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MICROINSURANCE DECISIONS: EVIDENCE FROM ETHIOPIA

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RESEARCH
PAPER No.19

MAY 2012

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ABSTRACT

We review experimental evidence collected from a framed microinsurance field experiment using poor subjects in rural Ethiopia. We find the shape of demand for index insurance to be broadly in line with predictions of DARA expected utility theory (EUT), for example by being hump-shaped in wealth. However, the level of demand for index insurance is higher than predicted by EUT. The pattern of demand is consistent with recent experimental evidence from developing countries suggesting an S-shaped probability weighting function, with underweighting of extreme events. Additionally, we find that higher background risk is associated with higher indemnity insurance take-up and that participants choose more insurance cover in the group index and indemnity decision problems than in the individual decision problems. These results have positive implications for the `puzzle' of low demand for actuarially unfair weather index insurance in developing countries, and normative implications for the design and sale of microinsurance products.

1. INTRODUCTION

Over the last ten years a variety of institutions have piloted the sale of weather indexed insurance policies to poor farmers, under which the net transfer between insurer and policyholders depends only on readings from a contractual weather station. However, despite the substantial welfare benefits that could arise from improved agricultural risk management, voluntary purchase of these products has been much lower than anticipated by proponents. This low demand has been referred to as a `puzzle' in need of an explanation (Cole et al. 2009, Karlan and Morduch 2009).

Of course, to be able to say anything meaningful about whether observed indexed insurance purchase is `too low', rather than just saying that it is `low', we must at the very least be able to argue that a well-informed financial advisor would advise a higher level of purchase. This turns out to be surprisingly difficult to do, particularly for real indexed insurance products where the contractual index is not perfectly correlated with the loss, and neither researcher nor consumer has a precise objective estimate of the joint probability distribution of losses and indexed claim payments.[2] For example, for all of the weather indexed products reported in the natural field experiments of Cole et al (2009) there are objectively reasonable joint probability distributions for which zero purchase is optimal for all risk averse expected utility maximisers (Clarke 2011a).

If we cannot learn about the level of indexed insurance demand through natural field experiments with real indexed insurance products, we must instead look to environments in which the researcher has a greater degree of control. This paper reports on such an insurance experiment conducted in rural Ethiopia in which both index and losses were generated with known joint probability distribution.

While the use of an experiment entails a tradeoff between control and realism, we attempted to maximize external validity with decision problems framed as agricultural insurance purchase problems, payoffs of up to one week's income, experimental subjects who would be offered real weather index insurance policies in the subsequent two years, and an experimental design that yielded clear theoretical predictions. Moreover, subjects were chosen from households in the Ethiopian Rural Household Survey, for which there already exists seven rounds of detailed panel data, including a long-standing module on risk.

Drawing on best practice and based on extensive piloting, decision problems were designed to be easily understood by subjects, project choices and payoffs were described orally with the help of visual aids, randomisation devices

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[2] Of particular importance to the expected utility maximiser is both the expected claim payment and the claim payment distribution conditional on a high loss having occurred. Even if the researcher had 20 years of matched data for both losses and indexed claim payments, the latter conditional distribution could not be estimated with any degree of accuracy. In practice researchers are likely to have much less than 20 years of matched data.

were physical and generated salient probabilities using familiar mechanisms, session money was physical, and understanding was confirmed and tested throughout the session (Barr and Genicot 2008, Fischer 2010).

Individual decision problems were designed to capture two elements of agricultural insurance for the poor. First, we considered both indemnity insurance, where the net transfer is a function of incurred losses, and indexed insurance, where the net transfer is correlated with, but not a function of, incurred losses. By considering both product types we are able to apply the normative theory of Clarke (2011a) to determine whether low demand for indexed cover can be explained by the overweighting of basis risk, the risk that the net indexed transfer from insurer to policyholder does not match the incurred loss. Second we considered both individual insurance, where an individual purchases insurance to protect themselves from their own loss, and group insurance, where individuals pool risk between themselves and purchase insurance to protect the group from aggregate group-wide losses. Clarke (2011b) argues that efficient contracting over agricultural uncertainty would involve risk-pooling within communities with formal insurance contracts designed to protect the group from group-systematic risk, and so it seems natural to consider such a distinction in the present experiment.

Compounding these two distinctions led to four insurance purchase decision problems, each framed in the loss domain, from which each subject played two: Individual Indemnity, Individual Index, Group Indemnity and Group Index. We also played a standard benchmark problem used for eliciting preferences, framed in the abstract and in the gain domain.

This experiment generated several interesting results. We find the shape of demand for indexed insurance to be broadly in line with that predicted by economic theory. As predicted, we find that the relationship between index insurance take-up and wealth is nonlinear, and subjects with intermediate levels of wealth have the highest take-up, with low demand for index insurance from the poorest and the richest. Higher background risk is significantly associated with higher demand for indemnity insurance, in accordance with gollier (1996) risk theory of risk vulnerability. Additionally, it seems that participants choose more insurance cover in the group index and indemnity decision problems than in the individual decision problems. Furthermore, we do not find strong evidence that schooling, understanding of the decision problems, or financial literacy increase index or indemnity insurance take-up.

Comparing different theories of individual choice, we find the level of demand for indexed insurance to be higher than can be explained using expected utility theory (EUT). Indeed, Quiggin's (1982) theory rank dependent utility (RDU) model with an `S-shaped' probability weighting function fits the data significantly better than expected utility theory (EUT). This contrasts with traditional laboratory experiments conducted with a standard sample of university students, which typically find an `inverse S-shaped' probability weighting function (Gonzalez and Wu 1999). Our finding of an S-shape is, however, consistent with recent traditional laboratory experiments, framed in the abstract and with samples drawn from developing country (Humphrey and Verschoor 2004a, Humphrey and Verschoor 2004b, Harrison et al. 2010). If S-shaped probability weighting is also a good model for decisions about real-world indexed insurance we would expect observed demand for index insurance policies from poor farmers to be higher, not lower than that which would be advised by a well-informed financial adviser.

The rest of this paper is organised as follows. Section 2 presents the experimental design, including discussion of the decision problems (2.1 and 2.2) and subjects (2.3). Section 3 outlines the theoretical predictions. Section 4 presents the results, beginning with summary statistics (4.1) and analysis under expected utility theory (4.2 to 4.3), and finishing with analysis under alternative models (4.4). Section 5 concludes.

2. EXPERIMENTAL DESIGN

The following experiment was designed to examine the demand for different types of formal insurance arrangements. In each session subjects played the benchmark decision problem, framed in the abstract, and two of four framed insurance decision problems.

Each subject made three decisions during their session but at the end of the session they played and were paid for only one of these three problems, in addition to the showup fee of 5 Birr. Each subject randomly selected the decision problem they would play and be paid for by choosing one out of three numbered tokens placed face down on a table. The daily wage for casual farm labour in the areas we ran the experiment was between 15 and 20 Birr (1.2 to 1.6 USD). Minimum and maximum earnings were 15 and 20 Birr and mean actual earnings, including show up fee, was 40 Birr.

Since many of the subjects were likely to be illiterate, each problem was presented orally with the help of visual aids, and physical randomisation devices were used to assist understanding. One of the authors implemented the randomisation device in all experimental sessions. In total, sessions lasted two hours, plus time for payment.

There were three types of sessions, one with both individual insurance products, one with both group insurance products and one with both index insurance products. Each set of three problems was presented in two different orders, so as to enable control for order effects (Table 1).

2.1 BENCHMARK

The benchmark decision problem (B) used the Ordered Lottery Selection design of Binswanger (1980, 1981) to elicit risk preferences. Whilst alternative methodologies have become popular in recent years for experiments with standard samples (Harrison and Rutström 2008), the simplicity of the Ordered Lottery Selection design makes it well suited to nonstandard samples with low levels of education (Barr and Genicot 2008, Van Campenhout et al. 2008). Moreover the design of our individual indemnity insurance decision problem allows direct comparison with our benchmark problem.

Each subject was presented with a choice of six lotteries, shown in each row of Table 2. Alternatives were ordered to be increasing in both the average payoff_ and the variance around that payoff. Alternative A is the safe option, offering a certain amount, and alternative F has the highest payoff_ mean and variance. Following Barr and Genicot (2008) the gamble was framed in the gain domain and, whichever gamble was chosen, the payoff_ was determined by playing a game that involved guessing which of the author's hands contained a blue rather than a yellow counter. The decision problem was explained privately to each subject, who made a private decision. Once a subject had made a decision they were seated separately from other subjects and were not allowed to talk to each other.

Table 1: Decision problems

Session type	Decision Problem			Number of sessions	Number of subjects
	First	Second	Third		
Individual	B	T_{IX}	T_{IM}	7	68
Individual (reversed)	T_{IM}	T_{IX}	B	7	68
Group	B	T_{GX}	T_{GM}	5	48
Group (reversed)	T_{GM}	T_{GX}	B	8	72
Index	T_{IX}	T_{GX}	B	6	58
Index (reversed)	T_{GX}	T_{IX}	B	6	64
				39	378

2.2 INSURANCE DECISION PROBLEMS

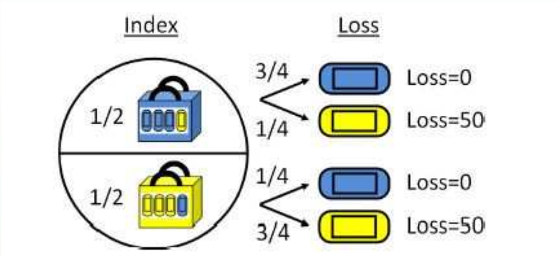
All four insurance purchase decisions were framed to be as similar as possible to a real insurance purchase decision, albeit in the controlled environment of the lab, with an objective probability structure, and with more time spent explaining and individually confirming understanding than would occur in the process of marketing for a real product.

At the start of each insurance purchase decision problem, each subject was physically given 65 Birr of game money and told that they might lose 50 Birr. 50 Birr was equivalent to between two and three days casual farm labour in experimental sites. Game money was smaller and more brightly coloured than Ethiopian currency but was otherwise recognisably similar. Subjects were randomly partitioned into pairs whose role will be explained below.

Enumerators spent 20 minutes explaining each insurance decision problem to the group of subjects, with an additional 10-20 minutes spent privately confirming understanding and recording decisions. Following common practice we referred to both indexed and indemnity insurance as insurance, rather than referring to the former as a derivative.

Insurance purchase decisions shared the following two-stage probability structure (see Figure1). First, a fair wheel was spun to determine whether the blue or yellow bag was to be used for the pair of subjects. The blue bag contained three blue tokens and one yellow, and the yellow bag contained three yellow tokens and one blue. Second, each member of the pair chose one token from the selected bag, with replacement. An outcome for a pair therefore comprised a bag and two tokens.

Figure 1: Two-Stage Probabibilistic Structure for Insurance Decision Problems



In addition to being given an explanation in terms of the wheel, bags and tokens, subjects were given an agricultural explanation for the probability structure. Subjects were told that the bags could be thought of as the weather, with the blue bag representing good weather and the yellow bag representing poor weather. The tokens were likened to the actual yield on a plot with a blue token representing a good year for the owner and a yellow token representing a bad year. Bad (good) weather was likely to lead to a bad (good) year for the owner, but this was not always the case: there was one yellow token in the blue bag and one blue token in the yellow bag. Given this probability structure, the treatments may therefore be briefly summarized as follows. For individual treatments each subject was liable for their own loss in full: if a subject drew a yellow token they lost 50 Birr. For group treatments the total loss for each pair was split evenly between the pair: each subject therefore lost 25 Birr for each yellow token drawn by either member of the pair. Indemnity insurance then corresponded to purchasing insurance against you (or your partner) drawing a yellow token and index insurance corresponded to purchasing insurance against your pair drawing a yellow bag. Indemnity insurance was priced with loading of 60% and index insurance with a loading of 20%.[3]

The purpose of pairs was as follows. Each insurance decision problem was explained to all subjects in the session but subjects could only ask questions privately at the level of the pair. In individual treatments, the sole effect of pairing was that each subject could hear any questions asked by their partner. In group treatments, a subject's earnings would also depend on their partner's random token draw. Pairs did therefore not have a strategic function; all insurance problems were individual decision problems, with own earnings depending only on own choices and chance.

The four treatments were therefore as follows, with respective visual aids displayed in Figure 2:

Individual Indemnity (T_{IM}): In T_{IM} a subject incurred a 50 Birr loss if they drew a yellow token, but could purchase between zero and five units of individual indemnity insurance against the loss occurring. One unit of indemnity insurance cost a premium of 8 Birr and reduced the retained loss on drawing a yellow token by 10 Birr. Each subject could therefore pay 0, 8,16, 24, 32 or 40 Birr to reduce the maximum loss to 50, 40, 30, 20, 10 or 0 Birr, respectively (see Table 2). The gamble choices available to individuals in T_{IM} were therefore numerically identical to those in B. However the framing of the choices was significantly different.

Individual Index (T_{IX}) The individual index insurance decision problem (T_{IX}) was identical to T_{IM} except that instead of being able to insure against drawing a yellow token §(crop loss), subjects could only purchase between zero and five units of index insurance against a yellow bag being selected. One unit of index insurance cost a premium of 3 Birr and led to a claim payment of 5 Birr in the event of the yellow bag being selected, and zero otherwise (see Table 3). When describing T_{IX}, substantial emphasis was placed on the 1 in 8 chance of incurring a 50 Birr crop loss despite the weather being good and therefore no claim payment being due.

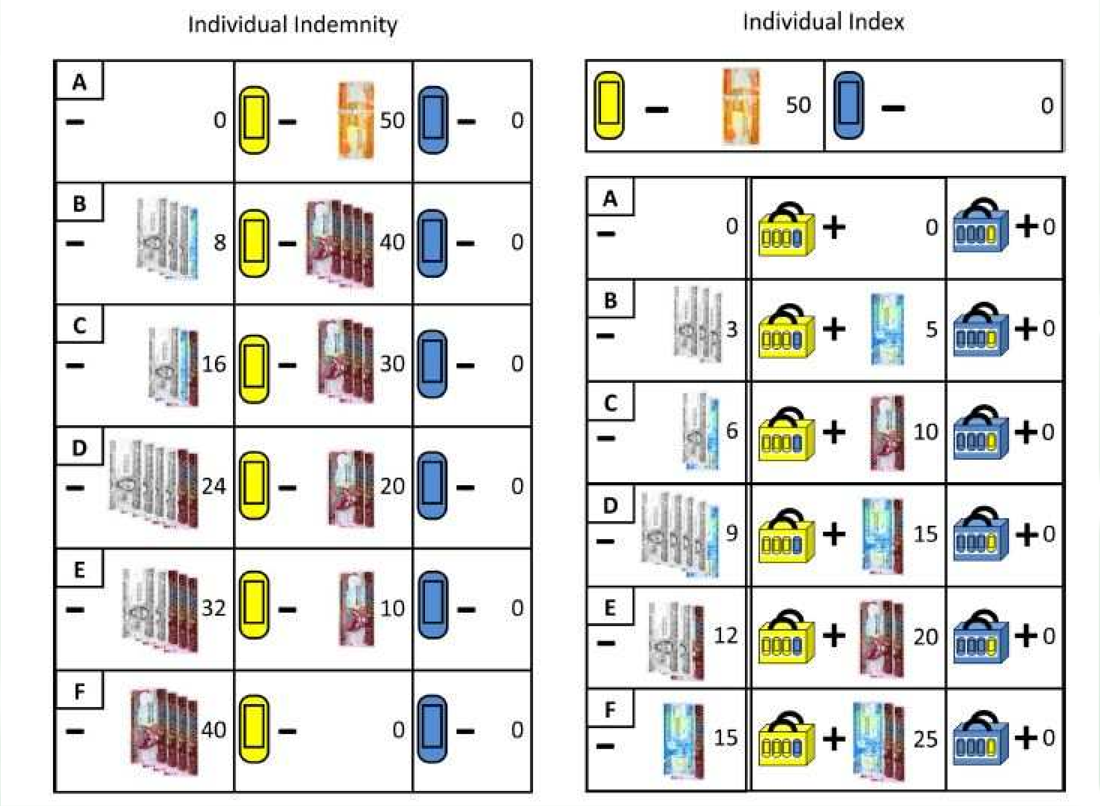
Group Indemnity (T_{GM}): The group indemnity insurance decision problem T_{GM} was identical to T_{IM} except that, instead of losing 50 Birr on drawing a yellow token, each subject lost 25 Birr for each yellow token drawn by the pair, and one unit of indemnity insurance reduced the retained loss on drawing each yellow token by 5 Birr. Each subject could therefore pay 0, 8, 16, 24, 32 or 40 Birr to reduce the loss incurred from each yellow token draw to 25, 20, 15, 10, 5 or 0 Birr, respectively (see Table 4). subjects were told that group losses of 0 Birr, 25 Birr or 50 Birr were approximately equally likely. (The true probabilities are10/32, 12/32 and10/32). Both members of a pair were subject

[3] An insurance loading is defined as (premium charged)/(expected claim income). Loadings of 20% and 60% are low compared to reported commercial loadings, ranging from 70% to 430% for weather indexed insurance (Cole et al. 2009, Table 1) and 140% to 470% for indemnity insurance (Hazell 1992, Table 1). However, the probability of claim payment in our experiment is much higher than that for commercial insurance products and so these loadings cannot be directly compared.

to the same uninsured crop loss for the pair but may have purchased different levels of insurance and therefore might earn different amounts.

