.018)	(0.017)	(0.017)	(0.018)	(0.017)
RT.Treat	-0.034**	-0.022	-0.036**	-0.034	-0.029*
(RA.Treat Kenya)	(0.016)	(0.025)	(0.016)	(0.023)	(0.015)
AA.RT.Treat	**0.046** **	**0.050** **	**0.049** **	**0.050** **	**0.050** **
(AA.RA.Treat Kenya)	**(0.020)**	**(0.022)**	**(0.020)**	**(0.021)**	**(0.020)**
Exp	-0.001	0.000	0.000	0.001	0.000
	(0.003)	(0.004)	(0.004)	(0.005)	(0.004)
Exp.Treat	-0.004	-0.002	-0.004	-0.008	-0.005
	(0.005)	(0.006)	(0.005)	(0.007)	(0.006)
AA.Exp	-0.002	-0.001	-0.002	-0.005	0.000
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)
AA.Exp.Treat	**0.010** **	**0.011***	**0.010** **	**0.014** **	**0.009***
	(0.005)	**(0.006)**	**(0.005)**	**(0.006)**	**(0.005)**
Mean DV	0.305	0.305	0.305	0.305	0.305
Treat = 0 AA = 0	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
Observations	731	731	731	731	731
R-squared	0.160	0.160	0.159	0.159	0.159

$^{***} \Rightarrow p < 0.01$, $^{**} \Rightarrow p < 0.05$, $^{*} \Rightarrow p < 0.1$. Standard errors clustered at the level of randomization. Controls Malawi: Region, age, female, female household head, years of schooling, house quality, land owned, income at baseline, saving account and committee member. Controls Kenya: Region, age, female head, head schooling, head literate, house quality, saving account, land owned, officer of SHG, time with SHG .

2.8 Conclusions

I argue that ambiguity aversion implies low demand for index insurance. The theoretical argument is strongly supported using data from two experiments in Africa. The theory suggests that index insurance will be more effective in areas where the production technology is well known and will be ineffective in promoting take-up of new technologies. A policy of short term subsidization and long-term insurance may help to alleviate low demand for the insurance and encourage take-up at the same time.

3 Risk Sharing Under Ambiguity

3.1 Introduction

In this part of the paper I consider whether ambiguity aversion can provide an explanation for the failure of complete risk sharing documented, for example, by Townsend (1994). I show theoretically that ambiguity aversion, operationalized through an assumption of VEA preferences, can explain partial but incomplete risk sharing. I then derive simple testable implications of the theory for a panel data set which has measures of consumption and income at a household level. I test the theory using two panel data sets from developing countries – the ICRISAT data and Townsend's Thai monthly panel. I am unable to reject the model using either of these data sets and I conclude that ambiguity aversion is a sufficient explanation for incomplete risk sharing in these two diverse settings.

The intuition for the theory is given by the example of the Jones's in the introduction. The theory has two testable implications. First, if the income process is symmetric in a sense made precise below, and all households are equally ambiguity averse, households that are giving (receiving) transfers in a given period will have the same beliefs. Common beliefs imply households that are giving (receiving) have the same allocation (controlling for Pareto weights). The same reasoning behind Townsend's (1994) test then implies that consumption should not be correlated with income within the group of giving (receiving) households. Second, differences in beliefs between giving and receiving households create a wedge between their consumption levels. Households whose income falls inside this wedge will choose not trade, consuming their own income. For this group of households consumption increases one-to-one with income. I simultaneously test these two implications by estimating a non-linear least squares model which estimates the "wedge" between giving and receiving households. I test that the coefficient on income is one within the wedge and zero elsewhere. The results in this paper can be seen as a simple generalization of Townsend's (1994) work. While Townsend assumes all households have the same preferences and beliefs, I relax the second assumption. All households have the same risk preferences and ambiguity preferences, but beliefs will differ at the optimal because of CDC.

Given the *vast*[1] literature on the full risk sharing hypothesis and the many plausible explanations already available for its failure, the reader may well question the need for another explanation. In my view there are two good reasons for being concerned about *exactly* why risk sharing is incomplete.

First, the model matters for policy. A typical explanation for incomplete risk sharing invokes some kind of incentive problem, for example limited commitment, moral hazard or hidden income. In each of these cases the incentive to comply with a risk sharing contract is provided by the threat of expulsion from the contract in the future. The effectiveness of informal insurance is therefore dependent on the difference in utility under the future contract and autarky.[2] Policies which seek to provide financial access to households – for example insurance, credit or saving – will tend to increase the value of autarky, thus making enforcement more challenging for the informal arrangement. Formal access to finance, therefore, has the potential to crowd out informal insurance and the policy value of such interventions is ambiguous.[3]

In contrast, risk sharing in the presence of ambiguity aversion leads to an outcome that is Pareto optimal given equilibrium beliefs of the households and there need be no incentive problem to be overcome. The finding of correlation between consumption and idiosyncratic income is therefore compatible with an absence of incentive problems.[4] As a consequence, policies that provide access to finance need not crowd out informal risk sharing. Further, while the empirical work in this paper does not allow for heterogeneity of ambiguity attitude, it is easy to show that an ambiguity neutral households that shares risk with an ambiguity averse household can benefit from an insurance policy that further mitigates idiosyncratic risk. Thus an ambiguity based explanation of risk sharing implies that formal access to insurance may be valuable, and need not have deleterious effects on informal arrangements.

Second, it is a growing consensus that explaining the relative economic deprivation of the developing world requires not just misallocation across countries, as in Lucas (1990), but also misallocation within countries (Banerjee and Duflo 2005). Understanding the frictions leading to this missalocation should, therefore, be a priority for development economists. Risk sharing contracts are one very simple setting in which it is possible to formulate rigorous tests of theories of misallocation. This justifies the emphasis on *why* risk sharing is incomplete. While studies

[1]See for example Kinnan (2010) for a brief discussion of the current literature

[2]See, for example, Ligon et al. (2002) in the context of limited commitment.

[3]See Ligon et al. 2000 for a formal proof of this possibility in the context of saving and Arnott and Stiglitz 1991 for a related discussion the context of moral hazard and insurance and Attanasio and Rios-Rull 2000 for some empirical evidence.

[4]Perfect risk sharing in the presence of heterogenous risk preferences, as studied by Mazzocco and Saini (2009) and Schulhofer-Wohl (2010), also has this implication.

that attempt to describe network based risk sharing (eg. Fafchamps and Lund 2003) may well describe what risk sharing looks like, they do not tell us why the remaining risk cannot be traded away and therefore do not give any policy direction on removing misallocation. While not a focus of this paper, an ambiguity based theory of misallocation has potentially different policy implications from the more traditional incentive based theories.

The remaining discussion of risk sharing is organized as follows. Section 3.3 introduces a formal model of risk sharing under ambiguity aversion and shows by way of example that VEA preferences can explain a positive correlation between consumption and income. Section 3.3 discusses the empirical implications of the model. The focus of that section is on formalizing a notion of symmetry which is required if the model is to have testable implications. Section 3.4 briefly discusses other relevant literature. Section 3.5 briefly describes the data and 3.6 presents the empirical results. Finally, section 3.7 offers some conclusions.

