Smallholder Farmer Risk Preferences in Northern Ghana: Evidence from a Controlled Field Experiment

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Abstract

We conduct a controlled field experiment to elicit risk preferences among maize farmers in Northern Ghana. Farmers participating in the experiment were asked to choose from a menu of lotteries representing different hypothetical probability distributions over yields produced by "traditional" and "high yield" maize varieties. We estimate a Rank-Dependent Utility Model (RDU) with an Expo-Power utility function, allowing for systematic subjective underweighting or overweighting of outcome probabilities and non-constant relative risk aversion. Based on our estimates, we cannot reject the hypotheses that decisions made by farmers in our study can be uniformly characterized by conventional Von Neumann-Morgenstern expected utility theory (EUT), but reject the hypothesis that farmers exhibit constant relative risk aversion.

Keywords: Field Experiment, Risk Aversion, Expected Utility Theory, Rank-Dependent Utility, Finite-Mixture Models

1. Introduction

Poor smallholder farmers in developing countries face price and production risks that can profoundly affect their production decisions. Drought typically presents the greatest risk due to the widespread use of rainfed rather than irrigated agricultural practices (Shiferaw et al., 2014)[1]. Drought risk, moreover, is exacerbated by lack of access to efficient credit and insurance markets that would otherwise allow the farmer to self-insure or transfer risk to a third parties (Miranda and Farrin, 2012). As a result, smallholder farmers in drought-prone areas are often forced to employ low-return production practices to minimize their exposure to the adverse consequences of drought (Binici et al., 2003; Hurley, 2010).

Although risk is pervasive in agricultural decision-making, there exists gaps in our understanding of the risk preferences of smallholder farmers, particularly in Sub-Saharan Africa. Over the past three decades, numerous studies have employed experimental methods to elicit risk attitudes among smallholders in developing countries. Expected Utility Theory (EUT), introduced by von Neumann and Morgenstern (1953), has been the model of choice for framing these experiments (Binswanger, 1980; Miyata, 2003; Wik et al., 2004; Hill, 2009). However, numerous studies have found that EUT may not be the best model of choice under uncertainty for smallholders in developing countries (Harrison & Rutström, 2009; Tanaka et al., 2010; Liu, 2013; de Brauw & Eozenou, 2014).

Numerous alternatives to EUT have been proposed to explain decisions under uncertainty, including Prospect Theory and Rank-Dependent Utility Theory (Kahneman & Tversky, 1979; Quiggin, 1993). Prospect Theory extends EUT by allowing the utility function to depend on reference points, with losses below the reference point weighted disproportionally more than gains above the reference point (Pennings & Garcia, 2009, Tversky & Kahneman, 1992). Rank-Dependent Utility Theory allows the "subjective" probabilities assessments by the decision maker to deviate from "objective" probabilities by allowing weighting of probability events (Hurley, 2010). Other recent studies posit that two (or more) latent decision-making processes (i.e. Expected Utility Theory and Rank-Dependent Utility Theory) may simultaneously generate the same observations or data (Harrison & Rutström, 2009).

The experimental literature provides mixed results regarding whether there are differences in behavior between hypothetical and real incentive responses. Some studies have argued that subjects generally respond the same way to hypothetical incentives as they do to real incentives on the grounds that subjects have no reason to hide their true preferences (Kahneman & Tversky, 1979). However, some studies, including Hold & Laury (2002), subjects comparing hypothetical incentives and real incentives behave differently, especially that subjects tend to become increasingly risk averse as payoffs increase with real incentives, whereas increasing the scale of hypothetical incentives has no effect on risk aversion. Harrison (2006) reviews evidence for hypothetical bias over uncertain outcomes and finds that subjects respond differently to risky prospects when they face real economic consequences instead of hypothetical economic consequences. However, these differences might be mitigated if the tasks are less complex, or framed in non-monetary outcomes.

In this paper, we test competing models of decision making under uncertainty among smallholder farmers in Northern Ghana. Specifically, based on data collected from a controlled field experiment, we estimate a Rank-Dependent Utility model that explicitly allows us to test the assumptions of Expected Utility Theory and constant relative risk aversion. The remainder of this paper is organized as follows: Section 2 reviews previous experimental studies of risk preferences in developing countries. Section 3 describes the setting for our experiments and explains our experimental procedures. Section 4 presents the methodology used to study the adoption of high yield variety maize (HYV) in Ghana. Section 5 presents our empirical findings. Section 6 provides a summary of our findings, presents our main conclusions, and offers suggestions for further research.