Group Index (T_{GX}): The group index insurance decision problem T_{GX} was identical to T_{IX} except that, instead of losing 50 Birr on drawing a yellow token, each subject lost 25 Birr for each yellow token drawn by the pair (see Table 5). Prices for and payment from index insurance were the same as for T_{IX}. Both members of a pair were subject to the same uninsured crop loss but may have purchased different levels of indexed insurance and therefore might earn different amounts.

Figure 2: Presentation of the insurance decision problems to the experimental subjects.



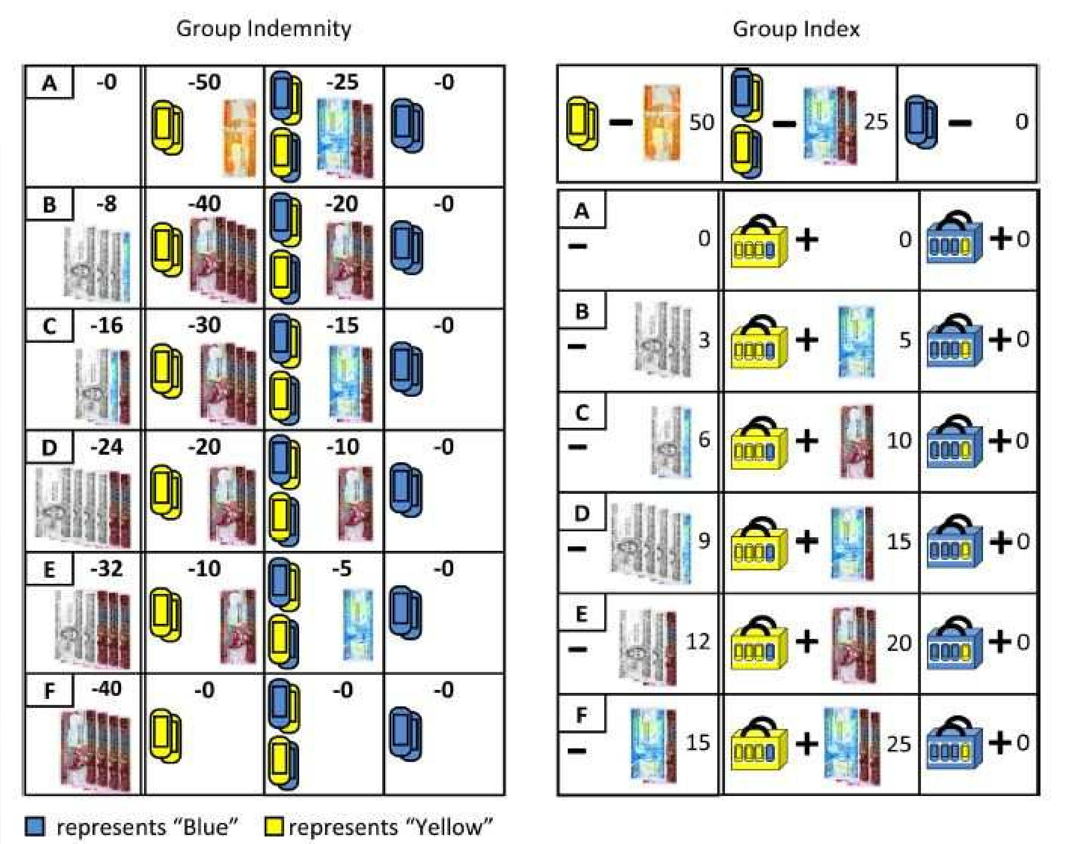


Table 2: Individual Indemnity insurance purchase decision (T_{IM}) and Benchmark decision (B)

	Premium Choice (T_{IM})	Equivalent Choice in Benchmark (B)	Net Payoff (Ethiopian Birr)		Expected Payoff	Risk Aversion Range (CRRA)*
Total Loss:			50	0		
Probability:			1/2	1/2		
	0	F	15	65	40	$(-\infty, 1.036)$
	8	E	17	57	37	$(1.036, 1.285)$
	16	D	19	49	34	$(1.285, 1.715)$
	24	C	21	41	31	$(1.715, 2.698)$
	32	B	23	33	28	$(2.698, 8.553)$
	40	A	25	25	25	$(8.553, +\infty)$

* Risk aversion range denotes range of coefficients for which choice would be optimal for a subject with CRRA preferences over earnings from experiment, excluding show up fee.

The compound probability structure for insurance treatments was much more complex than the simple fair draw for the benchmark. Whilst experimental economist might argue that this could be too complex for subjects to understand, we consider it to be much less difficult to understand than the joint probability structure for a real weather indexed insurance policy; although a farmer might have a good understanding of the marginal loss distribution for their farm, they are unlikely to have a good understanding of the conditional distribution of weather indexed claim payments (Giné et al. 2005, Giné et al. 2007, Hill and Nobles 2010). Moreover, each stage of the randomisation device was chosen to have salient probabilities of 1/4, 1/2 and 3/4.

Table 3: Individual Index insurance purchase decision (T_{IX})

	Premium Choice	Net Payoff (Ethiopian Birr)				Expected Payoff	Risk Aversion Range (CRRA)
Index:		Good	Bad	Good	Bad		
Loss:		50	50	0	0		
Probability:		1/8	3/8	3/8	1/8		
	0	15	15	65	65	40	$(-\infty, 0.723)$ and $(3.888, +\infty)$
	3	12	17	62	67	39.5	$(0.723, 3.888)$
	6	9	19	59	69	39	N/A
	9	6	21	56	71	38.5	N/A
	12	3	23	53	73	38	N/A
	15	0	25	50	75	37.5	N/A

Table 4: Group Indemnity insurance purchase decision (T_{GM})

	Premium Choice	Net Payoff (Ethiopian Birr)			Expected Payoff	Risk Aversion Range (CRRA)
Total Loss:		50	25	0		
Probability:		5/16	6/16	5/16		
	0	15	40	65	40	$(-\infty, 1.517)$
	8	17	37	57	37	$(1.517, 1.911)$
	16	19	34	49	34	$(1.911, 2.598)$
	24	21	31	41	31	$(2.598, 4.182)$
	32	23	28	33	28	$(4.182, 13.714)$
	40	25	25	25	25	$(13.714, +\infty)$

Table 5: Group Index insurance purchase decision (T_{GX})

	Premium Choice	Net Payoff (Ethiopian Birr)						Expected Payoff	Risk Aversion Range (CRRA)
Index:		Good	Bad	Good	Bad	Good	Bad		
Total Loss:		50	50	25	25	0	0		
Probability:		1/32	9/32	6/32	6/32	9/32	1/32		
	0	15	15	40	40	65	65	40	$(-\infty, 0.603)$ and $(9.702, +\infty)$
	3	12	17	37	42	62	67	39.5	$(0.603, 0.863)$ and $(3.029, 9.702)$
	6	9	19	34	44	59	69	39	$(0.863, 3.029)$
	9	6	21	31	46	56	71	38.5	N/A
	12	3	23	28	48	53	73	38	N/A
	15	0	25	25	50	50	75	37.5	N/A

2.3 EXPERIMENTAL SAMPLE AND MATCHED ERHS DATA

Our experiment involved 378 subjects from seven sites of the Ethiopian Rural Household Survey (ERHS), spanning three regions of the country. The ERHS is a longitudinal household dataset covering 15 villages and nearly 1600 households in rural Ethiopia and was conducted over seven rounds from 1994 to 2009. The data collection was coordinated by the Economics Department at Addis Ababa University in collaboration with the Centre for the Study of African Economies at Oxford University and the International Food Policy Research Institute. For the purpose of this paper, we use data mostly from the latest round of the survey, conducted between April and August 2009, since the timing closely matches that of this experiment, which was conducted during November and December 2009. However, we also utilize certain panel aspects of the data, as will be described later in this section. The seven ERHS sites chosen for the experiment were Sirbana Godeti, Korodegaga, Indibir, Milki, Komargefia, Karafino and Bokafia.

The ERHS dataset has detailed information on various socioeconomic and demographic characteristics of households in the sample, such as asset ownership, income, consumption, membership in risk-sharing groups and household size.[4] It has been used extensively in published studies regarding various aspects of the rural Ethiopian economy (e.g Dercon and Krishnan 2000, Dercon 2004, Fafchamps and Quisumbing 2005). The ERHS sample is not a random sample of rural communities in Ethiopia - the sampled villages were initially selected since they had suered from the drought in the mid-1980s (Dercon 2004). However, though the survey covered a relatively small set of villages that were chosen non-randomly, it can still give us useful and relevant policy information on the lives of rural households in Ethiopia (Porter 2008)

The experiment was conducted with 378 subjects, all of whom are from households surveyed by the ERHS. Therefore, the data from the experimental sessions was matched to the data from the main ERHS using the unique household identification number from the ERHS, allowing us to create a combined dataset with both data from ERHS and the experiment for each subject in the experiment. In addition to subjects' choices in the various microinsurance decision problems, the experimental dataset contains information on literacy, schooling, financial literacy, understanding of the decision problems, occupation and various other demographic characteristics of the subjects. Data from the latest round of the ERHS, which covers nearly 1600 households, is combined with data from the experiment to provide a fairly extensive set of factors which could determine the risk aversion of the 378 subjects in the experiment, and hence their choices in the decision problems. Thus, this combined dataset is used to test which factors affect risk aversion and microinsurance take-up in rural Ethiopia.

Table 6 provides the summary statistics for the both the ERHS and experiment variables used as explanatory variables to test which factors affect risk aversion and microinsurance take-up in rural Ethiopia.

There are two measures of household wealth used in this study -- tropical livestock units (TLUs) and total land owned. TLUs are standardized units of different types of livestock, and they are used as a measure of total livestock ownership in numerous studies set in the context of developing economies (e.g. Dercon 2004, Barrett and McPeak 2006).[5] Dercon (2004), in a study of growth and shocks in rural Ethiopia, observes that livestock typically accounts for over 90% of the value of household assets and is the most marketable asset in this region - therefore, in rural Ethiopia, as in many of the poorest rural regions of the world, livestock ownership is an appropriate measure of household wealth. Following Porter (2008), we also use the total land owned by the household (measured in hectares), including agricultural and non-agricultural land, as an alternate measure of wealth. The households in the experiment own three hectares of land and 10.5 TLUs, on average, and it is worth noting that all of them own at least some land and some livestock. For both measures of wealth, the mean wealth of the experimental subjects is slightly greater than that of the complete sample of ERHS households.

[4] For details on the survey, see Dercon and Krishnan (1998).

[5] TLUs provide a single _gure that expresses the total amount of livestock owned, allowing di_erent species to be described in relation to a common unit. For the purposes of the ERHS, it is calculated using the following conversions: oxen=1, cows=0.70, bulls=0.75. horse=0.50, goat=0.10, sheep=0.10 and other similar values (Dercon 2004).

Table 6: Summary Statistics

Variables	Experiment Subjects: No. of Observations	Mean	Standard Deviation	All ERHS Round 7 households: No. of Observations	Mean	Standard Deviation
ERHS Variables						
Total livestock units	372	10.54	2.900	1576	9.216	1.974
Total land owned[a]	372	3.033	4.844	1573	2.052	2.810
Std. dev. of consumption[b]	370	528.8	335.4	1577	375.6	298.5
No. of iddir	366	2.246	1.643	1562	1.781	1.443
Can obtain 100 Birr in emergency	369	0.827	0.379	1565	0.754	0.431
If equb member	372	0.247	0.432	1575	0.135	0.342
Household size	372	5.551	2.341	1576	5.772	2.582
Experiment Variables						
Understanding	378	0.721	0.149			
How many decision problems paid for?	378	0.653	0.477			
Which decision problem paid for?	378	0.934	0.249			
Which colour token is bad?	378	0.976	0.153			
Wheel spin or bag draw first?	378	0.894	0.308			
No. of yellow tokens in yellow bag?	378	0.880	0.324			
Yellow or blue token draw more likely?	378	0.835	0.368			
Financial literacy	378	0.514	0.210			
$5+3=?$	378	0.862	0.345			
$3\times 7=?$	378	0.545	0.498			
$\frac{1}{10}$th of $300=?$	378	0.300	0.458			
5% of $200=?$	378	0.013	0.114			
Riskier to plant one crop or multiple crops?	378	0.852	0.356			
If literate	378	0.770	0.421			
Schooling obtained[c]	377	4.149	3.795			
Age[c]	378	45.14	15.94			
If female	378	0.325	0.469			
If household head	378	0.696	0.461			
If farmer	378	0.664	0.473			
Fraction of earnings kept	378	0.432	0.463			

[a] Measured in hectares
[b] Measured in 1994 Ethiopian Birr
[c] Measured in years

For a particular decision problem, all subjects face the same risky outcomes and are given the same choices. However, subjects differ significantly in the risk they face in the natural course of their lives. Subjects' earnings in the experiments are statistically independent of this background risk and so if subjects have risk vulnerable preferences then, following Gollier and Pratt (1996),, we may expect to associate a higher level of background risk with a higher level of indirect risk aversion over earnings from the experiment. We use the standard deviation of household consumption over all seven rounds of the ERHS survey as a measure of the level of background risk to consumption faced by the household in recent past, before the present experiment was conducted. Numerous studies use measures based on the standard deviation of consumption and income as measures of risk and shocks affecting rural households (e.g. Jalan and Ravallion 1998, Kamanou and Morduch 2004). In this case, the standard deviation of consumption is used rather than that of income because the ERHS income data are far less reliable than the consumption data (Porter 2008). In addition, we want to measure the final level of risk faced by the household -- that which could have a significant welfare impact on the household -- after it has utilized all available consumption smoothing measures, which would not be captured by the standard deviation of income[6]. Consumption is measured as the total monthly household consumption in 1994 Ethiopian Birr. It includes consumption of food, purchased food and non-investment non-food items (that is, excluding expenditure on durables, health and education) -- this consumption measure has been utilized by various other studies of consumption and poverty that have been conducted using the ERHS dataset (Porter 2008).

[6] Hill et al. (2010) also include the standard deviation of ERHS household consumption as an explanatory variable in their specifications used to analyze the determinants of hypothetical take-up of indexed insurance.

Table 6 shows that the inter-temporal standard deviation of consumption is higher for households participating in the experiment -- for these households, the mean standard deviation of around 530 Birr represents a significant fraction (just under half) of the average consumption measured in round 7 (about 1100 Birr). This indicates that subjects in the experiment face considerable risk to consumption, just like most households included in the survey.