3.2 Model

3.2.1 Setting

Consider a world with one non-storable consumption good and N households. Time is discrete and there are $T+1$ time periods, $\{0, 1, \ldots, T\}$. There are S states of nature, indexed by s, and one state is realized in each period. Ea ch household receives, in each period, an endowment of the single consumption good. The endowment depends on the state s realized in the period. Denote the endowment of household i in state s, y_s^i. All household are ambiguity averse and share a common (closed convex) *set* of priors Π where $\pi \in \Pi$ is a prior $\{\pi_1, \ldots, \pi_S\}$ such that $\pi_s \in (0,1)$ for all $s \in S$ and $\sum_{s \in S} \pi(s) = 1$.

Households assess streams of state contingent consumption $c^i = \{c_{st}^i\}_{s \in S, t \in T}$ according to the criterion

$$U(c^i) = \sum_{t=0}^{T} \delta^t \min_{\pi_t \in \Pi} \left(\sum_{s \in S} \pi_{st} \left(u(c_{st}^i) - u(y_s^i) \right) \right), \tag{3.1}$$

where u is a twice continuously differentiable, strictly concave utility function that is common to all households, δ is a common discount rate and π_t denotes an element of Π which the household chooses in order to assess consumption in period t. Objective (3.1) is a dynamic extension of the VEA preferences in (1.1) and embodies the assumption that households behave consistent with backward induction and reassess probabilities in each period.

An optimal risk sharing contract in this setting is a state contingent consumption plan, $c = \{c^1, \ldots, c^N\}$, which specifies for each household i a consumption level c_{st}^i for each state and time period and is the solution to

$$\begin{aligned} &\underset{c}{\text{argmax}} \sum_{i=1}^{N} \mu_i U(c^i) \text{ subject to} \\ &\sum_{i=1}^{N} c_{st}^i \leq \sum_{i=1}^{N} y_{st}^i \; \forall s \in S \;\&\; t \in T. \end{aligned} \tag{3.2}$$

I return to the general solution to this problem in section 3.3, but begin by discussing a simple static two state example that illustrates the main characteristics.

3.2.2 An Edgeworth Box Economy

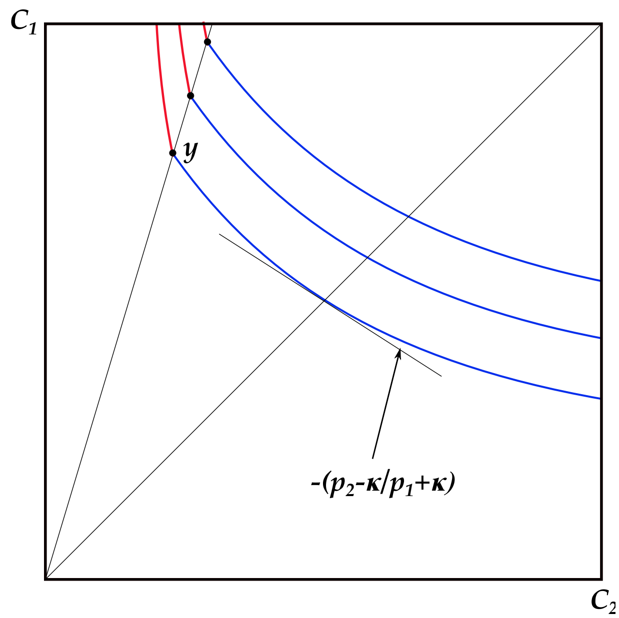
In this section I discuss the solution to problem (3.2) in a static example with two households, A and B, two states of the world, 1 and 2, and no aggregate uncertainty. In this context the set of priors can be parameterized so that $\Pi = \{p_1 + \alpha, p_2 - \alpha\}$ with $\alpha \in [-\kappa, \kappa]$ and $p_1 + p_2 = 1$. The paremeter κ determines the size of the set Π and is a measure of ambiguity.[5]

Figure 3.1 shows an example of a housholds indifference curves. The point y is the endowment point and the indifference curves are "kinked" along a ray from the origin through the endowment point. "Below" the endowment point, the indifference curves have a slope $-(p_2 - \kappa)u'(c_2)/(p_1 + \kappa)u'(c_1)$ and "above" the endowment point the indifference curve has slope $-(p_2 + \kappa)u'(c_2)/(p_1 - \kappa)u'(c_1)$. As a consequence, the kink becomes more extreme as κ increases.

In the absence of ambiguity ($\kappa = 0$), if households have the same utility function, agree on probabilities, and there is no aggregate uncertainty, the optimal risk sharing contract lies on the certainty line. With ambiguity, however, this is no longer the case. Figure 3.2 illustrates this implication in an Edgeworth box. The certainty line lies below the endowment for household A, but above the endowment for household B. As a consequence, the indifference curves do not have the same slope at the certainty line. When considering an allocation on the certainty line, household A believes that state 1 is relatively more likely and state 2 is relatively less likely. Household B's beliefs are the opposite and, as a consequence, household A is willing to make a transfer to household B in state 2 in return for a transfer in state 1. This moves the optimal contract away from the certainty line toward the endowment. This effect enables ambiguity

[5] κ can be thought of as a measure of both ambiguity and ambiguity aversion. I assume throughout that all households have the same degree of ambiguity averse and perceive the same amount of ambiguity in any state. The distinction between the two concepts, therefore, has no relevance in this context. For a discussion of the issues involved see, for example, Ghirardato et al. (2004).

Figure 3.1: Indifference Curves for VEAP Preferences



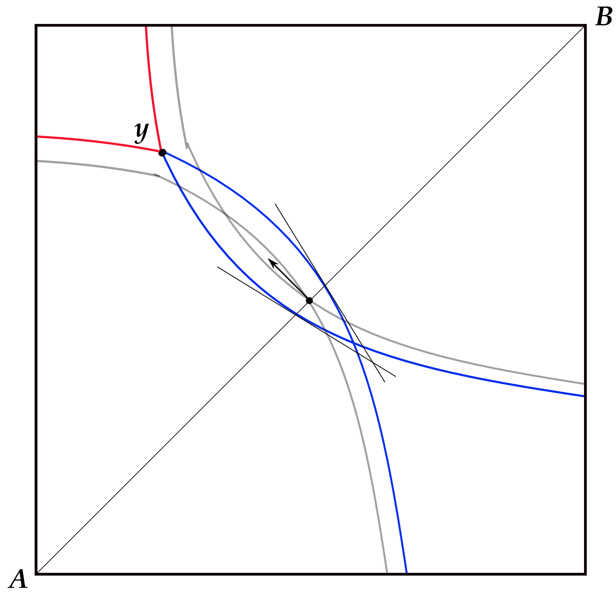
aversion with VEA preferences to explain partial, but incomplete insurance.