2. Farmer Risk Preferences in Developing Countries

Development economists and psychologists have employed a variety of experimental methods to elicit risk attitudes, including self-assessment (Dohmen et al., 2011; Jung & Treibich, 2014), psychometric or Likert scale household surveys (Baron, 1970) and experimental lotteries (Binswanger, 1980, 1981; Holt & Laury, 2002; Harrison, Lau, & Rutström, 2007, 2011).

Binswanger (1980, 1981) provides early tests for risk aversion among Indian farmers using lottery experiments with hypothetical and real monetary payoffs. Under the assumptions of Expected

Utility Theory, the author finds that most of the farmers surveyed exhibited aversion to risk that increased with the monetary payoff of the lotteries. Based on these results, the author concludes that farmers' choices are consistent with increasing relative risk aversion and decreasing absolute risk aversion.

Barr & Genicot (2008) conducts an experiment with Zimbabwe farmers that allows for group consultation. Like Binswanger, they find that most farmers exhibit aversion toward risk, but less so if they can pool risk collectively. The experiments conducted by Wik et al. (2004) with Zambian villagers closely mirror Binswanger's. They find that risk attitudes change from risk aversion to risk neutrality as lottery payoffs are reduced. The authors conclude that risk attitudes are consistent with decreasing absolute risk aversion and increasing partial risk aversion. Estimates based on a random effects interval regression model also indicate that risk attitudes depend on a variety of other observable factors. They find, for example, that partial relative risk aversion decreases as wealth increases.

Unlike earlier experimental studies based on Expected Utility Theory, Tanaka et al. (2010) employ Cumulative Prospect Theory to evaluate risk attitudes among Vietnamese villagers. The authors find that their subjects, on average, are risk averse over gains (risk seeking over losses), over-weight low probability events and under-weight high probability events. About 90 per cent of their experimental subjects exhibit loss aversion.

Harrison, Humphrey, & Verschoor (2010) also relax the assumptions of Expected Utility Theory. They evaluate the choices of Ethiopian, Indian and Ugandan villagers over eight binary lottery pairs. A novel feature of their analysis is that it allows choices to be described by either Expected Utility Theory or Rank-Dependent Utility Theory within the context of a finite mixture model. They find that their experimental subjects tend to underweight low and overweight high probability events, a tendency that intensifies as household size increases. They also find that less than half of the choices can be adequately explained by Expected Utility Theory.

de Brauw & Eozenou (2014) conduct a lab-in-the-field experiment to explore risk preferences among sweet potato producers in northern Mozambique and test whether they are consistent with constant relative risk aversion (CRRA), Expected Utility Theory or a more general Rank-Dependent Utility Theory. They find that CRRA poorly predicts risk preferences among those who are less risk averse. They also find that less than 30 percent of choices made by the farmers in their study are consistent with Expected Utility Theory.

Holden (2014), in a study of the risk preferences of poor rural households in Malawi using monetary incentive experiment, finds that experimental results are sensitive to framing. The author finds that risk aversion estimates based on the Holt and Laury framework may be upwardly biased due to measurement error arising from inconsistent responses. The author also finds that recent exposure to a drought is associated with greater risk aversion, regardless of whether subjective probability weighting is used.

3. Experimental Procedures

In this study, we employ a variant of the Holt and Laury experimental approach to investigate risk preferences among smallholder farmers in Northern Ghana.

3.1. Context of the Experiment

The experiment was conducted as part of a three-year randomized controlled trial (RCT) impact evaluation study of the effects of index insurance-backed contingent credit on production technology adoption among smallholders in Ghana. The study was conducted in collaboration with 14 members of the Association of Rural Banks (ARB) and the Ghana Agricultural Insurance Pool, which offered index-insured loans to smallholder lending groups. For the RCT baseline survey, 779 farmers randomly selected from 279 farmer groups serviced by ARB lenders were interviewed. Farmer groups were selected based on several criteria, including: (1) groups in good standing with their lender as well as groups qualified to receive loans but had not applied for one; (2) groups whose primary or secondary crop is maize; and (3) groups that take out a loans of less than 10,000 GHC.

In order to elicit farmer risk attitudes, 333 farmers were randomly selected from the 779 farmers participating in the broader RCT to participate in our controlled field experiment. Participants in the experiment included 136 males and 197 females, 57 from Bawku West district, 42 from Bawku Municipal district, 42 from Binduri district, and 192 from Garu Tempane district (see figure 1).