Giné et al. (2008) and Cole et al. (2009) note that cognitive ability, financial literacy and understanding of financial products such as index insurance are instrumental in their proper valuation and rapid take up. When the experiment was conducted we went to great lengths to make all decision problems understandable to both literate and illiterate subjects. We spent a great deal of time providing detailed explanations of each decision problem to the subjects, including the use of visual aids and tangible randomization devices. However, in spite of this, it is quite likely that people with different education levels and literacy status had different levels of understanding of the decision problems. Therefore, we include as explanatory variables both the number of years of schooling obtained by the experimental subject and a literacy dummy to test whether better cognitive ability leads to more index insurance take-up[7]. While 77% of the experimental subjects are literate, the average subject had only obtained around four years of formal schooling. However, years of schooling may be a poor proxy for education and the ability to solve the math problems one encounters in everyday life (Cole et al. 2008). Therefore, in line with the work of Cole et al. (2009), we also include direct measures of understanding and financial literacy -- these are the fraction of six questions relating to the understanding of the problems answered correctly and five questions assessing probability and mathematical skills answered correctly (refer to Table 6 for more details on these questions). While the subjects exhibit a fairly good understanding of the decision problems (correctly answering 71% of the understanding questions, on average), the subjects answered only 54% of the financial literacy questions correctly, on average. Though this measure indicates a relatively low level of financial literacy, it is still higher than that measured by Cole et al. (2009), who find that respondents in their sample of rural Gujarat (India) correctly answer 34% of similarly framed financial literacy questions.

Giné et al. (2008) hypothesize when a new technology or financial product is not well understood by rural farmers, as is the case for index insurance, households will draw inferences based on experience and familiarity with the product and other similar products. In addition, the literature on the adoption of new technologies and financial products indicates that households rely heavily on the large information flows between members of social groups in deciding whether to take-up new products (e.g Feder et al. 1985, Bandiera and Rasul 2006). Therefore, we hypothesize that farmers with larger social networks and more prior experience with financial products, have more information on, and a better understanding of, insurance products, and so are more likely to purchase index insurance in the experiment. Three additional ERHS variables are included to capture the subject's prior experience with financial products such as savings and insurance, as well as access to informal insurance networks. These are dummy variables indicating whether the household is part of an equb group (a mutual savings association, similar to a ROSCA) and whether the household can obtain 100 Birr within a week in case of an emergency. Further, the number of iddir groups that the subject's household is a member of is used as an indicator of both the size of a household's social network as well as the household's, and thus the subject's, prior experience with informal insurance. Iddirs are informal insurance groups indigenous to Ethiopia that were originally formed cope with the high cost of funerals -- however, currently many iddirs also provide informal insurance and credit to its members when they experience other adverse shocks, such as fires, illnesses and loss of livestock (Hoddinott et al. 2005). Hoddinott et al. (2005) observe that iddir members have better access to informal insurance, and also larger social networks, than non-iddir members. Iddirs are quite widespread in rural Ethiopia, and over 85% of ERHS households are members of at least one iddir. Table 6 shows that for experimental subjects, households are members of two iddir on average; on the other hand only 25% of the households are members of an equb group[8]. However, a large fraction (nearly 83%) of the experimental subjects report that their households can obtain 100 Birr within a week in case of an emergency.

Other characteristics of the subjects that are expected to affect insurance take-up are also considered -- these include sex (represented by a dummy taking the value one if the subject is female), whether his/her primary occupation is farming or not (indicated by the dummy variable `If farming', which takes the value one if the subject is a farmer), and

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[7] The literacy dummy variable is based on how the subject preferred sign for receipt of income from the experiment, and equals one if the subject signed with a pen and zero if signed with a thumb print.

[8] Equbs are not as widespread as iddirs in rural Ethiopia, as the summary statistics indicate. Most households that are equb members are members of only one equb. Therefore, data on the number of equbs that a household is a member of was not collected in the ERHS, and we only use a dummy variable indicating whether the household is an equb member or not. On the other hand, iddir membership is extensive and many households are members of multiple iddir (Hoddinott et al. 2005).. Thus, to distinguish between households on the basis of iddir membership, we use the number of iddir (which was noted in the ERHS) rather than simply a dummy indicating whether the household is a member of at least one iddir.

household size[9]. These are similar to the demographic characteristics included by Giné et al. (2008) and Cole et al. (2009) in their studies of index insurance take-up in rural India. In addition to these variables, the self-reported fraction of the total earnings from the experiment that the subject intends to keep for himself is also included as a determinant of index insurance take-up. We hypothesize that those subjects keeping a larger fraction for themselves are expected to choose riskier options in the experiment (thus choosing lower levels of insurance cover) than subjects who intend to share their experimental earnings with others, and hence are wary about returning with very little (or no) money from the experiment other than the participation fee of 5 Birr.

3 THEORY

We assume three competing theories of decision under uncertainty to explain these data: expected utility theory (EUT), rank dependent utility (RDU) and mean variance utility (MV). We consider EUT to be an appropriate normative framework for making decisions about insurance purchase and therefore consider this to be our baseline model of decision under uncertainty. As usual we assume a constant relative risk averse (CRRA) utility function. However, EUT is known to be somewhat limited as a positive theory of decision under uncertainty and so we will also compare EUT with both RDU, where decision makers may weight objective cumulative probabilities, and MV, where the value function is linear in the mean and variance of income.

In particular, we will see that these three theories differ in both the level and shape of optimal index insurance purchase. Relative to EUT, both RDU and MV can account for either a higher or lower level of purchase. However, the shape of optimal indexed demand under MV is different to that under EUT and RDU.

For each of the decision problems considered there are six possible choices, denoted $i \in \{1,\ldots,6\}$. The number of possible outcomes N is 2 for B and T_{IM}, 3 for T_{GM}, 4 for T_{IX} and 6 for T_{GX} (see Tables 2-5).

3.1 EXPECTED UTILITY THEORY SPECIFICATION

For our EUT specification we assume that the indirect utility of income from the experimental session is given by:

$$U(x) = \begin{cases} \frac{x^{1-r}}{1-r} \text{ if } r \neq 1 \\ \ln(x) \text{ if } r = 1 \end{cases} \qquad (1)$$

Where x is the lottery prize and r is the coefficient of relative risk aversion.[10] With this CRRA specification, $r > 0$, $r = 0$ and $r < 0$ correspond to risk aversion, risk neutrality and risk loving, respectively. Under expected utility theory (EUT) the decision maker weights each possible outcome $k \in \{1,\ldots,N\}$ using objective probabilities $p(k)$ and so expected utility from choice i is:

$$EU_i = \sum_{k=1}^{N} p(k)U(k) \qquad (2)$$

Where probabilities and lottery prizes for each decision problem are given in Tables 2-5. As is common for indemnity insurance, a higher level of insurance cover in T_{IM} and T_{GM} leads to both a decrease in risk, specifically a mean preserving contraction [?] of income, and a decrease in expected income. Optimal insurance purchase in T_{IM} and T_{GM} is therefore monotonically increasing in r, as can be seen in Tables 2 and 4.

However, as noted by Clarke (2011a), optimal demand for index insurance is fundamentally different to that of indemnity insurance. First the optimal premium in problems T_{IX} and T_{GX} is not monotonic, but rather hump shaped in r, first increasing and then decreasing in r. This hump shape is caused by the combination of actuarially unfair

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[9] The average household size is greater than five for both the entire ERHS sample and the sub-sample participating in the experiment.

[10] We ignore the show up fee of 5 Birr in lottery prize x.

premiums, whereby premiums are greater than expected claim income, and basis risk, the risk that the income from index insurance will not accurately reflect the incurred loss. These cause demand to be low from both the risk neutral, for whom insurance purchase decreases mean income, and the very risk averse, for whom indexed insurance purchase decreases the minimum possible income. Only those with intermediate levels of risk aversion optimally purchase index insurance.

Second, under CRRA it is never optimal to pay an insurance premium of more than 3 for T_{IX} or 3 for T_{GX} (see Tables 3 and 5). It is important to note that this is not an artefact of our utility function specification in equation (1) but rather is a robust feature of preferences that satisfy decreasing absolute risk aversion (DARA). Clarke (2011a) shows that no risk averse expected utility maximising decision maker satisfying DARA would ever purchase more than 6 in T_{IX}; if they cared enough about risk to want to purchase the cover, they would care enough about the downside basis risk to limit the size of the hedge. Clarke (2011a), argues that DARA provides an appropriate basis for generic financial advice and that behaviour that is inconsistent with DARA is `inadvisable'.[11]

Finally, EUT provides predictions about the effect of wealth on purchase of indexed insurance. Wealth affects index insurance purchasing in two important ways. First, a household's wealth is indicative of the credit and liquidity constraints a household faces, and financial constraints may play a key role in its decision to purchase insurance in the field (Gine et al. 2008). Second, household wealth is an important determinant of risk aversion, which in turn affects take-up of insurance. In an experimental setting where each subject is given 65 Birr and the option to purchase insurance to offset adverse outcomes, the credit constraint effect of wealth would not be expected to impact insurance take up, and wealth would only affect purchase of index insurance through risk aversion. If subjects' preferences over aggregate wealth satisfy decreasing absolute risk aversion then the hump shape of demand relative to risk aversion is expected to carry over to wealth; both poor and rich subjects would have low demand for index insurance due to basis risk and actuarially unfair premiums respectively, leaving higher demand only for those with intermediate wealth.

3.2 RANK DEPENDENT UTILITY SPECIFICATION

There are two components to the RDU specification; the utility function and the probability weighting function (Quiggin 1982). As for EUT we assume the CRRA utility form defined in equation (1). However, instead of weighting outcomes with objective probability weight, we assume that subjects instead weight cumulative probabilities according to a weighting function , as follows:

$$RDU_i = \sum_{k=1}^{N} w(k)U(k) \tag{3}$$

where

$$w(k) = \begin{cases} \omega(p(1)) & for\ k = 1 \\ \omega(p(1)+\ldots+p(k)) - \omega(p(1)+\ldots+p(k-1)) & for\ k > 1, \end{cases} \tag{4}$$

States are ranked from worst $(U(1))$ to best $(U(N))$, and $\omega(p)$ is some probability weighting function.

We consider two functional forms for probability weighting function ω, the first due to Prelec (1998) and the second due to Tversky and Kahneman (1992). Both have well defined endpoints with $\omega(p) = 0$ for $p = 0$ and 1 for $p = 1$, and

$$\omega^P(p) = \exp\{-(-\ln(p))^{\phi}\} \tag{5}$$

$$\omega^{TK}(p) = p^{\gamma}/[p^{\gamma}+(1-p)^{\gamma}]^{1/\gamma} \quad \text{For } 0 < p < 1. \tag{6}$$

The usual case, for standard samples of university students, is that probability weighting is an inverse S-shape, concave for low probabilities and convex for high probabilities (Gonzalez and Wu 1999).. For equations (6) and (5) this

[11] See arrow 1965 tto and pratt 1964 risk for a more detailed defense of DARA as a normatively sound framework.

corresponds to and for index insurance decision problems and would lead to lower demand for index insurance than under SEU. Wakker et al. (1997) report on a set of `probabilistic insurance' decision problems, similar to our index insurance purchase problems but with a lower probability of basis risk, and find an extreme dislike of basis risk from a standard sample of subjects. They interpret this as providing evidence for an inverse S-shape probability weighting.

However, recent laboratory experiments, framed in the abstract and with nonstandard samples drawn from developing countries have found S-shaped probability weighting, convex for low probabilities and concave for high probabilities (Humphrey and Verschoor 2004a, Humphrey and Verschoor 2004b, Harrison et al. 2010). This correponds to $\gamma, \phi > 1$ and for index insurance decision problems T_{IX} and T_{GX} could lead to higher or lower demand for index insurance than under SEU.

Figure 3 presents the optimal choice for each of the insurance decision problems under RDU for the case of a Prelec probability weighting function, where $\phi = 1$ collapses to the special case of EUT. Conditional on a probability weighting function, that is for fixed ϕ, optimal purchase of indexed cover is hump shaped in r and optimal purchase of indemnity insurance is increasing in r. Moreover, index insurance premiums of more than 3 for the case of T_{IX} and 6 for the case of T_{GX} may be explained for $\phi > 1.$

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3.3 MEAN VARIANCE

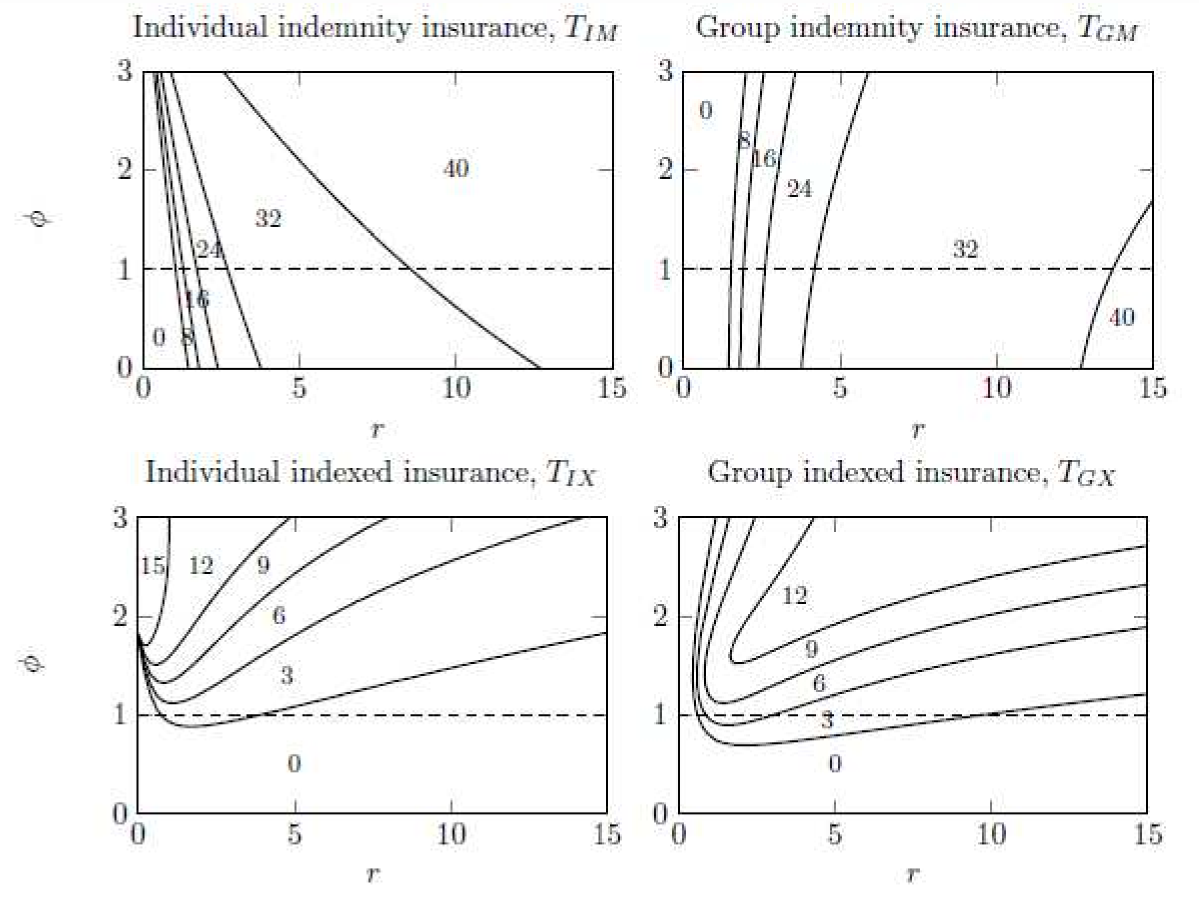
Following Gin´e et al. (2008), in the MV framework subjects maximise expected quadratic utility:

$$MV_i = \mathbb{E}[X_i] - b \times Var[X_i] \tag{7}$$

Parameter b corresponds to the weight placed on the variance of income, with a higher b leading to a greater emphasis on reducing the variance of income. It is not related to Arrow's (1965) notion of absolute risk aversion.