To give a concrete example, suppose $u = \ln$, $p_1 = p_2 = \frac{1}{2}$, $\kappa = \frac{1}{4}$, $y^1 = \{25, 5\}$ and $y^2 = \{5, 25\}$. The optimal risk sharing contract in this setting is

$$
\begin{aligned}
c^1 &= \{\frac{45}{2}, \frac{15}{2}\} \\
c^2 &= \{\frac{15}{2}, \frac{45}{2}\}.
\end{aligned}
$$

with $\alpha = -\kappa$ for household A and κ for households B. In the example $c_i = 3.75 + 0.75 y_i$ showing that consumption is correlated with income even after controlling for a fixed effect for each household and a time effect (both of which are zero in this setting). Thus the model generates an explanation for the correlation between consumption and income that is found in many empirical studies. The correlation occurs because households that have high income believe that they will be giving it away. The model then implies that these households believe that this state is more likely and as a consequence households with higher income receive more of the aggregate endowment.

Figure 3.2: Perfect Risk Sharing is Not Optimal With VEAP



3.3 Testable Implications

I this section I derive testable implications of the theory. I first provide some intuition and then discuss the more general case including the symmetry assumption alluded to in the introduction.

3.3.1 Intuition For a Test of The Theory

Having established that the model is capable of explaining the results of Townsend (1994), this section provides some intuition for a test of the theory. I continue with the Edgeworth Box example and use Figure 3.3 to illustrate the argument.

Suppose that there are an even number of households $\{1, \ldots, N\}$ that can be paired (A, B) so that $y_s^A + y_s^B = constant$ for all pairs and states. Further assume that expected income $(\frac{1}{2}y_1^i + \frac{1}{2}y_2^i)$ is the same for all households as are the Pareto weights. In Figure 3.3 these assumptions imply that all endowments lie on the line DD' with A households having $y_1^A \geq y_2^A$ and B households having $y_1^B \leq y_2^B$.

Consider first a pair of households with endowment at y. An optimal contract between this pair (with equal Pareto weights) is found where their indifference curves are tangent. This is some point c, below the endowment. Because the indifference curves are kinked at the endowment point, all pairs of households with an endowment between c and D also have tangent indifference curves at c. As a consequence, for those pairs with endowments above c, all B households will have the same consumption as will all A households. Next consider pairs of agents with endowments between c and D'. For these agents there is no feasible allocation which dominates the endowment and therefore these households will not trade.

This discussion suggests that there are three groups of households. Those with endowment below c consume their own endowment. For those agents with endowments above c, A households consume relatively more in state 1 while B households consume relatively more in state 2. The key implication of the theory is that for those who are above c, if we know whether they are A or B households, income is not correlated with consumption. Fortunately, it is possible in any state to divide the households into groups A and B as households in these groups are either all making transfers or all receiving transfers. That is we can write consumption as

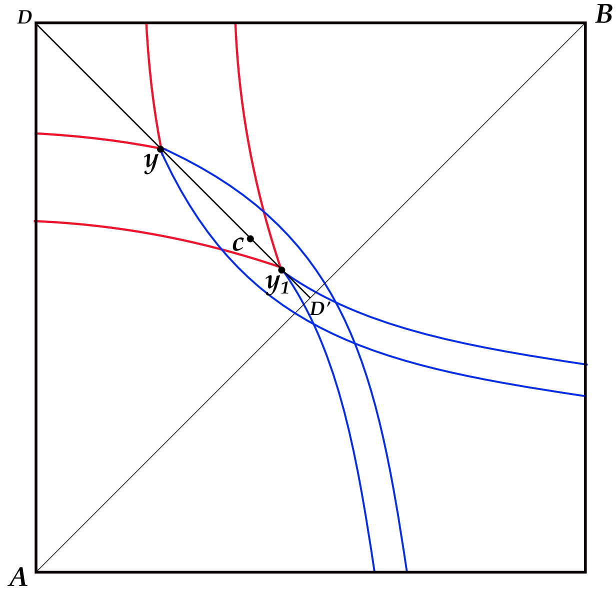
$$c_i = \begin{cases} \lambda + f(\kappa) & if \quad y_i > \lambda + f(\kappa) \\ y_i & if \quad y_i \in [\lambda - f(\kappa), \lambda + f(\kappa)] \\ \lambda - f(\kappa) & if \quad y_i > \lambda + f(\kappa) \end{cases}$$

where λ is average income and f is an increasing function of κ, the degree of ambiguity. In Figure 3.3, $c = \{\lambda - f(\kappa), \lambda + f(\kappa)\}$.

This implication of the theory can be tested in a manner analogous to the test in Townsend (1994). Controlling for λ and $f(\kappa)$, consumption should be uncorrelated with income for those with income outside the set $[\lambda - f(\kappa), \lambda + f(\kappa)]$ and perfectly correlated for those within that set. This is essentially the test proposed in this paper. The next section considers extending the discussion of this section to a more general setting.[6]

[6]The structure of this test, which essentially looks for perfect risk sharing within two groups – the giving households and the receiving households – also suggests a novel test for the limited commitment risk sharing model of Kocherlakota (1996) and Ligon et al. (2002). In that model, risk sharing is imperfect as households with high incomes are "constrained" in their willingness to make sufficiently large transfers. Informally, households are only willing to make transfers for which they expect to receive recompense in the future. This logic implies that households receiving transfers in two consecutive periods cannot be constrained in either period and consequently, within this set of households, consumption should not be correlated with income. This test is not strictly implied by the test I present here as the fixed effects I estimate are not valid for this model. I, therefore, leave the implementation of this test for future work.

Figure 3.3: Empirical Implications of VEAP



3.3.2 General Testable Implications

The empirical test outlined above is feasible because it is possible to infer the "group" that a household is in simply by observing consumption and income in one state. This is essential as any data set will contain only a subset of the households and a subset of the states. In this section I first discuss two examples in which income in a (potentially unobserved) state implies that consumption differs among otherwise identical households, rendering the theory untestable. This discussion motivates an assumption regarding the perceived income process, which rules out this type of behavior. Given the symmetry assumptions inherent in the Edgeworth Box example, it will be no surprise that the assumption requires a degree of symmetry regarding the income process and ambiguity relative to a household's Pareto weight. Having outlined the assumption I discuss its interpretation and show that it leads to a multi-state analog of the test discussed in the previous section.

Example 3 (The Adding Up Problem)**.** *Suppose there are three households A, B, C, three states of the* *world* $\{1,2,3\}$ *and* $u = \ln$. *All households have the same Pareto weight and endowments are*

$$\begin{aligned} A &= \{10, 23, 1\} \\ B &= \{10, 5, 1\} \\ C &= \{1, 2, 28\}. \end{aligned}$$

Assume that $\Pi = \{\frac{1}{3} + \alpha, \frac{1}{3} - \alpha - \beta, \frac{1}{3} + \beta\}$ *for* $\alpha, \beta \in \left[-\frac{1}{12}, \frac{1}{12}\right]$.