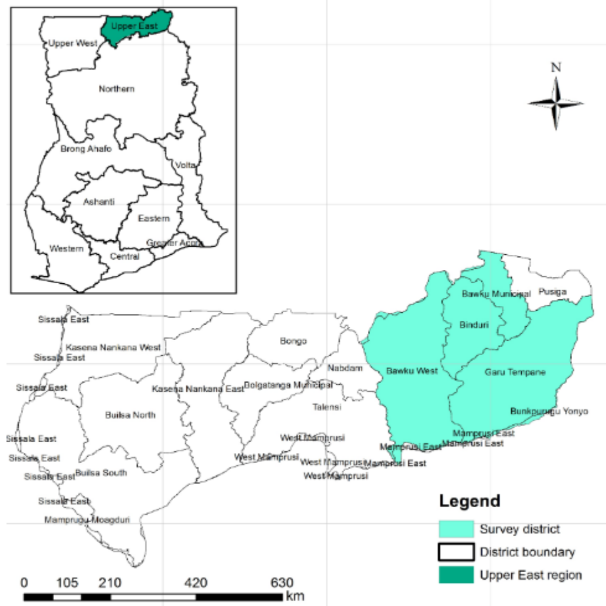

Figure 1: Survey area.

Farmers selected for the risk preference elicitation study were given the option to participate in the risk elicitation field experiments and all but two elected to do so. Because the farmers were already included in the general baseline survey, we had data available regarding household demographic and socio-economic characteristics, including agricultural production practices, landholdings, experience growing maize, non-agricultural income, credit and saving, historical experience with drought, and drought adaptation and mitigation strategies.

The research team conducting the experiment was composed of four research supervisors and coordinators and 10 enumerators, all post-graduate students from the University of Development Studies, Tamale, who spoke the local language. The research team organized five training sessions for farmers (one in Bawku Municipal, one in Bawku West, one in Binduri, and two in Garu Tempane) to explain concepts such as “chance”, “risk”, and “hypothetical”. The experimental instructions given by enumerators to farmers is presented in the Appendix.

3.2. Experimental Design

The experiment to elicit risk preferences is framed around the hypothetical adoption of "high yield variety" (HYV) maize and consisted of offering a menu of ordered lottery choices over hypothetical gains to the farmers from doing so. Option $j = 0$, the safer option, provides a hypothetical "traditional" maize seed that yields 350 kg per acre with good rains, but a slightly lower 250 kg per acre with bad rains. Option $j = 1$, the riskier option, provides a hypothetical "high yield variety" (HYV) maize seed that yields 750 kg per acre with good rains, but only 50 kg per acre with bad rains. Farmers were asked to choose between these two maize seeds under 10 different scenarios in which the probabilities of good rains were systematically increased from 10 per cent to 100 per cent.

The payoff matrix for the experimental lotteries is presented in table 1. Each row of the table represents a scenario presented to the farmer in which she was asked to choose between the safer traditional maize $j = 0$ and the riskier HYV maize $j = 1$, assuming a particular rainfall probability distribution. The expected net gain in yield from adopting HYV maize (not revealed to the farmer) under scenario k is computed as:

$$G_k = \sum_{s=1}^{2} p_{ks} y_{1s} - \sum_{s=1}^{2} p_{ks} y_{0s},$$

where s is the state of nature, with $s = 1$ indicating good rains and $s = 2$ indicating poor rains, p_{ks} is the probability of occurrence of state s under scenario k, and y_{js} is the yield produced by maize seed j on occurrence of state s. Under the aforementioned outcomes, the expected yield is the same for both choices when the probability of good rain equals 38.5 per cent. Thus, as shown in table 1, the expected yield is higher for the risky HYV maize option $j = 1$ than the safer traditional maize option $j = 0$ for choices involving probabilities of good rains of 40 per cent and above, and lower for choices involving probabilities of good rains of 30 per cent and below.

Table 1. Expected net gain from adopting HYV maize under alternative hypothetical rainfall probabilities.