The MV framework is consistent with any level of indemnity or indexed cover, and so may lead to a higher or lower level of demand than EUT, depending on the parameter b. However, unlike the relationship between EUT and r, demand for indexed cover in all insurance decision problems under MV is increasing in parameter b, and so we would expect choices to be comonotone. Since experimental income is statistically independent of background wealth, insurance purchase in all of our decision problems should be unrelated to wealth, as opposed to the hump shape predicted by EUT and RDU.

Figure 3: Optimal insurance premiums for RDU decision maker with different Coefficients of Relative Risk Aversion r and Prelec probability weighting parameters φ



4 RESULTS

4.1 HEAT MAPS

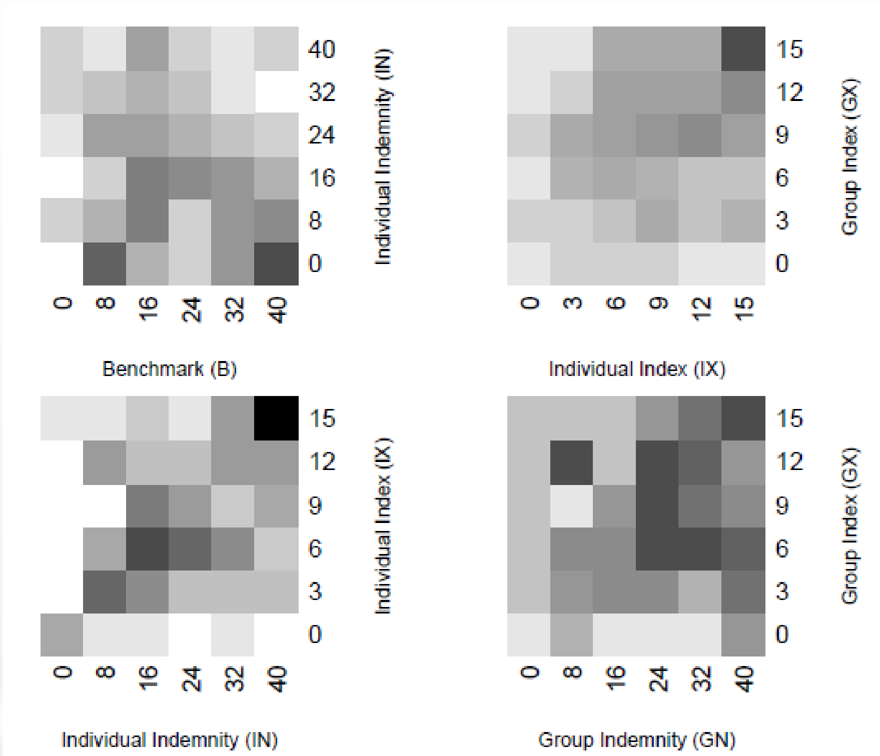
Before we begin statistical analysis of decisions, which implicitly includes both within and between subjects analysis, we present selected pairs of decisions chosen by the same subject.[12]

Figure 4 consists of heat maps for selected pairs of subjects, where the axes of the heat maps correspond to subjects' choices in a pair of decision problems considered, and darker squares on the heat map imply that more subjects chose the corresponding pair of choices.

The first thing to notice is that, despite B and T_{IX} being numerically identical choices, par- ticipants rarely made numerically consistent choices, along the 45° line. This suggests significant framing effects from the loss versus gain domain frame, abstract versus insurance frame and one-stage versus two-stage lottery randomisation device. We will not explore the implications of these framing effects in the current paper. meanwhile, the relationship between T_{IM} and T_{IX} appears to be approximately linear: those subjects choosing low (high) levels of indemnity insurance in TIM also seem to be choosing low (high) levels of index insurance cover in T_{IX} . Additionally, 16 out of 136 subjects who chose the maximum level of insurance cover in both problems.

The heat map for T_{GM} and T_{GX} is indicative of a non-linear, hump-shaped relationship between choices in T_{GM} and T_{GX} . The majority of subjects that choose intermediate levels of insurance cover in T_{GM} also choose higher levels of index insurance in T_{GX} than those that choose higher and lower levels of indemnity insurance in T_{GM}. Lastly, the relationship between choices in T_{IM} and T_{IX} does not exhibit a clear pattern, but once again we can see that many subjects chose the maximum level of insurance in both problems.

[12] As described in Section 4.6, our statistical analysis relies most heavily on between subjects analysis, and our results are robust to dropping the second and third decision made by each participant.



The darker the background, the higher the proportion of subjects that made that combination of choices. For insurance treatments, choices are denoted by the insurance premium paid. For the benchmark decision problem, choices are denoted by the insurance premium payable in TIM which would result in the same numerical gamble; that is, choice A is denoted 40, choice B is denoted 32, etc.

4.2 DETERMINANTS OF INDEX INSURANCE TAKE-UP

The reduced form specification used to test the impact of the variables mentioned in Section 2.4 on index insurance take-up is:

$$\begin{aligned}&\text{Decision Problem Choice}_i = \beta_0 + \beta_1\text{Wealth}_i + \beta_2\text{Wealth}_i^2 + \beta_3\text{Std. Dev. of Consumption}_i + \beta_4\text{No. of iddir}_i\\&+ \beta_5\text{Can Obtain 100 Birr in emergency}_i + \beta_6\text{If equb}_i + \beta_7\text{Household size}_i + \beta_8\text{Understanding}_i\\&+ \beta_9\text{Financial literacy}_i + \beta_{10}\text{If literate}_i + \beta_{11}\text{Schooling}_i + \beta_{12}\text{Age}_i + \beta_{13}\text{If female}_i\\&+ \beta_{14}\text{If household head}_i + \beta_{15}\text{If farmer}_i + \beta_{16}\text{Fraction of earnings kept}_i + \epsilon_i \qquad (8)\end{aligned}$$

:Where I is the individual subscript

Table 7 presents the results for the estimation of this specification with the subject's choice in T_{IX} as the dependent variable and Table 8 presents the results with the choice in T_{GX} as the dependent variable. These choices can take on the values 1, 2, 3, 4, 5 or 6, where higher values indicate more index insurance purchased (refer to Tables 3 and 5). In both tables columns (1)-(4) list the results for the specifications with total livestock units as the measure of wealth and columns (5)-(8) present the results for the specifications with land as the measure of wealth. The specification is estimated with and without dummy variables which control for the order of decision problems in the session, the enumerator for the session and the location of the session. Each specification is also estimated using both an Ordinary Least Squares (OLS) model (results listed in the odd-numbered columns) and an Ordered Probit model[13] (results listed in the even- numbered columns), given that the dependent variable is an ordinal, ordered response that is not continuous. In such a case the OLS model may suffer from some important shortcomings, such as heteroskedasticity and having an unbounded range for the coefficient estimates, which arise from the assumption of the model that the dependent variable, which is non-continuous and can only take integer values from one through 6, is linearly related to the various continuous explanatory variables for all values of the explanatory variables (Wooldridge 2002).

[13] Note that the reported coefficient estimates are not marginal effects. Also, the Ordered Probit model esti- mates coefficients using a maximum likelihood estimator - see Wooldridge (2002) for more details on the model.

Additionally, standard errors clustered at the session level and robust to heteroskedasticity are used to construct the t-statistics reported in the tables for all specifications in this study. This accounts for both heterokedasticity and the possibility that the error term i in the specification is correlated between individuals within a particular session – we might expect this to be the case, as sessions differed in location and enumerator. However, this procedure still assumes that the error is uncorrelated between subjects across different sessions. [14]

Empirical studies on rainfall index insurance by Gine et al. (2008) and Cole et al. (2009) find that index insurance take-up decreases with risk aversion and is particularly low for the most risk averse. They attribute this deviation from the benchmark model to a lack of understanding of the product and an unwillingness to experiment on the part of farmers. Karlan and Morduch (2009) summarize this view in the recent entry to the Handbook of Development Economics: "The most likely explanation [for demand falling with risk aversion] is that it is uncertainty about the product itself (Is it reliable? How fast are pay-outs? How great is basis risk?) that drives down demand."

However, both these studies rely on predictions from the benchmark model of insurance, which does not explicitly take into account basis risk, that is, the probability that the buyer of the contract suffers a loss but the insurance does not pay out. This would happen in the case of rainfall index insurance, for example, when rainfall is above the threshold that triggers payout but the farmer's crop is destroyed by pests. Thus, the farmer faces significant losses but does not receive any insurance payout. Therefore, while the theoretical benchmark model considered by Gin´e et al. (2008) may be appropriate for analyzing the take-up of indemnity insurance, it is not suitable for evaluating the take-up of index insurance, which involves considerable basis risk.

As referred to in Section 3.1, the theory of rational hedging provided by Clarke (2011a) implies that the low take-up rates – found by Gin´e et al. (2008) and Cole et al. (2009) – amongst the most risk averse consumers may be rational choices and are not necessarily evidence of poor understanding, irrationality or unwillingness to experiment. Furthermore, it predicts that the take-up of index insurance in T_{IX} and T_{GX} would be low for participants with very low wealth and high wealth, and take-up would be greater for participants with intermediate levels of wealth. To test this theory, and therefore reject the theory that index insurance take-up is monotonically decreasing with wealth, we include a measure of wealth and its square as explanatory variables, that is, determinants of index insurance take-up in T_{IX} and T_{GX}.[15] If the coefficient estimate on the level term is significantly positive and that on the squared term is significantly negative, we can reject that that relationship between take-up and wealth is monotonically decreasing in wealth, and this is indicative of the hump-shaped relationship between take-up and wealth.

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[14] If the correlation of errors within sessions is not accounted for, the estimated standard errors may bequite wrong, leading to incorrect inference of coefficient estimates – this problem is magnified in small samples (Wooldridge 2002). Using clustered-robust standard errors to correct for this correlation of errors within groups is the norm when analyzing experimental data (see Harrison and Rutstrom 2008), and many studies cluster at the session level (e.g. Barr 2003, Barr and Genicot 2008).

[15] The Clarke (2011a) model also predicts that index insurance take-up is hump-shaped in the coe_cient of relative risk aversion r, and the impact of wealth on take-up in this model is driven purely by risk aversion. Though we can estimate r from participants' choices in B, we cannot directly test the hump-shaped relationship between index insurance take-up and r. This is because each choice in B corresponds to a range of implied r, and the only way to reduce the ranges to point values is to use a rather arbitrary averaging technique, as suggested by Binswanger (1981). In addition, including the level and squared terms of this discrete, quite arbitrarily chose point value of r to test the non-linear relationship seems inappropriate. Therefore, we prefer to test the prediction of the Clarke (2011a) model that the relationship between index insurance take-up and the continuous variable wealth is hump-shaped. Further, given that we only expect the impact of wealth on take-up to be through risk aversion, testing the relationship between index insurance take-up and wealth can provide strong implications of the relationship between take-up and the coe_cient of relative risk aversion

Table 7: Determinants of index insurance take up: Decision problem T_{IX}

Variables	(1) OLS	(2) O. Probit	(3) OLS	(4) O. Probit	(5) OLS	(6) O. Probit	(7) OLS	(8) O. Probit
Total livestock units	0.452***	0.414***	0.398**	0.405**				
	(3.579)	(3.364)	(2.445)	(2.554)				
Livestock squared	-0.0165***	-0.0154***	-0.0147***	-0.0153***				
	(-4.366)	(-3.408)	(-3.126)	(-2.759)				
Total land owned					0.172	0.120	0.372	0.285
					(1.222)	(1.090)	(1.548)	(1.471)
Land squared					-0.0290	-0.0207	-0.0440	-0.0332
					(-1.257)	(-1.187)	(-1.445)	(-1.375)
Std. dev. of consumption	0.000157	0.000123	0.000205	0.000167	0.000256	0.000195	0.000213	0.000165
	(0.540)	(0.552)	(0.719)	(0.750)	(0.874)	(0.902)	(0.726)	(0.744)
No. of iddir	-0.0266	-0.0277	0.0390	0.0125	-0.0488	-0.0452	0.0446	0.0207
	(-0.385)	(-0.556)	(0.467)	(0.209)	(-0.732)	(-0.917)	(0.507)	(0.320)
Can obtain 100 Birr	0.692**	0.554***	0.709***	0.582***	0.707**	0.553**	0.629**	0.512**
	(2.558)	(2.735)	(2.906)	(3.150)	(2.418)	(2.497)	(2.310)	(2.459)
If equb	0.0162	0.0482	-0.163	-0.109	0.0891	0.102	-0.170	-0.115
	(0.0733)	(0.285)	(-0.645)	(-0.558)	(0.398)	(0.597)	(-0.671)	(-0.592)
If household size	-0.00252	-0.00832	-0.00198	-0.00511	0.0301	0.0191	0.0108	0.00612
	(-0.0632)	(-0.264)	(-0.0523)	(-0.167)	(0.707)	(0.573)	(0.281)	(0.197)
Understanding	-0.384	-0.308	-0.151	-0.237	-0.498	-0.392	-0.0764	-0.164
	(-0.519)	(-0.525)	(-0.158)	(-0.306)	(-0.679)	(-0.690)	(-0.0812)	(-0.217)
Financial literacy	0.590	0.532	0.629	0.583	0.557	0.496	0.465	0.450
	(0.944)	(1.130)	(1.030)	(1.263)	(0.850)	(1.018)	(0.776)	(0.992)
If literate	0.359	0.309	0.476	0.409*	0.396	0.328	0.548*	0.452**
	(1.342)	(1.507)	(1.703)	(1.893)	(1.504)	(1.636)	(1.875)	(2.000)
Schooling obtained	0.0330	0.0250	0.00682	0.00499	0.0253	0.0192	-0.00248	-0.00170
	(1.197)	(1.178)	(0.259)	(0.244)	(0.944)	(0.934)	(-0.0944)	(-0.0830)
Age	0.00129	0.000276	0.00174	0.000470	0.00251	0.00150	0.000778	-9.65e-05
	(0.186)	(0.0526)	(0.245)	(0.0859)	(0.392)	(0.315)	(0.112)	(-0.0180)
If female	0.513*	0.366	0.497	0.360	0.503*	0.351	0.492*	0.357
	(1.778)	(1.617)	(1.690)	(1.512)	(1.814)	(1.642)	(1.724)	(1.559)
If household head	-0.710***	-0.565***	-0.607**	-0.509***	-0.762***	-0.604***	-0.619**	-0.520***
	(-3.101)	(-3.136)	(-2.705)	(-2.817)	(-3.400)	(-3.463)	(-2.638)	(-2.761)
If farmer	0.448*	0.315	0.384	0.291	0.456*	0.317	0.398	0.299
	(1.766)	(1.567)	(1.472)	(1.383)	(1.754)	(1.559)	(1.508)	(1.417)
Fraction of earnings kept	-0.137	-0.147	-0.408*	-0.379**	-0.0816	-0.0949	-0.414*	-0.376**
	(-0.616)	(-0.846)	(-1.820)	(-2.094)	(-0.351)	(-0.533)	(-1.861)	(-2.123)
Constant	-0.0817		0.171		2.471***		2.127**	
	(-0.103)		(0.141)		(4.252)		(2.364)	
Threshold 1		1.455**		1.298		-0.832*		-0.705
		(2.051)		(1.307)		(-1.812)		(-0.984)
Threshold 2		2.446***		2.290**		0.103		0.237
		(3.390)		(2.271)		(0.247)		(0.336)
Threshold 3		3.088***		2.955***		0.739*		0.903
		(4.120)		(2.866)		(1.759)		(1.297)
Threshold 4		3.694***		3.590***		1.338***		1.535**
		(4.791)		(3.351)		(3.131)		(2.146)
Threshold 5		4.295***		4.222***		1.928***		2.159***
		(5.460)		(3.947)		(4.459)		(3.076)
Order Controls	No	No	Yes	Yes	No	No	Yes	Yes
Enumerator Controls	No	No	Yes	Yes	No	No	Yes	Yes
Location Controls	No	No	Yes	Yes	No	No	Yes	Yes
Observations	248	248	248	248	248	248	248	248
R-squared	0.149		0.207		0.120		0.192	
Log-likelihood		-391.6		-382.6		-396.7		-386.1

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Robust t-statistics based on standard errors clustered at the session level in parentheses. Dependent variable is the respondent's choice in the group (pair index insurance problem TGX.