A conjecture for equilibrium beliefs is that $\alpha_A = \beta_A = -\frac{1}{12}$, $\alpha_B = \frac{1}{12}$, $\beta_B = -\frac{1}{12}$ *and* $\alpha_C = -\frac{1}{12}$, $\beta_C = \frac{1}{12}$. *This follows as household A believes that state* 2 *will lead to the largest loss relative to the endowment, while state* 3 *will lead to the greatest gain. Hence households A will choose a prior that maximizes the probability of state* 2 *and minimizes the probability of state* 3. *A similar argument applies to the other households. These beliefs lead to an optimal allocation*

$$\begin{aligned} A &\approx \{5.7, 12.9, 8.2\} \\ B &\approx \{9.5, 8.6, 8.2\} \\ C &\approx \{5.7, 8.6, 13.6\}, \end{aligned}$$

and it is then possible to check that the minimizing prior given this allocation is as conjectured.

As these allocations show households A and B are giving in state 1, and they are both identical, but they receive different amounts. Thus it is not feasible to run the test discussed in the previous section because beliefs of the households are not controlled only by their income relative to the optimal in a particular state. The problem occurs because in state 2, which may not be observed, household A receives a very large allocation relative to B. Therefore, for A, state 1 is the most costly state while for households B state 1 is the most costly state. The requirement that the probabilities add to 1 then implies that households A and B cannot have the same beliefs in state 1.

Example 4 (Optimistically Giving)**.** *Suppose that there are three agents* $\{A, B, C\}$, *two states of the world* $\{1,2\}$ *and that* $u = \ln$. *Agent A has endowment* $\{4.75, 10\}$ *agent B has endowment* $\{5.25, 0\}$ *and agent C has endowment* $\{4.75, 5.25\}$. *Let* $\Pi = \{\frac{1}{2} + \alpha, \frac{1}{2} - \alpha\}$ *where* $\alpha \in [-0.05, 0.05]$.

Consider first agent C. There is a prior in Π *such that the endowment point is preferred to any other allocation* $\{4.75 + t, 5.25 - t\}$ *for all t. As a consequence C does not trade. Next consider households A and B. It seems reasonable to conjecture that state* 2 *will be the worst state for agent A and the best state for agent B regardless of what occurs in state* 1. *This in turn implies that* $\pi_2^A = 0.55$ *and* $\pi_2^B = 0.45$.

Under this assumption the social planner solves

$$\max_{\{c_1^i, c_2^i\}_{i=A,B}} \left(0.45\ln(c_1^A) + 0.55\ln(c_2^A) + 0.55\ln(c_1^B) + 0.45\ln(c_2^B)\right),$$

subject to

$$c_1^A + c_1^B = 10 = c_2^A + c_2^B.$$

Solving this problem we find final allocations

$$\begin{aligned} c^A &= \{4.5, 5.5\} \\ c^B &= \{5.5, 4.5\} \\ c^C &= \{4.75, 5.25\}. \end{aligned}$$

Suppose that the econometrician knows the Pareto weights for the agents $\mu_i = \frac{1}{3}$ then if only state is observed 1 households A and C look identical, but do not act the same. This occurs because the endowments of A and C differ in the unobserved state 2. Household A has a very high endowment in state 2 and consequently this will be the worst state relative to the endowment even if households A actually gives money away in state 1. For households C, on the other hand

This outcome is ruled out in the Edgeworth Box example above as I impose individual rationality. That is, the contract has to be preferred to the endowment point. This is clearly not the case for the optimal contract calculated here as households 1 is making a transfer in both states. If, for example, the Pareto weight is ~ 0.704929 for household A then the equilibrium is one with trade in both states and with imperfect risk sharing and the same as the equilibrium respecting individual rationality.

Both examples occur due to a lack of symmetry. The adding up problem cannot occur if, for each state in which a households makes a transfer there is a state with the same amount of ambiguity in which the household receives a transfer. Similarly the optimistic giving example cannot occur if, for each state in which a household has an endowment "close" to the optimal such that trade would not be optimal for some $\alpha \in [-\kappa, \kappa]$ there is another state for which this is also true.

To state this assumption formally, assume that the set S can be partitioned in to two subsets S' and S'' and that for all states $s' \in S'$ the set Π is such that $\pi_{s'} = p_{s'} + \alpha$ for $\alpha \in [-\kappa_{s'}, \kappa_{s'}]$. I assume the following regarding the states in S''.

Assumption 3 (Symmetry)**.** *Let $\hat{c}_s$ be the solution to the problem*

$$\underset{c_s^i}{\operatorname{argmax}} \sum_{i=1}^{N} \mu_i \left(\min_{\alpha^i \in [-\kappa_s, \kappa_s]} (p_s + \alpha^i) \left(u(c_s^i) - u(y_s^i) \right) \right)$$

subject to

$$\sum_{i=1}^{N} c_s^i \leq \sum_{i=1}^{N} y_s^i.$$

For all s' there exists s'' such that $\pi_{s''} = p_{s''} + \alpha$ for $\alpha \in [-\kappa_{s'}, \kappa_{s'}]$, and:

1. $\hat{c}_{s'}^i < y_s^i \Leftrightarrow c_{s''}^i > y_{s''}^s$;
2. $\hat{c}_{s'}^i > y_{s'}^i \Leftrightarrow c_{s''}^i < y_{s''}^s$; *and*
3. $\hat{c}_{s'}^i = y_{s'}^i \Leftrightarrow c_{s''}^i = y_{s''}^s$.

Section 3.3.3 is devoted to the discussion of Assumption 3. That discussion shows that there are income distributions which are consistent with the assumption and gives a "psychological" interpretation of the assumption. Proposition 3 shows that Assumption 3 implies that the solution to the general programming problem (3.2) has the same simple structure as indicated by the discussion of the Edgeworth Box example.

Proposition 3 (First Order Conditions for Optimal Risk Sharing With Ambiguity)**.** *Given assumption 3 the first order conditions for problem (3.2) are*

$$u'(c_{is}) = \begin{cases} \frac{\lambda_s}{\mu_i(p_s+\kappa_s)} & \text{if} \quad u'(y_{is}) < \frac{\lambda_s}{\mu_i(p_s+\kappa_s)} \\ u'(y_{is}) & \text{if} \quad u'(y_{is}) \in [\frac{\lambda_s}{\mu_i(p_s+\kappa_s)}, \frac{\lambda_s}{\mu_i(p_s-\kappa_s)}] \\ \frac{\lambda_s}{\mu_i(p_s-\kappa_s)} & \text{if} \quad u'(y_{is}) > \frac{\lambda_s}{\mu_i(p_s-\kappa_s)}. \end{cases}$$

Proof. See Appendix F ☐

3.3.3 A Discussion of Assumption 3

The assumption essentially has three parts.

1. For all states s, there is another state s' that is equally ambiguous.
2. If state s is such that their exists an $\alpha \in [-\kappa_s, \kappa_s]$ such that households i would prefer not to trade in state s, then this is also the case in state s'.

3. If state s is such that household i will make (receive) a transfer in state s, then households i will receive (make) a transfer in state s'.