Probabilities		Expected Yields		
Good Rains	Bad Rains	Traditional Maize	HYV Maize	Net Gain
0.1	0.9	260	120	-140
0.2	0.8	270	190	-80
0.3	0.7	280	260	-20
0.4	0.6	290	330	40
0.5	0.5	300	400	100
0.6	0.4	310	470	160
0.7	0.3	320	540	220
0.8	0.2	330	610	280
0.9	0.1	340	680	340
1.0	0.0	350	750	400

Figure 2 gives the proportion of farmers that chose to adopt the riskier HYV maize for different probabilities of good rains. For reference, the dotted line indicates the proportion of farmers that hypothetically would adopt HYV maize if they were risk neutral and simply maximized expected yield. As seen in figure 2, the proportion of farmers that adopted HYV maize increases monotonically as the probability of good rains (and thus the expected gain from adopting HYV maize) increases. However, the proportion rises at a slower rate than would be expected if all farmers in the study were risk neutral, implying that the average farmer in our sample is risk averse.

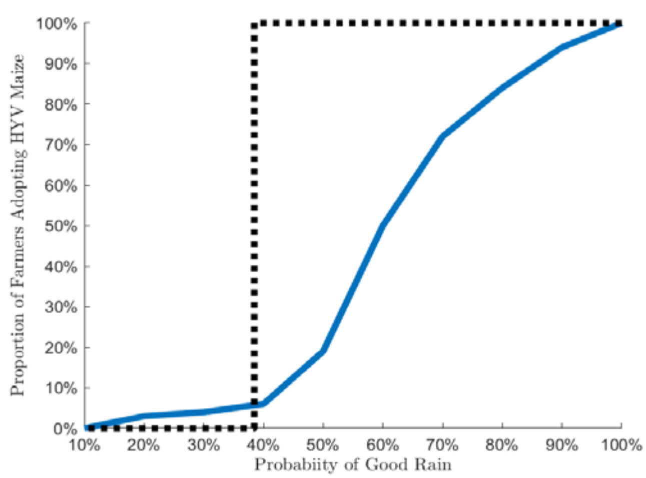

Figure 2. Proportion of farmers adopting HYV maize versus probability of good rains.

3.3. Profile of Experimental Subjects

The demographic characteristics and production practices of the 331 Northern Ghanaian smallholder farmers who participated in our experiment are summarized in table 2.

Table 2. Summary of demographic characteristics of experimental subjects.

Variable	Percent Reporting	Variable	Average
Female	60%	Age (years)	47
Married	85%	Household Members	7.6
Experienced Drought in 2014	36%	Dependency Ratio	1.1
Technology Adoption Experience	13%	Farm Size (Hectares)	5.9
Operate Non Farming Business	58%	Livestock Endowment (TLU)	5.6
Access to Irrigation Facilities	2%	Number of Droughts Past 5 Seasons	2.5
Completed Primary School	20%	Annual Agricultural Income (GHC)	1,149
Drought Perception	82%	Household Saving (GHC)	296
Food Secure	16%		
Moderate Food Insecure	42%		
Severe Food Insecure	42%		

Most farmers who participated in our experiment, 60 per cent are women, and 85 per cent are married. They average 47 year of age. Less than 20 per cent completed six years of primary school. Their households average 7.6 members, with 1.1 inactive members per active member.

The overwhelming majority of farmers grow maize for their main crop. Virtually all employ rain-fed agricultural practices, with only 2 per cent having access to irrigation. Their farms tend to be small, with a mean size of fewer than six hectares spread over an average of three plots. Only 13 per cent of farmers have adopted new production technologies over the past five years.

Farmers on average derive a net annual income of 1,149 GHC from farming. However, a significant proportion, 58 per cent, report earning supplementary income from non-farming businesses. Farmers hold an average of 296 GHC in cash savings. Livestock, including chickens, bulls, cows, sheep, and goats, are a significant asset held to finance consumption needs, especially during drought. Most farmers own at least one livestock and on average stock 5.6 tropical livestock units (TLU)[2].

The food security status of each farmer is measured by the food insecurity experience scale (FIES) of the FAO-Voices of the Hungry (VOH)[3]. Using this measure, 16 per cent of farmers report being food secure, 42 per cent report being moderately food insecure, and 42 per cent report being severely food insecure. Farmers were asked whether they had experienced a drought that adversely affected their maize yields over the previous five growing seasons. More than 90 per cent of farmers reported having experienced at least one drought over the preceding five growing seasons, with more than 60 per cent having experienced at least three droughts, for an average of 2.5 droughts during that period. Approximately 36 per cent of farmers experienced a drought in 2014, the year immediately preceding the conduct of the experiment and 82% of farmers perceived that there is going to be drought in the next 5 years.