For the Ordered Probit specifications, the Wald test for null hypothesis that all coefficients are zero has a 2 -distributed Wald test statistic with p-value less than 0.001 in all four cases. For the OLS specifications, the F test for null hypothesis that all coefficients are zero has a F -distributed test statistic with p-value less than 0.0025 in all four cases

Table 8: Determinants of Index Insurance Take-up: Decision Problem T_{GX}

Variables	(1) OLS	(2) O. Probit	(3) OLS	(4) O. Probit	(5) OLS	(6) O. Probit	(7) OLS	(8) O. Probit
Total livestock units	0.474***	0.371***	0.327***	0.269***				
	(4.503)	(3.364)	(3.656)	(3.737)				
Livestock squared	-0.0127***	-0.00974***	-0.00885***	-0.00707***				
	(-4.419)	(-4.082)	(-3.309)	(-3.410)				
Total land owned					0.157*	0.129**	0.0820	0.0763
					(1.992)	(2.184)	(0.964)	(1.214))
Land squared					-0.00170*	-0.00141**	-0.000843	-0.000799
					(-1.968)	(-2.170)	(-0.907)	(-1.168)
Std. dev. of consumption	-0.0000470	-0.0000951	-0.0000769	-0.0000584	0.000287	0.000238	0.000143	0.000137
	(-0.102)	(-0.124)	(-0.223)	(-0.209)	(0.84)	(0.898)	(0.391)	(0.637)
No. of iddir	-0.0630	-0.0544	0.0195	0.00912	-0.0905	-0.0739	0.0169	0.00499
	(-1.018)	(-1.185)	(0.315)	(0.201)	(-1.349)	(-1.513)	(-0.0238)	(0.105)
Can obtain 100 Birr	-0.0332	-0.0230	-0.0566	-0.0444	0.0610	0.0571	-0.00741	-0.000216
	(-0.106)	(-0.100)	(-0.180)	(-0.186)	(0.204)	(0.273)	(-0.0238)	(-0.000942)
If equb	-0.0289	-0.00535	-0.0882	-0.0485	0.00463	0.0107	-0.119	-0.0812
	(-0.106)	(-0.0263)	(-0.276)	(-0.198)	(0.0156)	(0.0495)	(-0.354)	(-0.320)
Household size	-0.0546	-0.0357	-0.0515	-0.0364	-0.0290	-0.0166	-0.0331	-0.0215
	(-1.203)	(-1.009)	(-1.138)	(-1.018)	(-0.696)	(-0.538)	(-0.806)	(-0.679)
Understanding	0.721	0.523	1.548	1.146	0.281	0.202	1.290	0.923
	(1.153)	(1.126)	(1.657)	(1.584)	(0.417)	(0.416)	(1.362)	(1.286)
Financial literacy	-0.296	-0.295	-0.110	-0.165	-0.586	-0.518	-0.219	-0.262
	(-0.838)	(-1.152)	(-0.242)	(-0.481)	(-1.251)	(-1.512)	(-0.422)	(-0.672)
If literate	0.649***	0.516**	0.560**	0.457***	0.714***	0.551***	0.598***	0.482***
	(3.084)	(3.348)	(2.654)	(2.753)	(3.269)	(3.649)	(2.808)	(2.952)
Schooling obtained	-0.0287	-0.0234	-0.0500*	-0.0400**	-0.0279	-0.0220	-0.0536**	-0.0419**
	(-1.404)	(-1.579)	(-2.059)	(-2.127)	(-1.315)	(-1.441)	(-2.152)	(-2.191)
Age	-0.00381	-0.00335	-0.00534	-0.00512	-0.00255	-0.00241	-0.00456	-0.00457
	(-0.531)	(-0.592)	(-0.710)	(-0.854)	(-0.326)	(-0.397)	(-0.585)	(-0.740)
If female	0.378	0.266	0.441	0.314	0.335	0.227	0.432	0.302
	(1.565)	(1.469)	(1.703)	(1.620)	(1.292)	(1.194)	(1.595)	(1.503)
If household head	-0.110	-0.108	-0.113	-0.111	-0.230	-0.197	-0.170	-0.154
	(-0.445)	(-0.589)	(-0.478)	(-0.614)	(-0.930)	(-1.089)	(-0.774)	(-0.914)
If farmer	0.288	0.211	0.399*	0.296*	0.327	0.227	0.435*	0.317**
	(1.117)	(1.165)	(1.791)	(1.936)	(1.287)	(1.331)	(1.968)	(2.110)
Fraction of earnings kept	0.00678	-0.00608	-0.153	-0.128	0.0748	0.0483	-0.156	-0.130
	(0.0276)	(-0.0329)	(-0.530)	(-0.556)	(0.290)	(0.253)	(-0.532)	(-0.556))
Constant	0.122		1.332		3.441***		3.758***	
	(0.142)		(1.391)		(5.830)		(5.492)	
Threshold 1		1.174*		0.390		-1.398***		-1.566***
		(1.850)		(0.564)		(-3.042)		(-2.598)
Threshold 2		2.030***		1.280*		-0.545		-0.674
		(3.117)		(1.802)		(-1.231)		(-1.154)
Threshold 3		2.588***		1.856**		-0.000508		-0.104
		(3.955)		(2.566)		(-0.00118)		(-0.181)
Threshold 4		3.220***		2.519***		0.614		0.550
		(4.754)		(3.388)		(1.353)		(0.947)
Threshold 5		3.781***		3.107***		1.157**		1.126*
		(5.449)		(4.145)		(2.560)		(1.958)
Order Controls	No	No	Yes	Yes	No	No	Yes	Yes
Enumerator Controls	No	No	Yes	Yes	No	No	Yes	Yes
Location Controls	No	No	Yes	Yes	No	No	Yes	Yes
Observations	235	235	235	235	235	235	235	235
R-squared	0.121		0.185		0.081		0.165	
Log-likelihood		-371.9		-363.3		-377.0		-366.2

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Robust t-statistics based on standard errors clustered at the session level in parentheses. Dependent variable is the respondent's choice in the group (pair) index insurance problem TGX .

For the Ordered Probit specifications, the Wald test for null hypothesis that all coefficients are zero has a 2 -distributed Wald test statistic with p-value less than 0.001 in all four cases. For the OLS specifications, the F test for null hypothesis that all coefficients are zero has a F -distributed test statistic with p-value less than 0.0025 in all four cases

Columns (1)-(4) of both of the above tables show that, in all specifications using livestock as the measure of wealth, the coefficient estimate of livestock is positive and the coefficient estimate on livestock-squared is negative. In each case, both coefficient estimates are statistically significant (in two cases at the 5% level and in all other cases at the 1% level). This implies that the take-up of index insurance in decision problems TI X and TGX is first increasing and then decreasing in wealth. That is, the level of take-up in both problems is highest for those with intermediate levels of wealth, and lower for those with low and high levels of wealth. The sign and large statistical significance of these coefficient estimates indicates a rejection of the Gin´e et al. (2008) benchmark model of insurance which implies that insurance take-up should be monotonically decreasing in wealth. The coefficient estimates of β1 and β2 in column (1) of Table 7, for example, imply that take-up in TI X is highest for subjects whose households own 13.7 total livestock units (the average among experimental households is 10.5 total livestock units). Furthermore, though we are not able to explicitly test the exact hump-shaped relationship between index insurance take-up and wealth, these results are at least consistent with that prediction of the Clarke (2011a) model of rational hedging. The lower take-up by subjects from low-wealth households also indicates that the low take-up observed among the most risk averse farmers by Gin´e et al. (2008) and Cole et al. (2009) may be a result of rational choice rather than poor understanding or irrationality on the part of rural consumers. It is also important to note that while we find the non-linear relationship between index insurance take-up and wealth to be consistent with the Clarke (2011a) model of rational hedging, the levels of wealth are significantly greater than those predicted by the model. Therefore, we only use this empirical analysis to explore, and draw inference from, the shape of the relationship and not the exact levels of wealth which describe the relationship. This is in line with the work of Gine et al. (2008), who do not make theoretical predictions about the levels of wealth and risk aversion in the relationship between these factors and index insurance take-up, but only focus on predicting, and empirically testing for, the shape of the relationship between this factors and take-up.

Columns (5)-(8) of Table 7 show that while the coefficient estimates of land are positive and those of its square are negative, they are not statistically significant at the 10% level.16 For take-up of index insurance in T_{GX} , the results in columns (5) and (6) show that the coefficient estimates of land owned are positive and statistically significant and those and of land-squared are negative and statistically significant. However, these estimates are no longer statistically significant with addition of session controls (for order, enumerator and location). Despite the use of land ownership as a measure of wealth in other studies of rural Ethiopia (e.g. Porter 2008), it must be noted that its suitability as a measure of wealth in rural Ethiopia is subject to debate. Dercon (2004) notes that in this region, all land is state-owned and subject to repeated redistribution – therefore, there is not much scope for long-term investment in landholdings, and livestock is the most suitable asset to proxy for wealth. Therefore, in future specifications in this paper, only livestock is used as a measure of wealth.

There is also some evidence that more literate subjects take-up more index insurance, particularly in T_{GX} . The coefficient estimate of the literate variable is positive and statistically significant in all columns of Table 8, and in columns (4), (7) and (8) of Table 7. However, the coefficient estimates of the schooling variable are negative and statistically significant in Table 8 for the specifications which include session controls, implying that an increase in the years of schooling obtained decreases index insurance take-up. In addition, in all the specifications in Tables 7 and 8, the coefficient estimates of financial literacy and understanding are statistically insignificant. This may be an indication that what really matters for the take-up of index insurance is basic literacy, rather than the exact years of schooling or financial literacy. This is in contrast to the results of Cole et al. (2009), who find that respondents with higher financial literacy (measured using similar quantitative questions) have higher take-up of index insurance. Additionally, these results are not consistent with the hypothesis of Gine et al. (2008) and Cole et al. (2009) that low levels of education and financial literacy are responsible for the low take-up of index insurance.

The coefficient estimate of the dummy indicating whether the subject's household is able to obtain 100 Birr in the case of an emergency is positive and statistically significant in all columns of Table 7. This supports the hypothesis mentioned in Section 2.3 that subjects who have better access to informal insurance probably have more prior experience with, and more information on, insurance – therefore, they are more likely to understand and purchase more of the index product offered in the experiment. This is in line with the empirical results obtained by Gine et al. (2008) and Cole et al. (2009), who find that membership in social groups increases the take-up of index insurance by farmers in rural India. Additionally, the results in Table 7 show that subjects who are not household heads tend to purchase more index insurance in T_{IX} . This may be because those subjects who are answerable to their household head – and probably have to give most (or all) of their experimental earnings to their household head – are averse to returning with little (or no) money from the experiment (other than the participation fee) and thus are more likely to choose safer options that imply more index insurance take-up. In line with this explanation, the fraction of experimental earnings kept by the subject has a negative and statistically significant impact on index insurance take up in the T_{IX} specifications that include session controls.

Columns (3), (4), (7) and (8) of Table 8 show that farmers tend to choose more index insurance in T_{GX} , as compared to subjects whose primary occupation is not farming. Since index insurance is most needed by – and aimed primarily at – farmers, this might be an indication that farmers better understand and are able to relate to the concept of index insurance, or that farmers are signalling the need for such an insurance product.

We also note that the coefficient estimates do not differ in sign between the OLS and Ordered Probit models. Furthermore, while the addition of session controls increases the R-squared (for the OLS estimations) and the maximum value of the log-likelihood function (for the Ordered Probit estimations), it does not considerably alter the estimates for the statistically significant results. These factors give us confidence about the robustness of the results found in this section, relating to the determinants of index insurance.

4.3 DETERMINANTS OF RISK AVERSION AND INDEMNITY INSURANCE TAKE-UP

We now turn our attention to the decisions made by subjects in the benchmark decision problem B and the two indemnity insurance problems, T_{IM} and T_{GM} , to test which of the factors mentioned above also impact risk aversion and indemnity insurance take-up. In line with the work of Harrison and Rutstrom (2008), we use two models to evaluate risk attitudes and indemnity insurance take-up – an interval regression model and a structural maximum likelihood model.

It should be pointed out that decision problem B differs from decision problem T_{IM} and T_{GM} in two important ways. First, B is framed in the gain domain while decision problem T_{IM} and T_{GM} are framed in the loss domain with the initial endowment of 65 Birr provided up-front at the start of the decision problem. Harbaugh et al. (2002) note that could there could be significant framing effects which cause subjects to play decision problems framed in the gain and loss domains differently. Second, B is a simple Binswanger (1980) lottery, while decision problems T_{IM} and T_{GM} are more complicated decision problems involving indemnity insurance decisions and require a greater level of understanding than B. Given that both these factors could significantly impact, and cause to differ, the decisions people make in them, we analyze the decisions from B in a separate specification from that used to analyze problems T_{IM} and T_{GM} . That is, for both the interval regression model and the structural maximum likelihood model, we analyze the data from B and that from T_{IM} and T_{GM} (together) in separate specifications.

If we assume subjects have a CRRA utility function given by equation (1) then each choice in the problems B, T_{IM} and T_{GM} implies a choice of, and corresponds to, a particular range of the coefficient of relative risk aversion r (see rightmost column of Tables 2 to 5)[16] We allow r to differ between individuals on the basis of all the characteristics used to describe the take-up of index insurance in Section 4.2. The only difference is that the square of wealth is no longer included as an explanatory variable, as wealth is not expected to have a non-linear effect on risk aversion and indemnity insurance take up; additionally, Harrison and Rutstrom (2008), who use an interval regression model to analyze risk attitudes, using data from experiments conducted by Holt and Laury (2002) involving university students and employees in the United States, include only linear terms for wealth in their specifications estimating the impact of observable characteristics on risk aversion.

Both models assume the core parameter r (higher values of which indicate more risk aversion) to be a linear function of the observable characteristics mentioned above.[17] Also, both use a maximum likelihood estimator to obtain estimates of β, the vector of coefficients on these explanatory variable. Though we do not directly observe r for the subjects, for both models the coefficients on the explanatory variables are interpretable as if we observed r for each subject and estimated $E(r|x) = x\beta$ by OLS, where x is the vector of explanatory variables and is the vector of corresponding coefficients (Wooldridge 2002, Harrison and Rutstrom 2008). Thus the coefficient estimates are

[16] It is important to note that we cannot use either of these models to analyze data from decision problems T_{IX} or TGX, since there are certain choices in the problems which do not correspond to any level of r (see Tables 3 and 5). That is, certain choices in the index insurance problems are not optimal for any level of r; however, we still nd that a considerable number of people choose these options. This might indicate that subjects are not playing problems T_{IX} or T_{GX}, which are quite complicated, within the framework of EUT and CRRA utility. However, it may still be the case that the assumptions of EUT and CRRA utility hold for the simpler problems B, T_{IM} and T_{GM}. Therefore, in line with the work of other experimental studies (e.g Harrison and Rutstrom 2008, Harrison et al. 2010), we begin the analysis of problems B, T_{IM} and T_{GM} assuming EUT and CRRA utility, and then go on to explore the validity of alternate models to EUT (see Section 4.4).

[17] Individuals with $r < 0$, $r = 0$ and $r > 0$ are said to be risk loving, risk neutral and risk averse, respectively.

interpreted as the impact of the observable characteristics on risk aversion for B, and on both risk aversion and the corresponding indemnity insurance take-up for TIM and T_{GM} . B is simpler, easier to understand and has no insurance take-up aspect to it therefore, it only has a risk aversion interpretation and such Binswanger lotteries (framed in a gain framework) have been used in numerous experiments and surveys to gauge risk aversion. However, decision problems T_{IM} and T_{GM} are framed in the loss framework, are notably more complicated and are framed in order to highlight the insurance take-up aspect. Thus, though the choices in these problems imply (implicitly) choices of r, it may not be appropriate to use these problems to simply calibrate the level of risk aversion, and it is important to consider what these choices imply in terms of both insurance take-up and risk aversion r.