The combination of the first and second assumptions rules out Example 4 while the combination of part 1 and 3 rules out Example 3. The assumption is consistent with a situation in which two households have perfectly negatively correlated incomes, equal Pareto weights and income distributions that are symmetric with respect to ambiguity.

Assumption 3 It is also consistent with the following psychological interpretation. There are a set of rainfall states R and for each rainfall state there are two possible outcomes ϕ_1 and ϕ_2. In state ϕ_1 incomes are given by some state $s' \in S'$ while in state ϕ_2 incomes are given by the equivalent state $s'' \in S''$. The household does not know exactly the probability of sub-states ϕ_1 and ϕ_2 but $p(r, \phi_1) \in [p_r - \kappa_r, p_r + \kappa_r]$. The psychology of this interpretation is as follows. For each rainfall state there are unknown correlates ϕ (perhaps locusts as in Maggie's example) which mean that the household believes there are two possible village income distributions determined by ϕ_1 and ϕ_2. Further, these distributions are opposite, in the sense that in one the household believes they will be making a transfer and in the other they will be receiving a transfer. Under this interpretation it seems natural to view κ_r as being related to the rarity of the rainfall state r. If state r is observed often, then the households are can put probabilities on state ϕ_1 and ϕ_2 so κ_r is small. On the other hand, if state r is rarely observed, households may have no idea whether they will be giving or receiving transfers implying that κ_r is large.

3.3.4 Estimating Equations and Empirical Approach

I follow much of the risk sharing literature and assume that u is either CARA or CRRA. With either of these assumptions the first order conditions in Proposition 3 can be rewritten

$$\tilde{c}_{is} = \begin{cases} \ln \mu_i - \ln \lambda_s + \ln(p_s - \kappa_s) & \text{if } \tilde{y}_{is} < \ln \mu_i - \ln \lambda_s + \ln(p_s - \kappa_s) \\ \ln \mu_i - \ln \lambda_s + \ln(p_s + \kappa_s) & \text{if } \tilde{y}_{is} > \ln \mu_i - \ln \lambda_s + \ln(p_s + \kappa_s) \\ \tilde{y}_{is} & \text{otherwise} \end{cases}$$

where $\tilde{y}$ and $\tilde{c}$ are in levels if preferences are CARA and in logs if preferences are CRRA. This motivates an empirical specification

$$\tilde{c}_{ivt} = \begin{cases} \hat{\mu}_{iv} + \hat{\lambda}_{vt} - \hat{\kappa}_{vt} + \epsilon_{ivt} & \text{if } \tilde{y}_{ivt} < \hat{\mu}_{iv} + \hat{\lambda}_{vt} - \hat{\kappa}_{vt} \\ \hat{\mu}_{iv} + \hat{\lambda}_{vt} + \hat{\kappa}_{vt} + \epsilon_{ivt} & \text{if } \tilde{y}_{ivt} > \hat{\mu}_{iv} + \hat{\lambda}_{vt} + \hat{\kappa}_{vt} \\ \tilde{y}_{ivt} + \epsilon_{ivt} & \text{otherwise} \end{cases} \tag{3.3}$$

where subscript v refers to the village, $\hat{\mu}_{iv}$ is a household fixed effect, $\hat{\lambda}_{vt}$ is a village year fixed effect capturing village levels shocks, $\hat{\kappa}_{vt}$ is a village year fixed effect capturing the degree of ambiguity in the state realized in village v at time t and ϵ_{ivt} is a mean zero measurement error in consumption.

The fundamental implication is that once $\hat{\lambda}$ and $\hat{\kappa}$ are controlled for, income does not affect consumption for those who are trading, and for those who are not trading, income perfectly predicts consumption. My empirical strategy is to test this assertion by estimating the model

$$\tilde{c}_{ivt} = \begin{cases} (1-\alpha)(\hat{\mu}_{iv} + \hat{\lambda}_{vt}) + (\beta - \alpha)\hat{\kappa}_{vt} + \alpha y_{ivt} + \epsilon_{ivt} & \text{if } y_{it} > \hat{\mu}_{iv} + \hat{\lambda}_{vt} + \hat{\kappa}_{vt} \\ (1-\alpha)(\hat{\mu}_{iv} + \hat{\lambda}_{vt}) - (\beta - \alpha)\hat{\kappa}_{vt} + \alpha y_{ivt} + \epsilon_{ivt} & \text{if } y_{ivt} < \hat{\mu}_{iv} + \hat{\lambda}_{vt} - \hat{\kappa}_{vt} \\ (1-\beta)(\hat{\mu}_{iv} + \hat{\lambda}_{vt}) + \beta y_{ivt} + \epsilon_{ivt} & \text{otherwise.} \end{cases} \tag{3.4}$$

The empirical content of thetheory is that there exist numbers $\hat{\lambda}, \hat{\kappa}$ and $\hat{\mu}$ such that, once these are controlled for, $\alpha = 0$ and $\beta = 1$.

Figure 3.4 presents a graphical illustration of both the empirical strategy and why ambiguity aversion can explain the correlation between consumption and income. The figure shows observations from a particular village year. The blue piecewise linear line in both panels represents the model (3.3). Tests of risk sharing typically run regressions of the form

$$c_{it} = \mu_i + \lambda_t + \gamma y_{it} + \eta_{it}. \tag{3.5}$$

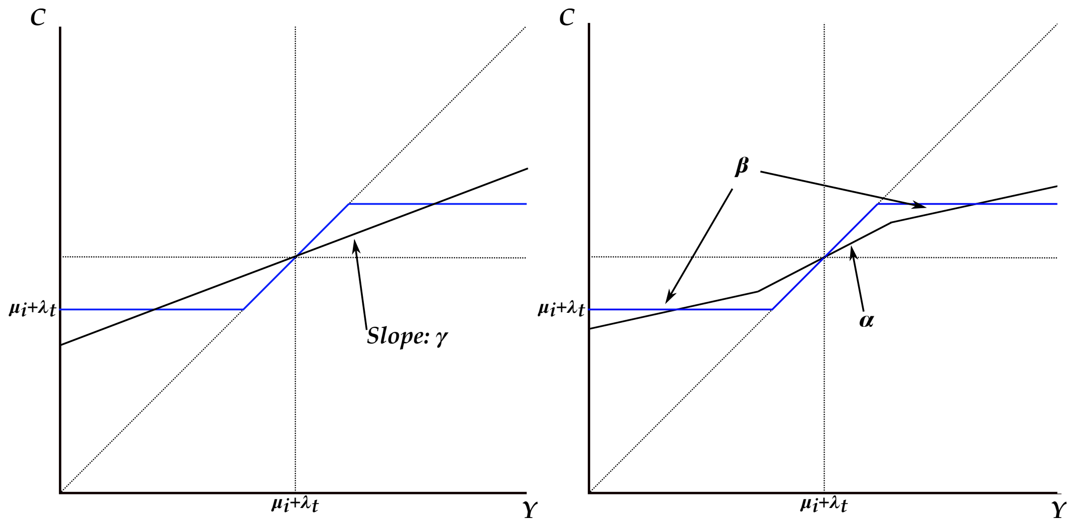
The black line in the left panel shows the fitted values from this regression if the data is generated by (3.3) and there is no heterogeneity in κ over time. The regression will find a positive estimate of γ reflecting the "wedge" created by ambiguity. The black line in the right panel illustrates the possible outcome from estimating (3.4). If the true model of the world is (3.3) then the estimates will show $\alpha = 0$ and $\beta = 1$. If, on the other hand, the kink generated by ambiguity is insufficient to explain the positive correlation between consumption and income the estimates will show $\alpha > 0$ and/or $\beta \neq 1$.