As mentioned in Section 3.1 for the case of CRRA utility, subjects with higher wealth, as measured by total livestock units, are expected to be less risk averse.[18] Additionally in an experimental setting where each subject is given an initial endowment of 65 Birr to buy insurance in the problems, we do not expect wealth to have a direct impact on insurance take-up through affecting credit and liquidity constraints, as is expected in the field. Therefore, the impact of wealth on insurance take-up is through the effect of background wealth, that is wealth excluding the lottery choice provided in the experiment itself, on risk aversion, which in turn impacts insurance take-up. Given this, the traditional insurance theory informs us that the take-up of indemnity insurance should be increasing (monotonically) in risk aversion, and thus decreasing (monotonically) in wealth. Similarly, as mentioned in the data section, for a particular decision problem, all subjects face the same risky outcomes and are given the same choices, but differ significantly in the background risk they face. If individuals have risk vulnerable preferences, then an increase in background risk increases the risk aversion of the indirect utility function – subjects who face more background risk would also exhibit more risk aversion in the experiment, demanding more indemnity insurance in the (Gollier and Pratt 1996). Therefore, we test this implication of background risk theory by testing whether the coefficient on the standard deviation of consumption (which we use to capture background risk) is positive and statistically significant in the interval regression and structural maximum likelihood estimations which are used to determine risk aversion and indemnity insurance take-up in decision problems B, T_{IM} and T_{GM} .

However, it may be the case that the standard deviation of consumption does not perfectly capture the total risk faced by households. Therefore, as a proxy for the level of risk facing the household, we use the membership of the subject's household in risk-sharing groups, credit groups and its access to better risk pooling and informal insurance. We would expect that those subjects with better access to informal risk-coping mechanisms would be better able to cope with risk and thus have lower background risk.20 Additionally, Dercon and Krishnan (2000) note that the household is an important institution for risk pooling, and significant risk sharing takes place amongst members of the same family through informal insurance arrangements. Furthermore, larger households are also expected to be better able to cope with risk than smaller households (Cox and Jimenez 1998). Thus, household size is not only an important control variable in this specification but in terms of background risk theory, being in a larger household is expected to have an effect on insurance take-up similar to being a member of more iddir, being a member of an equb and being able to obtain 100 Birr in the case of an emergency. Thus, background risk theory implies that, if standard deviation of consumption does not perfectly capture all of the risk facing households, then the coefficients on the 'number of iddir', 'if equb', 'can obtain 100 Birr' and 'household size' variables should be negative – greater values of these variables implies better access to informal risk coping mechanisms and lower background risk, thus should be associated with lower insurance take-up and lower risk aversion in the problems.

On the other hand, as referred to in Section 2.3, the technology adoption literature suggests that those subjects with larger social networks and more prior experience with informal insurance have more information on, and a better understanding of, insurance and so would be more likely to purchase a greater amount of insurance in the experiment. Additionally, it could also be the case that those participants with greater background risk access more informal risk-coping mechanisms, in order to protect themselves from income fluctuations in the absence of formal insurance. These arguments imply that the coefficients on the 'number of iddir', 'if equb', 'can obtain 100 Birr' and 'household size' are expected to be positive.

Therefore, the access to risk-sharing networks and informal insurance could impact indemnity insurance take-up in two possible ways. Moreover, the background risk argument and the technology adoption theory imply very different impacts on insurance take-up, and the sign of the coefficient estimates of the above-mentioned variables will provide an indication of which effect dominates. However, most subjects have, in all likelihood, had some prior experience

[18] We use livestock ownership as the only measure of wealth because of the issues associated with the use of land as a unit of wealth in rural Ethiopia, which are highlighted in Section 2.3.

with indemnity insurance; even though formal insurance is scarce in this region, almost all subjects have access to, and past experience with, informal insurance, which incorporates aspects of indemnity insurance.21 Thus, they probably have a better understanding of the concepts of indemnity insurance than those of index insurance. Therefore, given their past experience with important aspects of indemnity insurance, the technology adoption argument is probably not as appropriate for indemnity insurance as it is for index insurance, which is a relatively new product that the subjects have not had much exposure to in the past. Therefore, we expect the background risk effect to dominate and the sign on the risk sharing and informal insurance variables to be negative.

Along the same lines, we also expect that subjects from households with higher wealth also have more precautionary savings, more assets to draw on when impacted by adverse shocks, and better access to credit and informal insurance mechanisms – therefore, wealthier households should be better able to cope with risk (Dercon and Krishnan 2000), lowering their potential background risk. Therefore, this would strengthen the negative effect of wealth on risk aversion and indemnity insurance take-up in the experiment.

Since B is a simple Binswanger lottery without any insurance take-up aspect to it, we do not have any prior expectation of the sign of the coefficients on the 'understanding', 'financial literacy', 'if literate' and 'schooling obtained' variables. However, for the other decision problems, the work of Gine et al. (2008) and Cole et al. (2009) suggests that the coefficients of these variables should have a positive sign, as they argue that lower cognitive ability hinders the understanding of insurance products and deters their take-up. On the other hand, the Clarke (2011a) model and the results in Section 4.2 indicate that low cognitive ability may not be a significant factor causing the low take-up of insurance products. In addition, we believe that since most subjects have had some experience with indemnity insurance (or important aspects of it), the level of measured education, financial literacy and understanding is not as important for take-up in the indemnity insurance decision problems, as compared to the index insurance problems. Therefore, the direction of the expected impact of cognitive ability on risk aversion and indemnity insurance take-up is ambiguous, and we can empirically test between the two arguments outlined above.

In relation to the other explanatory variables in the analysis, we expect them to have conceptually similar effects on risk aversion and indemnity insurance take-up as on index insurance take-up, which are described in Section 4.2. The next two sub-sections provide the description, and present the results from the estimation of, the interval regression and structural maximum likelihood models.

4.3.1 INTERVAL REGRESSION MODEL

The interval regression model utilizes information of the bounds of risk aversion implied by the observed choices in the experiment (Harrison and Rutstrom 2008). Harrison and Rutstrom (2008) note that it is only suitable for analyzing choices under one-parameter utility functions, such as CRRA. It utilizes a maximum likelihood estimator and is similar to an Ordered Probit model but uses the implied values of r that each subject implicitly chose when they chose a particular choice as the latent variable – thus, it uses additional information on the magnitude of r, which is the implicit dependent variable and not just the ordinal value of the choice in the decision problem. However, the interval regression model makes the strong assumption that latent variable r, given the vector of explanatory variables x, satisfies the classical linear model predictions – without these assumptions the model does not consistently estimate x (Wooldridge 2002). Most importantly, as Wooldridge(2002) notes, it assumes that $r|x \sim \text{Normal}(x\beta, \sigma^2)$, where $\sigma^2 = \text{Var}(r|x)$.

Table 9 presents the results of this interval regression analysis for decision problems B and T_{IM} and T_{GM}, both with and without session controls. The results in columns (1) and (2) of the table suggest that subjects with greater wealth have a higher coefficient of relative risk aversion r, as measured by choices in B. The estimate of the coefficient on total livestock income is negative and significant at the 10% level in column (1) and at the 5% in column (2) when session controls are included. The estimates in columns (1) and (2) indicate that a one unit increase in the total livestock units (or the addition of the TLU equivalent of one ox) reduces the r measured in B by 0.13 and 0.175, respectively. Also, for B, the coefficient estimates of the standard deviation of consumption are positive and significant (at the 5% level), supporting the argument that subjects from those households that face more background risk display a higher level of risk aversion in the decision problem. These estimates indicate that an increase in the standard deviation of consumption by 100 Birr raises r by around 0.14. For decision problems T_{IM} and T_{GM}, however, the coefficient estimates of wealth and standard deviation of consumption are of the wrong sign, but are not statistically significant at the 10% level.

The coefficient estimate of the number of iddir is significant and negative in column (3), indicating that membership to an additional iddir lowers the indemnity insurance take-up in problems T_{IM} and T_{GM} , and lowers the implied r by 0.245; however, this result is no longer significant when session controls are added. The results in column (2) indicate that being in an equb and having access to 100 Birr in the case of an emergency reduce the subject's risk aversion r (as implied by their choices in B) by 0.87 and 0.62 respectively. The coefficient estimate of household size is also negative and significant in both specifications for B – the estimates in columns (1) and (2) indicate that an increase in household size by one member decreases r by approximately 0.2. These results – coupled with the fact that 13 out of the 16 coefficients on these four variables in all specifications are negative – provide evidence for the validity of the background risk argument, as opposed to the technology adoption hypothesis. They indicate that the standard deviation of consumption probably does not capture all the risk facing the household, and access to informal risk-coping mechanisms lowers the background risk faced by household, thus lowering risk aversion and insurance take-up in decision problems B, T_{IM} and T_{GM} .

The results in column (1) and (2) show that literate subjects have a higher CRRA coefficient r that is approximately 1.1 higher than illiterate subjects, ceteris paribus – these results are statistically significant at the 10% level. The coefficient estimates on the financial literacy variable in columns (3) and (4) are positive and significant at the 1% level indicating that increased financial literacy raises indemnity insurance take-up. However, none of the other cognitive ability coefficient estimates are statistically significant in the specifications for T_{IM} and T_{GM}; this may suggest that financial literacy is the aspect of cognitive ability that matters for understanding, and purchasing, indemnity insurance. The estimates show that answering an additional financial literacy question increases the r implied by the choices in the decision problems by 0.85. The coefficient on the fraction of earnings kept by the subject is negative in all specifications but statistically significant (at the 10% level) only in column (2) – these results are consistent with the hypothesis that those individuals who keep a smaller fraction of the experimental earnings for themselves tend to choose safer options in the problems.

We also observe in column (1) that women have a coefficient of relative risk aversion r that is around one lower than men (as implied by their choices in B) – the coefficient estimate of the 'if female' dummy is significant at the 10% level in this case, but is no longer statistically significant when session controls are added.22 Columns (3) and (4), however, show that women purchase more indemnity insurance in decision problems T_{IM} and T_{GM}. The estimates show that women have an r implied by the choices in T_{IM} and T_{GM} that is over 1.7 more than men. These apparently contradictory results highlight two important aspects that must be considered when analyzing choices from decision problems B, T_{IM} and T_{GM} . Firstly, we must keep in mind that the B is very different to T_{IM} and T_{GM} in framing and the inclusion of the insurance aspect. Therefore, it would not be surprising to find that subjects play these decision problems very differently, implying coefficients estimates of differing sign and magnitude in the specifications involving choices from B as compared to those involving choices from T_{IM} and T_{GM}. Secondly, B is much simpler and has been used in many studies to measure r; thus, we should rely on specifications from B, rather than T_{IM} and T_{GM}, to estimate the r and the impact of observable factors on r. In other words, our interpretations of the impact of observable characteristics purely on risk aversion r should be derived from the coefficient estimates of the specifications involving B, as the explanatory variables in these specifications can be considered solely as determinants of risk aversion r. Since T_{IM} and T_{GM} have a significant insurance take-up aspect, the coefficients in specifications involving these two problems might capture the effect of the observable factors on both risk aversion and indemnity insurance take-up. Therefore, we must be cautious about considering the observable factors in the specifications involving T_{IM} and T_{GM} as purely determinants of risk aversion r (even though each decision problem choice implies a range of r), and must also consider them to be determinants of indemnity insurance take-up.

This issue is once again highlighted in Figure 4.3.1, where we plot the distribution of the predicted CRRA coefficients from the interval regression model. The average r for the B specifications with and without controls is 1.44 and 1.45 respectively. To put these estimates into perspective, we note that Harrison and Rutstrom (2008) survey a number of important experimental studies and find that most of them predict an average r between 0 and 1. In particular, Harrison and Rutstrom (2008), in their interval regression analysis of the Holt and Laury (2002) data, find an average predicted r in the region of 0.5. In relation to the r estimated in developing countries, Botelho et al. (2005) obtain an estimate of r of around 0.6, when analyzing experimental data from Timor-Leste. Therefore, the estimates of r obtained from B specification indicate a rather high level of risk aversion as compared to other experimental studies. However, they are not unrealistically high, given that the amount at stake in the decision problems (50 Birr) is significant – it is equivalent to between two and three days casual farm labour in the areas the experiment was conducted. Harrison and Rutstrom (2008) note that measured risk aversion is higher for experiments involving larger payoffs.

On the other hand, the average implied r for the T_{IM} and T_{GM} specifications with and without controls is 4.15 and 4.58 respectively. These estimates indicate an improbably and unreasonably high level of risk aversion for subjects in the experiments, especially when we them to the r estimated in most other experimental studies (Harrison and Rutstrom 2008). This suggests that for the interval regression model, it may not be appropriate to interpret the coefficient estimates from the specifications involving T_{IM} and T_{GM} as the impact of the explanatory variables solely on risk aversion, since the magnitude of the estimated impact is probably misleading, even though the sign of the impact may be consistent. Other studies using the interval regression model (e.g. Coller and Williams 1999, Harrison and Rutstrom 2008) draw on experimental data from simpler decision problems which involve only choices between gambles in the gain framework (along the lines of B) and do not include more complicated aspects such as insurance take-up.

In the next section, we estimate similar specifications using the structural maximum likelihood model specified in Harrison and Rutstrom (2008), for determining the impact of observable factors on risk aversion and indemnity insurance take-up.

4.3.2 STRUCTURAL MAXIMUM LIKELIHOOD MODEL

The structural estimation model, along the lines of Harrison and Rutstrom (2008), is outlined below. Following Harrison and Rutstrom (2008), the expected utility EU_i for each potential choice of each lottery is calculated according to equation (2), where r is taken to be a linear combination of the observable factors mentioned earlier. Therefore, r = βx. The index ΔEU_i is then calculated for each lottery choice i as follows:

$$eu_i = \exp(EU_i) \tag{9}$$

$$\nabla EU_i = \frac{eu_i}{eu_1 + eu_2 + eu_3 + eu_4 + eu_5 + eu_6} \tag{10}$$

The latent index ∇EU_i, based on latent preferences, is in the form of a probability, and thus can be directly linked to the observed choices (Harrison and Rutstrom 2008). Therefore, the probability of a subject choosing lottery choice i is given by ∇EU_i. Given the observed choice y_a of individual a ($y_a \in \{1, 2, 3, 4, 5, 6\}$), the log-likelihood of the observed responses, conditional on EUT and CRRA utility, is:

$$\ln L^{EUT}(r; y, \mathbf{x}) = \sum_{a=1}^{N} \ln(\nabla EU_{y_a}) \tag{11}$$

where x is the vector of observable individual characteristics. N, the total number of subjects, is 378 for B, 136 for T_{IM}, 120 for T_{GM}, 258 for T_{IX} and 242 for T_{GX}.

The log-likelihood function ln L^{EUT} is therefore maximized with respect to β (where r = βx) to yield maximum likelihood estimates of the coefficients of the observable characteristics.

The above procedure describes how the structural maximum likelihood estimates are obtained using data from a single decision problem. To extend this procedure to multiple decision problems we make the strong assumption that the observed choices for an individual are independent across problems. Then, we obtain the maximum likelihood estimates of β from the maximization of the joint log-likelihood function (with respect to β):

$$\ln L^{EUT}(r; y, \mathbf{x}) = \sum_{b=1}^{5} \sum_{a=1}^{N} \ln(\nabla EU_{y_a}^{b})$$

where EU is the expected utility from lottery choice of individual a in decision problem b. Thus, we can restrict this specification to as many of the problems as we want – for the structural maximum likelihood estimates obtained in this section, we perform the above procedure with data from B and then with data from problems T_{IM} and T_{GM} . In Section 4.4 we then apply the procedure with data from all insurance problems.