3.4 Relation to Other Implications in the Literature

3.4.1 No Trade and Ambiguity

The possibility that ambiguity aversion (or Knightian uncertainty) could lead to a failure to trade is first formalized in Bewley (1989). Rigotti and Shannon (2005) further analyze that model in a general equilibrium setting. This paper is motivates by those two papers.

Figure 3.4: Tests of Risk Sharing



3.4.2 The Empirical Risk Sharing Literature

Beyond explaining the results of Townsend (1994), the model of section 3.2 can explain two other empirical features found in the literature. First, if members of the same "risk sharing network" as identified by, for example Caste or self report, have correlated incomes, then the model implies they will appear to share risk more effectively. Thus the model can accommodate the results of, for example, Fafchamps and Lund (2003).

Second, Mazzocco and Saini (2009) show that full risk sharing can be rejected in the ICRISAT villages because pairwise expenditure functions are not monotonic. This result is, however, consistent with risk sharing in the presence of ambiguity aversion. Consider a pair of households A and B and two states of the world. In the first state of the world and in that state household A is giving and B receiving. In the second state aggregate income is higher and household A is receiving and B is giving. If their is sufficient ambiguity consumption of household B can be lower in the second state of the world, despite the fact that aggregate income is higher.

3.5 Data

The data is taken from the ICRISAT vls data set. I use consumption and income measures computed as in Townsend (1994). I also use data from the Townsend Thai Monthly panel. I use

Table 3.1: NLLS Estimates of the Impact of Income on Consumption: ICRISAT

	Townsend Test	Non-Linear Model		
	1	2	3	4
Alpha	0.109***	-	0.016	0.000
	(0.026)	-	(0.029)	(0.030)
Beta	-	-	1.221***	-
	-	-	(0.309)	-
N	1040	1040	1040	1040
R^2	0.591	0.623	0.623	0.623
SSE/10000	761.021	701.433	697.847	701.432

*** $\Rightarrow p < 0.01$, ** $\Rightarrow p < 0.05$, * $\Rightarrow p < 0.1$. Standard errors in parentheses.

the same measures of income and consumption as in Kinnan (2010). The method of constructing these measures is discussed in detail in Samphantharak and Townsend (2009). I use income constructed according to the accrual method as outlined in that monograph.

3.6 Results

I estimate (3.4) using non-linear least squares. Tables 3.1 and 3.2 present the results for the ICRISAT and Townsend Thai villages respectively. In all regressions consumption and income are in levels. I have no way to determine whether households have CRRA or CARA preferences. Consequently the empirical content of the theory is that $\alpha = 0$ and $\beta = 1$ for either log or levels regressions. As I am unable to reject the theory using levels, the results for a log specification are irrelevant. In both tables all villages are pooled, but as indicated in (3.4) I allow for villages to have different aggregate shocks and ambiguity levels.

The first column of Tables 3.1 and 3.2 presents the familiar test for perfect risk sharing. I run the regression

$$c_{ivt} = \mu_{ivt} + \lambda_{vt} + \gamma y_{ivt} + \eta_{ivt}, \tag{3.6}$$

Table 3.2: NLLS Estimates of the Impact of Income on Consumption: Townsen

	Townsend Test	Non-Linear Model		
	1	2	3	4
Apha	0.023***	-	0.002	0.002
	(0.003)	-	(0.003)	(0.003)
Beta	-	-	1.057***	-
	-	-	(0.079)	-
N	4700	4700	4700	4700
R^2	0.622	0.661	0.662	0.662
SSE / 10000000	704.35	633.19	632.92	631.72

$^{***} \Rightarrow p < 0.01$, $^{**} \Rightarrow p < 0.05$, $^{*} \Rightarrow p < 0.1$. Standard errors in parentheses.

and consistent with Townsend (1994) for the ICRISAT villages and Kinnan (2010) for the Townsend Thai data, I find that the estimate of γ is positive and significant. The second column presents the sum of squared errors for non-linear least squares estimates of (3.3). The intuition presented in Figure 3.4 implies that if the kink caused by κ is a reasonable explanation of the excess sensitivity of consumption to income, then it must be the case that the sum of the squared errors for estimating (3.3) should be less than that from estimating (3.6). The table shows that this is the case for both data sets.

Next, column 3 in each of the tables presents the NLLS estimates of (3.4). It is not possible to reject the hypothesis that $\alpha = 0$ nor the hypothesis that $\beta = 1$ for either of the data sets and the estimate of β is in both cases substantially smaller than the estimate of γ in column 1. It should be noted that while $\beta = 1$ cannot be formally rejected, it is noisily estimated, particularly in the ICRISAT data. Finally, Column 4 re-estimates (3.4) constraining β to be equal to 1. The logic for including this test is that if β is overestimated it may spuriously lead to a low estimate of α. Once again it is not possible to reject the hypothesis that $\alpha = 0$.

Overall the results for the Townsend Thai villages seems to be compelling that allowing for the non-linear effect of κ_{vt} implies that there is little remaining correlation between consumption

Table 3.3: NLLS Estimates of the Impact of Income on Consumption: ICRISAT by Village

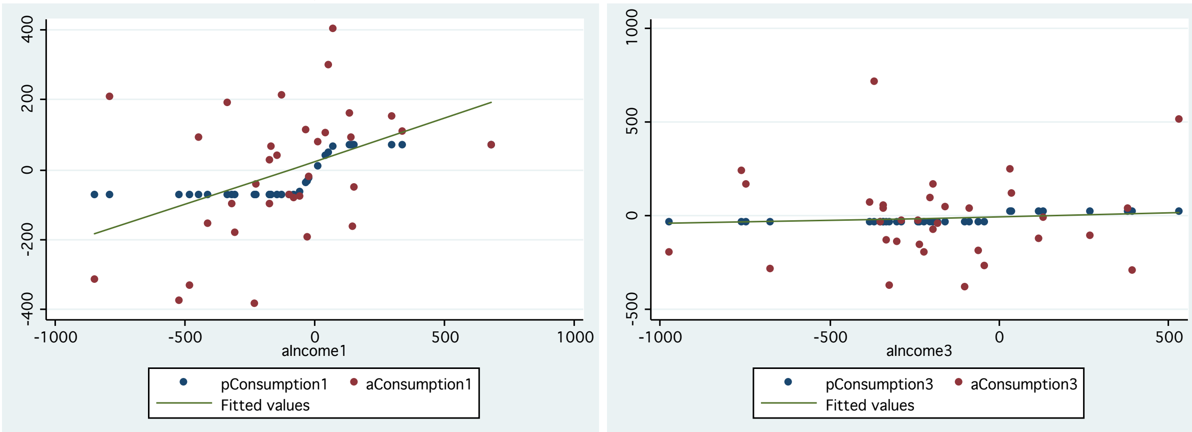
	Aurepalle			Shirapur			Kanzara		
	1	2	3	1	2	3	1	2	3
Alpha	0.139***	0.000	0.000	0.127**	0.006	0.002	0.303***	0.269***	0.251***
	(0.053)	(0.052)	(0.058)	(0.054)	(0.069)	(0.070)	(0.067)	(0.073)	(0.074)
Beta	-	1.051	-	-	1.087***	-	-	1.499	-
	-	(0.677)	-	-	(0.366)	-	-	(0.936)	-
Const	146.6	212.588*	212.588*	798.10***	876.91***	876.21***	407.4***	465.5***	560.1**
	(123.600)	(111.236)	(123.310)	(115.600)	(120.057)	(119.382)	(103.000)	-170.2	-223.1
N	210	210	210	198	198	198	216	216	216
R^2	0.643	0.689	0.688	0.712	0.736	0.736	0.709	0.731	0.73
SSE/10000	135.490	117.931	118.343	106.076	97.138	97.288	88.000	81.300	81.600

$^{***} \Rightarrow p < 0.01$, $^{**} \Rightarrow p < 0.05$, $^{*} \Rightarrow p < 0.1$. Standard errors in parentheses.

and income. For the ICRISAT villages, however, the estimate of α, while statistically insignificant, is still of a reasonable economic size. In order to further investigate this issue I estimate the model separately for each of the ICRISAT villages. The results are presented in Table 3.3. The results show that for Aurepalle and Shirapur the estimates of α are almost identical to zero. For these two villages I conclude that there is very little remaining correlation between consumption and income once ambiguity is controlled for. For Kanzara, in contrast, controlling for ambiguity has little impact and the estimate of α is extremely close to the estimate of γ from the traditional test of complete risk sharing. To be frank, I have no explanation for the differences between the villages. The disaggregated results simultaneously increase confidence in the model by showing the good fit for Aurepalle and Shirapur, but reduce confidence by showing that Kanzara's consumption income dynamics clearly cannot be explained by the model.

The results show that I cannot reject the VEA model, but one may wonder whether the results have other explanations. In particular the results may seem to be consistent with trade costs. One fact suggests that this is not the case. Figure **??** shows empirical plots of consumption against income for two years in Shirapur. The left panel shows 1976 and the right 1978. In both cases the red dots are the data and the blue dots fitted data points from the VEA model. The solid green line is a line of best fit. If trade costs is the true explanation, one would have to explain why risk sharing appears to be so bad in 79, but so good in 76? Explaining this fact would appear to require year specific trade costs. In contrast ambiguity aversion provides a

Figure 3.5: Consumption Income Plots for Shirapur



natural explanation in terms of how rare the rainfall event was. I intend to test this implication in future work.

3.7 Conclusion

In this section I showed evidence that consumption and income patterns in both the ICRISAT and Townsend Thai monthly data sets is consistent with a model of ambiguity aversion. I conclude that ambiguity aversion is a sufficient explanation for incomplete risk sharing.

Bibliography

Al-Najjar, N.I., "Decision Makers as Statisticians: Diversity, Ambiguity, and Learning," *Econometrica*, 2009, *77* (5), 1371–1401.

Arnott, R. and J.E. Stiglitz, "Moral Hazard and Nonmarket Institutions: Dysfunctional Crowding Out of Peer Monitoring?," *The American Economic Review*, 1991, *81* (1), 179–190.

Ashraf, N., X. Giné, and D. Karlan, "Finding missing markets (and a disturbing epilogue): evidence from an export crop adoption and marketing intervention in Kenya," *American Journal of Agricultural Economics*, 2009, *91* (4), 973–990.

Attanasio, O. and J.V. Rios-Rull, "Consumption smoothing in island economies: Can public insurance reduce welfare?," *European Economic Review*, 2000, *44* (7), 1225–1258.

Banerjee, A.V. and E. Duflo, "Growth theory through the lens of development economics," *Handbook of Economic Growth*, 2005, *1*, 473–552.

Bergemann, D. and J. Valimaki, "Bandit Problems," in Steven Durlauf and Larry Blume, eds., *The New Palgrave Dictionary of Economics*, 2nd ed., Macmillan Press, 2008.

Bewley, T., "Knightian decision theory and econometric inference," *Yale University, Cowles Foundation Discussion Paper*, 1988, *868.*

Bewley, T.F., "Knightian Decision Theory: Part 1," *Cowles Foundation Discussion Papers*, 1986.

_ , "Market Innovation and Entrepreneurship: A Knightian View," *Cowles Foundation Discussion Papers*, 1989.

Binswanger, H.P., "Attitudes toward risk: Experimental measurement in rural India," *American Journal of Agricultural Economics*, 1980, *62* (3), 395.

Cole, S.A., X. Giné, J. Tobacman, P.B. Topalova, R.M. Townsend, and J.I. Vickery, "Barriers to household risk management: Evidence from india," 2010.

Dana, F.R.R.A. and F. Riedel, "Intertemporal Equilibria with Knightian Uncertainty," 2010. Institute of Mathematical Economics Working Paper 440.

Dercon, S. and L. Christiaensen, "Consumption risk, technology adoption and poverty traps: evidence from Ethiopia," *Journal of Development Economics*, 2010.

Doherty, N.A. and H. Schlesinger, "Rational insurance purchasing: consideration of contract nonperformance," *The Quarterly Journal of Economics*, 1990, *105* (1), 243–253.

Ellsberg, D., "Risk, ambiguity, and the Savage axioms," *The Quarterly Journal of Economics*, 1961, pp. 643–669.

Epstein, L.G., "Three Paradoxes for The "Smooth Ambiguity" Model of Preference," 2010. Mimeo.

_ **and M. Schneider**, "Recursive multiple-priors* 1," *Journal of Economic Theory*, 2003, *113* (1), 1–31.

_ **and** _ , "Learning under ambiguity," *Review of Economic Studies*, 2007, *74* (4), 1275–1303.

Fafchamps, M. and S. Lund, "Risk-sharing networks in rural Philippines," *Journal of Development Economics*, 2003, *71* (2), 261–287.

Feder, G., R.E. Just, and D. Zilberman, "Adoption of agricultural innovations in developing countries: A survey," *Economic Development and Cultural Change*, 1985, *33* (2), 255–298.

Foster, A.D. and M.R. Rosenzweig, "Learning by doing and learning from others: Human capital and technical change in agriculture," *Journal of Political Economy*, 1995, *103* (6).

Ghirardato, P., F. Maccheroni, and M. Marinacci, "Differentiating ambiguity and ambiguity attitude," *Journal of Economic Theory*, 2004, *118* (2), 133–173.