The maximum likelihood optimization routine converged nicely in the specification for B, using all the observable characteristics as in the interval regression model.[23] However, the optimization routine did not converge when data from problems T_{IM} and T_{GM} were analyzed using all of the observable characteristics. These convergence problems are probably because of the smaller sample size of individuals who played T_{IM} and T_{GM} as compared to those who played B – while all the 378 subjects in the experiment played B, only 256 (in total) played T_{IM} and T_{GM} . It must be noted that when Harrison and Rutstrom (2008) analyze data from different experiments using this estimation procedure, they have a much larger sample of individuals and use a much smaller set of observable characteristics. For example, when they use the structural maximum likelihood estimation on data from the experiments of Harbaugh et al. (2002), they only use sex, age and order controls as determinants of r. Additionally, Harrison et al. (2010), using the same model on data from Ethiopia, India and Uganda, include only age, sex, education, household size and location and order controls as explanatory variables.

On the other hand, Harrison and Rutstrom (2008) report that the interval regression model is a more stable, robust statistical model and thus more appropriate for estimating detailed models where r is allowed to vary with a rich set of observable characteristics – when analyzing the Holt and Laury (2002) data using this model, they include a far larger set of observable characteristics to explain variation in r between individuals, including wealth, race, marital status, order and session controls. This may explain why the optimization routine for the interval regression model faces no convergence problems when a large set of observable characteristics is used, but that for the structural maximum likelihood model does face these problems.

Therefore, following Harrison and Rutstrom (2008), we use a smaller set of observable char- acteristics when applying the structural maximum likelihood estimation procedure to data from T_{IM} and T_{GM}. This set is chosen by first including the most important variable (or the variable with the most variation, and thus best able to discriminate between individuals) of each of the following groups of observable characteristics: wealth, background risk, membership of social groups, cognitive ability and demographic controls. Then, after choosing one variable from each of these groups to include in our specifications, we add other variables from the groups until the point where the optimization process breaks down. While this is clearly a rather ad-hoc method, it allows us to include the richest possible set, which permitted convergence, of ob- servable characteristics in the analysis of data from T_{IM} and T_{GM} , including what we believe to be the most crucial individual characteristics for explaining risk aversion r. Therefore, the basic set of characteristics included is standard deviation of consumption, the number of iddirs a household is a member of, years of schooling obtained, household size, age, sex and whether the subject is a household head or not. In addition, adding the understanding variable (from the cognitive ability group) did not lead to convergence problems, and hence it is included in the structural maximum likelihood specification for T_{IM} and T_{GM}.Table 10 presents the results for the structural maximum likelihood estimation. Columns (1) and (2) present the results of the analysis for B, using all the observable characteristics without and with session controls, respectively. Column (4) shows the results for T_{IM} and T_{GM}, using the smaller set of observable characteristics. Column (3) presents the results for B using the same observable characteristics as used for T_{IM} and T_{GM} , in order to compare results from B and T_{IM} and T_{GM} more directly. Table 10 shows once again that lower wealth leads to safer choices chosen in B, T_{IM} and T_{GM}. Columns (1)-(3) show that subjects that own more total livestock units exhibit more risk aversion in B – a one unit increase in total livestock units is estimated to decrease r by 0.03. Additionally, these columns also show that an increase in background risk increases the risk aversion implied by choices in B an increase in the standard deviation of consumption by 100 Birr increases r by around 0.017. While these results are statistically significant and of the same sign as the interval regression results, they are of smaller magnitude. Column (4) shows that an increase in total livestock units also leads to a reduction in indemnity insurance take-up in T_{IM} and T_{GM} , and a decrease in the implied r. This result is of similar magnitude to the results from the interval regression estimation for T_{IM} and T_{GM} . The results in columns (1) and (2) also show that subjects in households that are members of an equb group have a lower r, as implied by their choices in B. This is in line with the interval regression results which indicate that those households with greater access to informal credit and insurance groups have lower background risk, and hence choose riskier options in B, thus exhibiting a lower r. Similarly, the statistically significant negative coefficient estimate of household size in columns (1)-(4) indicate that those subjects from bigger households, which are better able to pool risk, choose riskier options in the three decision problems, opting for lower levels of indemnity insurance in T_{IM} and T_{GM} and exhibiting a lower r. However, these estimates also have lower magnitude than the corresponding interval regression estimates.

Table 10: Structural Maximum Likelihood Estimates of Risk Attitudes

Variable	(1) B	(2) B	(3) B	(4) T_{IM} and T_{GM}
Total livestock units	-0.0232**	-0.0300***	-0.0293***	-0.126**
	(-2.255)	(-2.831)	(-2.843)	(-2.179)
Std. dev. of consumption	0.000162*	0.000185*	0.000188*	-0.000920
	(1.847)	(1.874)	(1.806)	(-0.863)
No. of iddir	-0.00689	0.0189	-0.0157	0.156
	(-0.433)	(0.578)	(-1.191)	(0.695)
Can obtain 100 Birr	-0.112	-0.0779		
	(-1.187)	(-0.938)		
If equb	-0.108*	-0.165**		
	(-1.839)	(-2.117)		
Household size	-0.0270*	-0.0276*	-0.0271*	-0.160**
	(-1.791)	(-1.747)	(-1.726)	(-2.322)
Understanding	-0.540*	-0.516	-0.110	2.212**
	(-1.827)	(-1.312)	(-1.405)	(2.298)
Financial literacy	-0.144	-0.0727		
	(-0.780)	(-0.280)		
If literate	-0.199*	-0.112		
	(-1.721)	(-0.835)		
Schooling obtained	0.00988*	0.00573	0.00527	-0.0794**
	(1.789)	(0.928)	(0.818)	(-2.022)
Age	0.00425***	0.00388*	0.00503***	-0.0139
	(2.753)	(1.892)	(3.411)	(-1.164)
If female	-0.195***	-0.145**	-0.0714	-1.172***
	(-2.918)	(-1.984)	(-1.342)	(-2.902)
If household head	-0.103*	-0.0828	-0.133**	0.890**
	(-1.835)	(-1.272)	(-2.253)	(2.273)
If farmer	-0.0304	-0.0399		
	(-0.469)	(-0.487)		
Fraction of Earnings kept	-0.00842	-0.0384		
	(-0.120)	(-0.454)		
Constant	1.754***	1.818***	0.954***	5.844***
	(5.535)	(4.605)	(5.739)	(3.213)
Order Controls	No	Yes	No	No
Enumerator Controls	No	Yes	No	No
Location Controls	No	Yes	No	No
Observations	360	360	363	243
Log-likelihood	-577.0	-572.8	-591.0	-420.7

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Older subjects also seem to have a higher r, as implied by their choices in B. However, while the coefficient estimates of age are positive and statistically significant at the 1% level in columns (1)-(3), they are rather small in magnitude, indicating that a one year increase in age increase r by approximately 0.004. These estimates are of the same order of magnitude as those obtained by Harrison and Rutstrom (2008), who find that a one year increase in the age of the subject increases r by 0.014, when analyzing data from the Harbaugh et al. (2002) experiments using the same structural maximum likelihood model; meanwhile, Harrison et al. (2010) find that an increase in age by one year lowers r by 0.006. Additionally, the columns (1) and (2) show that women have a lower than men r by 0.195 and 0.145, respectively. This is in line with the results of Harrison et al. (2010), who also find that women are less risk averse than men, in their analysis of experimental data from developing countries using the same structural model. On the other hand, column (4) shows that women take up more indemnity insurance than men in T_{IM} and T_{GM}. These results are also in line with the interval regression results, which show that women exhibit less risk aversion in B, but choose more insurance in T_{IM} and T_{GM}. Column (1) of the table shows that literate subjects have a lower r by 0.2 as compared to illiterate subjects, but an increase in schooling by one year raises r by 0.01. Column (4) indicates that, for T_{IM} and T_{GM}, better understanding increases indemnity insurance take-up, but an increase in formal education obtained decreases insurance take-up. Thus, we do not find strong evidence to support the hypothesis that low cognitive ability is a major cause of low insurance take-up in developing countries. Households heads seem to display less risk aversion in B, but buy more indemnity insurance. This once again highlights that subjects play T_{IM} and T_{GM} quite differently from B. It must also be noted that the magnitude and statistical significance of all the estimates do not vary greatly for B when using the complete set of observable characteristics or the truncated set. The distributions of r predicted by each of the four specifications are presented in Figure 4.3.2. The average r is 0.58, 0.57, 0.55 and 3 for specifications (1), (2), (3) and (4) respectively. As with the interval regression model, the estimate of r implied by choices in T_{IM} and T_{GM} is significantly greater than that implied by choices in B. For both decision problems, however, the estimates of r are lower than those obtained from the interval regression model. The r estimated from the subjects choices in B, in the range of 0.5-0.6, is similar to the estimate of r (0.48) obtained by Harrison and Rutstrom (2008) and that (0.54) obtained by Harrison et al. (2010), where both studies use the same structural maximum likelihood model.

Figure 6: Structural Maximum Likelihood Estimates of Risk Aversion

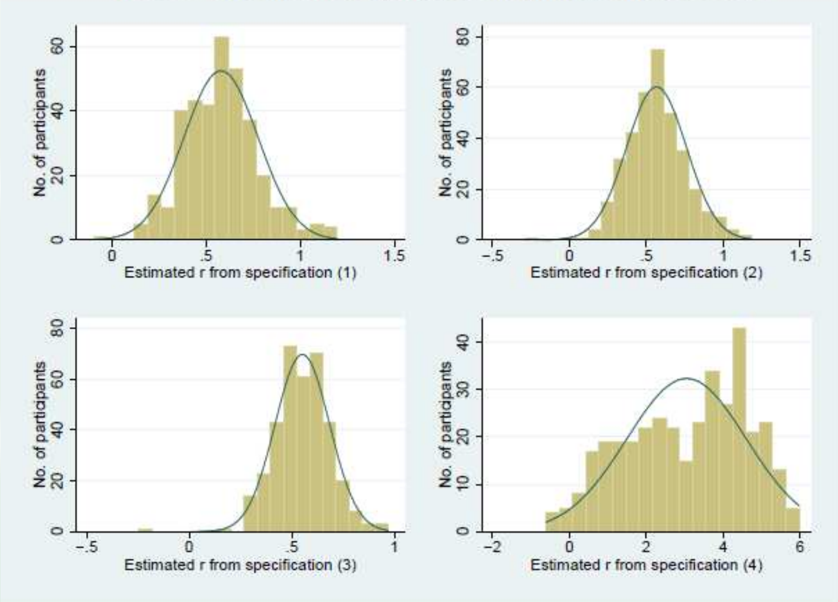
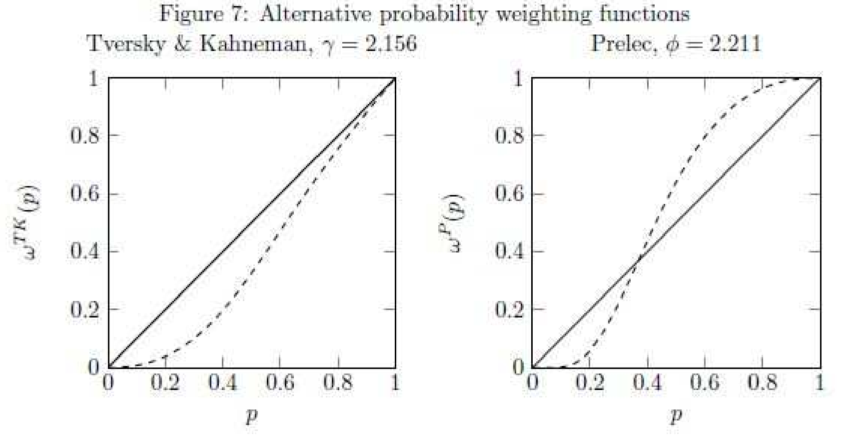


Figure 7: Alternative probability weighting functions



4.4 COMPARING THEORIES OF CHOICE

We now extend the structural estimation model of Section 4.3.2 to other models of decision under uncertainty, using data from all insurance decision problems. Specifically we apply data from all insurance decision problems to the five specifications of Table 11, excluding all covariates from the analysis.

Specification A is the EUT specification of Section 4.3.2, run for all data from all insurance decision problems and with no individual covariates. The coefficient of CRRA is estimated to be 0.774, broadly similar to that estimated by other studies. This coefficient may be directly compared with the coefficient of 0.891 reported by Harrison et al. (2010) for Ethiopian subjects in a traditional laboratory experiment, framed in the abstract. Specification B is the RDU specification with Prelec probability weighting function (5). As in Section 4.3.2 for EUT, we may construct the log likelihood function ln L^{RDU} as follows:

$$rdu_i = \exp(RDU_i) \tag{13}$$

$$\nabla RDU_i = \frac{rdu_i}{rdu_1 + rdu_2 + rdu_3 + rdu_4 + rdu_5 + rdu_6} \tag{14}$$

$$\ln L^{RDU}(r, \phi; y) = \sum_{a=1}^{N} \ln(\nabla EU_{y_a}) \tag{15}$$

:where RDUi is defined in equation (3).

As shown in Table 11, the joint maximum likelihood estimates for r and φ are 1.016 and 2.211. We may similarly construct the log likelihood function for the Tversky and Kahneman (1992) probability weighting function, replacing ω^P for ω^{TK} and φ for γ, yielding joint maxi- mum likelihood estimates for r and of 0.938 and 2.156. As can be seen in Figure 7 plots, both estimated probability weighting functions are S-shaped with convex weighting for low probabilities and concave weighting for high probabilities, rather than the more usual inverse S-shape. Moreover the S-shapes are statistically significant: Wald tests of the null hypotheses that there is no probability weighting (φ = 1 and γ = 1) have p-values of 0.000, and we may reject the nulls in the direction of φ > 1 and γ > 1.

Table 11: Maximum likelihood estimates of model parameters for insurance decision problems, with no individual covariates.

Coefficient	Estimate	Standard Error	p-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
A. EUT: $U(x) = \frac{x^{1-r}}{1-r}$					
r	0.774	0.017	0.000	0.740	0.807
B. RDU with Prelec Probability Weighting Function ω^P					
r	1.016	0.018	0.000	0.980	1.051
ϕ	2.211	0.325	0.000	1.574	2.848
$H_0 : \phi = 1$			0.000		
C. RDU with Tversky & Kahneman Probability Weighting Function ω^{PT}					
r	0.938	0.007	0.000	0.924	0.951
γ	2.156	0.186	0.000	1.790	2.521
$H_0 : \gamma = 1$			0.000		
D. Mean Variance					
b	0.029	0.002	0.000	0.026	0.032
E. Mixture model with RDU and Mean Variance					
r	1.113	0.035	0.000	1.045	1.181
ϕ	0.947	0.035	0.000	0.879	1.016
β	0.037	0.007	0.000	0.023	0.050
π^{RDU}	0.615	0.065	0.000	0.487	0.742
π^{MV}	0.385	0.065	0.000	0.258	0.513
$H_0 : \pi^{RDU} = \pi^{MV}$			0.078		
$H_0 : \phi = 1$			0.131		

This finding is not surprising given the data; a large number of participants purchased more index insurance than is consistent with EUT or RDU with an inverse S-shape. Moreover, it is consistent with Humphrey and Verschoor (2004a), Humphrey and Verschoor (2004b) and Harri- son et al. (2010) who find an S-shaped probability weighting function in traditional laboratory experiments, framed in the abstract and with samples drawn from developing country.

Specification D is the MV specification. As above we may construct the log likelihood function in L^{RDU} as follows:

$$mv_i = \exp(MV_i) \tag{16}$$

$$\nabla MV_i = \frac{mv_i}{mv_1 + mv_2 + mv_3 + mv_4 + mv_5 + mv_6} \tag{17}$$

$$\ln L^{MV}(b; y) = \sum_{a=1}^{N} \ln(\nabla EU_{y_a}) \tag{18}$$

where M Vi is defined in equation (7). The joint maximum likelihood estimate of 0.029 for b is not particularly pertinent since what we are most interested in is whether MV explains the data better than RDU or EUT. Unlike EUT and RDU, MV and RDU are not nested models and so we may not use the above procedure to discriminate between the models. However, we may estimate a mixture model for which MV, RDU and SEU are all special cases.

Following Harrison and Rutstrom (2009) let π^{RDU} denote the probability that the RDU model is correct and $\pi^{MV} = 1 - \pi^{RDU}$ the probability that the MV model is correct. Then the grand likelihood can be written as:

$$\ln L^{MM}(r,\phi,b,\pi^{RDU};y) = \pi^{RDU}\ln L^{RDU}(r,\phi;y) + (1-\pi^{RDU})\ln L^{MV}(b;y) \quad (20)$$

This log-likelihood is then maximized over all insurance decision problems, with estimated parameters reported in specification E of Table 11. Interestingly, the estimate for is statistically indistinguishable from unity (with p-value of 0.131) and so the data features that probability weighting was picking up in specifications B and C appear to be more naturally explained by allowing MV to partially describe the data generating process. As one would expect, given the theoretical predictions of EUT and observed behaviour in index insurance treatments we are able to reject EUT for either RDU with an S-shaped probability weighting function or MV. Moreover, a mixture model of MV and SEU appears to explain the data better than any other combination of MV, SEU and RDU.

4.5 INDIVIDUAL AND GROUP

As mentioned in Section 2.2, for both the index and indemnity insurance decision problems, a group and individual version was conducted. In the individual versions, subjects are exposed to own risks and can purchase insurance to match their own risk. In the group versions, subjects split losses evenly with a partner and may choose the amount of insurance they would like the group to purchase. Clarke (2011b) notes that for the case of index insurance, if individuals can soak up some of the basis risk by pooling the idiosyncratic risk with other group members, then the payouts from the index insurance product are more highly correlated with the group's losses than the individual's losses. Given the lower net basis risk associated with being a member of an idiosyncratic risk-pooling group, individuals would be expected to buy more insurance in the group decision problems than in the individual decision problems for the index insurance product. However, CRRA utility maximizers would choose lower insurance cover when in a group, as compared to the optimal amount they would choose individually. This is consistent with Gollier and Pratt's (1996) theory of risk vulnerability whereby the reduction of a zero mean background risk reduces indirect risk aversion[19] However, the magnitude of the difference between group and individual insurance take-up is predicted to be much smaller in the case of indemnity insurance than index insurance. Both predictions are highlighted by Figure 3 which shows that along the dotted line representing EUT theory with CRRA utility, individuals should chose more (less) insurance in the group decision problem than the individual decision problem in the case of index (indemnity) insurance. However, as can also be seen from Figure 3 this result is reversed if individuals subjectively weight probabilities with a sufficiently high enough, that is an S-shaped weighting function with sufficient curvature.

In order to highlight any systematic differences in take-up between group and individual insurance, we run the same OLS and Ordered Probit specifications listed in Section 4.2 using (1) decisions in T_{IM} and T_{GM} as the dependent variable and (2) decisions T_{IX} and T_{GX} as the dependent variable. However, we add, as an explanatory variable, a dummy which equals to one if the decision is from a group problem and zero if it is from an individual problem. Thus, a positive coefficient estimate on this variable would indicate that participants choose more insurance cover in the group decision problems than the individual decision problems. The results of the specifications for the indemnity insurance decision problems are presented in Table 12, while those for the index insurance specifications are presented in Table 13. We observe that in Table 12, the coefficient estimate on the group dummy for indemnity insurance is insignificant when session controls are not included, but is positive and significant at the 1% level for both the OLS and Ordered Probit specifications when session controls are included. This provides some evidence that individuals choose more indemnity insurance cover in the group decision problem than the individual decision problem. This is contrary to theoretical predictions of EUT with CRRA utility, but consistent with REU with an S-shaped probability weighting function.

However, Table 13 shows that in the case of index insurance, participants chose more insurance cover in the group decision problem – this is indicated by the positive coefficient estimate of the group problem dummy in all four specifications, which is statistically significant at the 10% level in both specifications where session controls are included. This is in line with the theoretical predictions of Clarke (2011b). Therefore, we have some evidence that selling index insurance to groups might lead to greater take-up, as individuals are able to lower basis risk associated with index insurance by pooling idiosyncratic risk within the group. However, both these results indicate the importance of further analysis on the subject, and also highlight the importance of testing alternative theories of individual choice.

[19] CRRA preference satisfy risk vulnerability (Gollier and Pratt 1996).

4.6 ROBUSTNESS CHECKS

There is a concern that outliers in the ERHS data on livestock and land may be driving the results involving these two variables; according to Chambers and Skinner (2003) this is often a worry when using survey data. One way to mitigate this problem is to use the logarithm of the variables instead of the levels. However, all the specifications used to determine the observable factors that impact risk aversion and the take-up of index and indemnity insurance produce similar results when the logarithm of these variables are used in the specifications instead of the levels. This indicates that the results obtained from these specifications are probably not driven by outliers in the wealth measures. Additionally, as indicated by Harbaugh et al. (2002), there is a concern that the choices of individuals, and thus our inferences in this study, are greatly affected by the order of decision problems played by the individual. Therefore, as a robustness check, we restrict our dataset to only include the choice from the first decision problem played by each individual. Then we re-run all our specifications, including the risk aversion and take-up specifications as well as the maximum likelihood specifications which test between the different theories of individual choice, using this truncated dataset. However, we find no notable differences in the results from the specifications using this dataset and those obtained using the original dataset, indicating that our results, and subjects' choices, are not purely driven by the order in which decision problems are played.

Table 12: Individual Versus Group Indemnity Insurance: Decision Problems T_{IM} and T_{GM}

Variable	(1) OLS	(2) O. Probit	(3) OLS	(4) O. Probit
Group problem dummy (1 if T_{GM})	-0.00653	-0.0166	0.623***	0.420***
	(-0.0342)	(-0.127)	(2.966)	(2.690)
Total livestock units	0.0256	0.0202	0.0117	0.0113
	(0.847)	(0.873)	(0.375)	(0.438)
Std. dev. of consumption	0.000161	5.88e-05	0.000107	2.08e-05
	(0.693)	(0.380)	(0.453)	(0.127)
No. of iddir	-0.0870*	-0.0501	-0.0542	-0.0349
	(-1.901)	(-1.519)	(-0.807)	(-0.720)
Can obtain 100 Birr	-0.0103	0.00292	0.0521	0.0463
	(-0.0420)	(0.0166)	(0.212)	(0.257)
If equb	0.213	0.161	0.0995	0.0819
	(0.817)	(0.903)	(0.314)	(0.376)
Household size	-0.0603	-0.0465	-0.0685	-0.0526
	(-1.208)	(-1.356)	(-1.375)	(-1.526)
Understanding	-0.195	-0.164	-0.0976	-0.152
	(-0.260)	(-0.281)	(-0.103)	(-0.199)
Financial literacy	1.582***	1.024**	1.829***	1.261***
	(2.788)	(2.464)	(3.322)	(3.075)
If literate	-0.280	-0.183	-0.291	-0.203
	(-0.794)	(-0.707)	(-0.751)	(-0.705)
Schooling obtained	0.0292	0.0207	0.0117	0.00838
	(1.068)	(1.066)	(0.474)	(0.456)
Age	0.00361	0.00224	0.00476	0.00291
	(0.419)	(0.379)	(0.500)	(0.443)
If female	0.205	0.120	0.292	0.183
	(0.846)	(0.703)	(1.146)	(0.998)
If household head	-0.164	-0.124	-0.206	-0.157
	(-0.668)	(-0.761)	(-0.831)	(-0.941)
If farmer	-0.128	-0.0727	-0.0129	0.0193
	(-0.561)	(-0.481)	(-0.0539)	(0.118)
Fraction of earnings kept	-0.181	-0.121	-0.393*	-0.282*
	(-0.785)	(-0.749)	(-1.841)	(-1.815)
Constant	3.212***		3.223***	
	(4.267)		(3.837)	
Threshold 1		-1.393***		-1.502***
		(-2.772)		(-2.675)
Threshold 2		-0.484		-0.573
		(-0.979)		(-0.960)
Threshold 3		0.261		0.203
		(0.525)		(0.351)
Threshold 4		0.675		0.637
		(1.311)		(1.072)
Threshold 5		1.289**		1.273**
		(2.482)		(2.130)
Order Controls	No	No	Yes	Yes
Enumerator Controls	No	No	Yes	Yes
Location Controls	No	No	Yes	Yes
Observations	240	240	240	240
R-squared	0.066		0.130	
Log-likelihood		-575.5		-567.3

*** p<0.01, ** p<0.05, * p<0.10

Table 13: Individual Versus Group Indexed Insurance: Decision Problems T_{IX} and T_{GX}

Variable	(1) OLS	(2) O. Probit	(3) OLS	(4) O. Probit
Group problem dummy (=1 if T_{GX})	0.157	0.112	0.457*	0.317*
	(0.947)	(0.875)	(1.764)	(1.753)
Total livestock units	0.370***	0.281***	0.273**	0.214**
	(3.664)	(3.339)	(2.645)	(2.556)
Livestock squared	-0.0122***	-0.00930***	-0.00945***	-0.00739***
	(-3.802)	(-3.250)	(-3.092)	(-2.736)
Std. dev. of consumption	0.000125	9.65e-05	2.90e-05	2.34e-05
	(0.531)	(0.568)	(0.112)	(0.125)
No. of iddir	-0.0169	-0.0210	0.0109	-0.00257
	(-0.330)	(-0.573)	(0.188)	(-0.0623)
Can obtain 100 Birr	0.514**	0.373**	0.529**	0.389**
	(2.170)	(2.250)	(2.195)	(2.304)
If equb	-0.0612	-0.0439	-0.131	-0.0990
	(-0.311)	(-0.294)	(-0.547)	(-0.558)
Household size	-0.0273	-0.0208	-0.0176	-0.0135
	(-0.784)	(-0.805)	(-0.478)	(-0.491)
Understanding	-0.00928	0.00288	-0.184	-0.221
	(-0.0172)	(0.00723)	(-0.267)	(-0.424)
Financial literacy	0.235	0.179	0.408	0.310
	(0.537)	(0.561)	(0.913)	(0.948)
If literate	0.366*	0.287*	0.344	0.269*
	(1.757)	(1.923)	(1.634)	(1.776)
Schooling obtained	0.0288	0.0213	0.0148	0.0121
	(1.399)	(1.377)	(0.675)	(0.745)
Age	0.00208	0.00100	0.00242	0.00107
	(0.392)	(0.262)	(0.413)	(0.252)
If female	0.554**	0.383**	0.565**	0.393**
	(2.669)	(2.452)	(2.697)	(2.452)
If household head	-0.430**	-0.334**	-0.419**	-0.336**
	(-2.089)	(-2.212)	(-2.088)	(-2.260)
If farmer	0.367	0.259	0.401*	0.296*
	(1.657)	(1.550)	(1.886)	(1.832)
Fraction of earnings kept	-0.0114	-0.0204	-0.172	-0.140
	(-0.0616)	(-0.147)	(-0.917)	(-0.989)
Constant	0.132		1.243	
	(0.189)		(1.427)	
Threshold 1		1.019*		0.0992
		(1.917)		(0.153)
Threshold 2		1.926***		1.006
		(3.657)		(1.530)
Threshold 3		2.474***		1.563**
		(4.601)		(2.366)
Threshold 4		3.080***		2.182***
		(5.570)		(3.251)
Threshold 5		3.667***		2.785***
		(6.574)		(4.252)
Order Controls	No	No	Yes	Yes
Enumerator Controls	No	No	Yes	Yes
Location Controls	No	No	Yes	Yes
Observations	360	360	360	360
R-squared	0.099		0.130	
Log-likelihood		-367.9		-359.3

*** p<0.01, ** p<0.05, * p<0.10

5 SUMMARY, DISCUSSION AND CONCLUSION

Recent empirical work on agricultural insurance in developing countries has focused on analysing the actual purchase of weather index insurance policies by poor farmers. However, without an objective joint distribution of losses and claim payments, analysis is limited to understanding who purchases rather than the more fundamental question of how observed purchase relates to 'rational' purchase (Clarke 2011a).

In this study we use data from the ERHS panel survey and a novel framed laboratory experiment conducted in rural Ethiopia to analyze the following questions: (1) What are the determinants of index insurance take-up and, in particular, what is the relationship between index insurance take-up and wealth? (2) What are the determinants of risk aversion and indemnity insurance take-up? (3) Is there evidence that purchase of index insurance is irrationally low relative to purchase of indemnity insurance? (4) Does expected utility theory describe insurance decisions well or do alternate theories of choice, such as rank dependent utility, perform better? (5) Is insurance purchase higher when individuals pool risk with each other than when they do not?

We find evidence that the relationship between index insurance take-up and wealth is nonlinear, and subjects with intermediate levels of wealth have the highest take-up, with low demand for index insurance from the poorest and the richest. This is consistent with the hump-shaped theoretical relationship between index insurance take-up and wealth derived by Clarke (2011a) in an expected utility framework, and is inconsistent with predictions from the mean variance theoretical model of Gine et al. (2008). We do not find strong evidence that schooling, understanding of the decision problems or financial literacy increase index or indemnity insurance take-up, suggesting that the low levels of index insurance take-up found by Gine et al. (2008) and Cole et al. (2009) are not a result of low cognitive ability or poor understanding of financial products.

We also find that background risk significantly impacts indemnity insurance take-up. Subjects with greater background risk and less access to informal insurance and credit to cope with this risk exhibit greater risk aversion and indemnity insurance take-up in the decision problems. This is broadly in line with Gollier and Pratt's (1996) theory of risk vulnerability. Additionally, it seems that participants choose more insurance cover in the group index and indemnity decision problems than in the individual decision problems. Also, men and women seem to make choices about insurance quite differently, and have systematically differing choices in most of the decision problems.

Following Harrison and Rutstrom (2008), we use the interval regression model and structural maximum likelihood model to explore the determinants of risk aversion. Though we find that most coefficient estimates have the same sign in the results from both models, the magnitudes of the estimates (and thus of the average predicted r) can differ greatly. This indicates, as noted by Harrison and Rutstrom (2008) as well, that parametric assumptions made by the models matter a great deal for the estimation of risk attitudes using these models – these assumptions, and their consequences, need to be explored in more detail and further work is required to determine which model is more appropriate for analyzing the determinants of risk aversion and indemnity insurance take-up. Also, we need to explore in more detail why the structural maximum likelihood estimation technique encounters convergence problems when using a large set of observable characteristics to explain r, unlike the more robust interval regression model, and how the convergence issues relate to the different assumptions made by both models. These are interesting avenues that could be explored in future research.

Finally, we find that purchase of indexed insurance products in our experiment is systematically higher than the generic financial advice of Clarke (2011a); in the simplest index insurance decision problem 66% of subjects purchased an inadvisably high level of cover, purchasing more cover than would be optimal for any decision maker with risk averse DARA preferences over aggregate wealth. Whilst the data can be better explained by RDU with an S-shaped probability weighting function that underweights extreme events, there is no evidence of demand for index insurance being lower than rational demand.

Development economists and insurance practitioners are rightly excited about the potential for agricultural insurance to substantially increase welfare for many of the world's rural poor (Banerjee 2002, Collins et al. 2009, Karlan and Morduch 2009). However, voluntary purchase of unsubsidised products remains low, despite recent innovations in the use of indices in product design (Skees et al. 1999). All too often this low demand is attributed to poor 'behavioural' decision making on the part of farmers, without proper consideration of whether the product provides good value to rational farmers. Subjects in the present experiment did suffer from behavioural biases, but these led to an inadvisably high level of index insurance purchase, lending support to the suggestion of Clarke (2011a) that the low observed demand for weather index insurance from poor farmers may be rational, or even too high.

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