Gilboa, I. and D. Schmeidler, "Maxmin expected utility with non-unique prior," *Journal of Mathematical Economics*, 1989, *18* (2), 141–153.

_ **and** _ , "Updating ambiguous beliefs," *J. Econ. Theory*, 1993, *59* (1), 33–49.

Giné, X. and D. Yang, "Insurance, credit, and technology adoption: Field experimental evidencefrom Malawi," *Journal of Development Economics*, 2009, *89* (1), 1–11.

Gine, X., R. Townsend, and J. Vickery, "Patterns of rainfall insurance participation in rural India," *The World Bank Economic Review*, 2008, *22* (3), 539.

Giné, X., R.M. Townsend, and J. Vickery, "Rational expectations? Evidence from planting decisions in semi-arid India," *Manuscript. World Bank, Washington, DC*, 2007.

Glaeser, E.L., D.I. Laibson, J.A. Scheinkman, and C.L. Soutter, "Measuring Trust*," *Quarterly Journal of Economics*, 2000, *115* (3), 811–846.

Goetzmann, W.N., A. Caplin, E. Hangen, B. Nalebuff, E. Prentice, J. Rodkin, T. Skinner, and M.I. Spiegel, "Home equity insurance: A pilot project," *Yale School of Management Working Papers*, 2003.

Hanany, E. and P. Klibanoff, "Updating preferences with multiple priors," *Theoretical Economics*, 2007, *2*, 261–298.

Hsu, M., M. Bhatt, R. Adolphs, D. Tranel, and C.F. Camerer, "Neural systems responding to degrees of uncertainty in human decision-making," *Science*, 2005, *310* (5754), 1680.

Kinnan, C., "Distinguishing barriers to insurance in Thai villages," 2010.

Klibanoff, P., M. Marinacci, and S. Mukerji, "A smooth model of decision making under ambiguity," *Econometrica*, 2005, *73* (6), 1849–1892.

Kocherlakota, N.R., "Implications of efficient risk sharing without commitment," *The Review of Economic Studies*, 1996, *63* (4), 595–609.

Ligon, E., J.P. Thomas, and T. Worrall, "Mutual insurance, individual savings, and limited commitment," *Review of Economic Dynamics*, 2000, *3* (2), 216–246.

_ , _ , and _ , "Informal insurance arrangements with limited commitment: Theory and evidence from village economies," *Review of Economic Studies*, 2002, pp. 209–244.

Lucas, R.E., "Why doesn't capital flow from rich to poor countries?," *The American Economic Review*, 1990, *80* (2), 92–96.

Maccheroni, F., M. Marinacci, and A. Rustichini, "Ambiguity aversion, robustness, and the variational representation of preferences," *Econometrica*, 2006, *74* (6), 1447–1498.

Marinacci, M., "Learning from ambiguous urns," *Statistical Papers*, 2002, *43* (1), 143–151.

Mazzocco, M. and S. Saini, "Testing Efficient Risk Sharing with Heterogeneous Risk Preferences," 2009. Working Paper.

Miguel, E., "Poverty and witch killing," *Review of Economic Studies*, 2005, *72* (4), 1153–1172.

Rigotti, L. and C. Shannon, "Uncertainty and risk in financial markets," *Econometrica*, 2005, *73* (1), 203–243.

Roca, M., R.M. Hogarth, and A.J. Maule, "Ambiguity seeking as a result of the status quo bias," *Journal of Risk and Uncertainty*, 2006, *32* (3), 175–194.

Rosenzweig, M.R. and H.P. Binswanger, "Wealth, weather risk and the composition and profitability of agricultural investments," *The economic journal*, 1993, *103* (416), 56–78.

Rustichini, A., "Emotion and Reason in Making Decisions," *Science*, 2005, *310*, 1624 – 1625.

Samphantharak, K. and R.M. Townsend, *Households as corporate firms: an analysis of household finance using integrated household surveys and corporate financial accounting*, Cambridge University Press, 2009.

Savage, L.J., *The foundations of statistics*, Dover Pubns, 1972.

Schulhofer-Wohl, S., "Heterogeneity and Tests of Risk Sharing," 2010. Manuscript, Princeton University.

Shiller, R.J. and A.N. Weiss, "Home equity insurance," *The Journal of Real Estate Finance and Economics*, 1999, *19* (1), 21–47.

Siniscalchi, M., "Dynamic Choice Under Ambiguity," *Discussion Papers*, 2006.

Stiglitz, J.E. and A. Weiss, "Credit rationing in markets with imperfect information," *The American economic review*, 1981, *71* (3), 393–410.

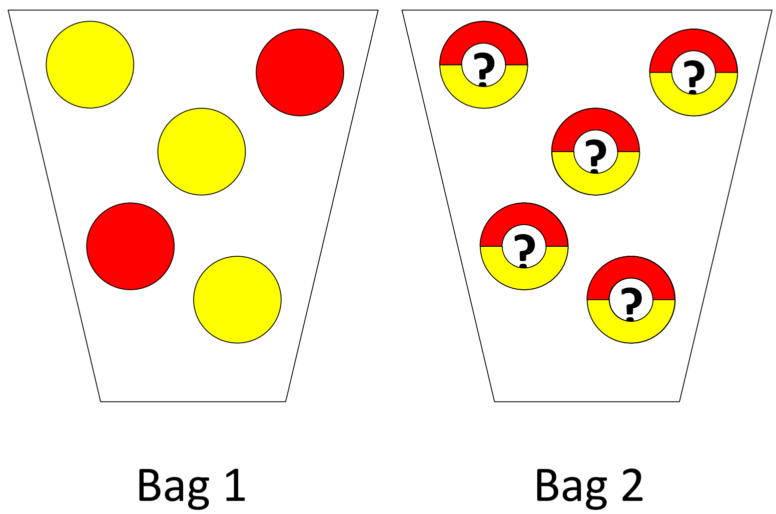
Townsend, R.M., "Risk and insurance in village India," *Econometrica: Journal of the Econometric Society*, 1994, *62* (3), 539–591.

A The General Model of Index Insurance and Technology Adoption

On its way ....

B Visual Aids

The following visual aid was given to respondents when asked Question 1.



C Risk Aversion Questions

Respondents were given the following hypothetical questions.

Question 2 (Measuring Risk Aversion – Kenya)**.** *Imagine you are going to flip a coin and you win if it lands on heads and you also win if it lands on tails. However, the amount you win depends on the bet you choose. Given the following, which bet would you choose:*

1. *1000/1000*
2. *900/1900*
3. *800/2400*
4. *600/3000*
5. *200/3800*
6. *0/4000*

Question 3 (Measuring Risk Aversion – Malawi)**.** *You are going to play a game, I am going to flip a coin. Imagine that you would get the money shown under the GREEN area if it lands on heads or the money shown under WHITE area if it lands on tails. The amount you would win depends on the bet you choose. Which bet would you choose?*

1. *50 / 50*
2. *40 / 120*
3. *30/160*
4. *20 / 190*
5. *10 / 210 f.0/ 220*

The visual aid contains photos of the monetary amounts.