4. Empirical Model

We employ a Rank Dependent Utility framework, which generalizes Expected Utility Theory by allowing decision makers to apply subjective weights to the probabilities of occurrence of different states of nature (Quiggin, 1982, 1993). Specifically, we assume that a farmer, given a choice between two lotteries $j = 1,2$, will choose the one that offers the greatest "prospective" expected utility

$$EU_j = \sum_s w(p_s)u(y_{js}). \quad (1)$$

Here, p_s is the probability of state of nature s, y_{js} is the payoff provided by lottery j in state of nature s, $w(\cdot)$ is the farmer's subjective probability weighting function, and $u(\cdot)$ is the farmer's utility function.

To proceed to empirical estimation, we assume the weighting function takes the parametric form proposed by Tversky and Kahneman (1992)[4]:

$$w(p;\mu) = p^\mu/(p^\mu + (1-p)^\mu)^{1/\mu} \quad (2)$$

As discussed by Gonzalez and Wu (1999), for $0 \leq \mu \leq 1$, the weighting function takes an inverse S-shape characterized by a concave section, indicating the overweighting of small probability outcomes up to a crossover-point where $w(p) = p$, beyond which there is a convex section indicating the underweighting of high probability outcomes. If $\mu > 1$, the weighting function takes an S-shape, indicating the underweighting of small probability outcomes and overweighting of high probability outcomes. If $\mu = 1$, $w(p) = p$ for all probabilities p and farmers choose among lotteries in accordance with the tenets of Von Neumann-Morgenstern Expected Utility theory.

We also assume an expo-power utility function form[5] (Saha, 1993; Xie, 2000) that includes constant relative risk aversion and constant absolute risk aversion as special cases:

$$u(y;\gamma,\sigma) = \frac{1}{\gamma}\left(1 - exp\left(-\gamma\left(\frac{y^{1-\sigma}-1}{1-\sigma}\right)\right)\right) \tag{3}$$

The expo-power utility function allows relative risk aversion (RRA) to vary with the payoff y:

$$RRA(y;\gamma,\sigma) = \sigma + \gamma y^{1-\sigma} \tag{4}$$

The expo-power utility function reduces to a standard constant relative risk aversion (CRRA) utility function as $\gamma \to 0$, in which case σ equals the constant RRA. If, in addition, σ equals 0, the agent is risk neutral.

In order to allow for observation error, we assume that computations of prospective expected utilities are further subject to an additive zero-mean error, unobservable by the econometrician, that possesses a logistic distribution with zero mean and scale parameter η (Harrison & Rutström, 2008). Under these assumptions, the probability that a farmer with preference parameters (μ,γ,σ) will be observed to choose seed option j when presented with rainfall probability distribution scenario k is

$$P_{kj}(\eta,\mu,\gamma,\sigma) = \frac{exp\left(\frac{EU_{kj}}{\eta}\right)}{exp\left(\frac{EU_{k0}}{\eta}\right)+exp\left(\frac{EU_{k1}}{\eta}\right)} \tag{5}$$

where

$$EU_{kj} = \sum_s w(p_s;\mu)u(y_{js};\gamma,\sigma). \tag{6}$$

Observation error may arise for a variety of reasons: experimental subjects could misunderstand the nature of the experiment; they could choose by accident; they could be in a hurry to complete the experiment; or they could simply be motivated by something other than maximizing their welfare from participating in the experiment (Hey & Orme, 1994).

5. Estimation Methods

We begin by estimating the decision model under the assumption that the structural parameters $(\eta, \mu, \gamma, \sigma)$ are homogenous across farmers participating in the experiment. From Harrison & Rutström (2008), the estimates are derived by maximizing the sample log likelihood

$$LL(\eta, \mu, \gamma, \sigma; d) = \sum_i \sum_k \sum_j d_{ijk} \log\left(P_{kj}(\eta, \mu, \gamma, \sigma)\right).$$

Here, $d_{ikj} = 1$ if farmer i chose maize seed j when presented with rainfall probability distribution scenario k, and $d_{ikj} = 0$ otherwise.

We then estimate the decision model under the assumption that risk aversion parameters vary across farmers according to $(\eta_i, \mu_i, \gamma_i, \sigma_i,) = \beta X_i$ where X_i is a column vector of covariates specific to farmer i (which includes 1 to allow for a constant term) and β is a row vector of parameters to be estimated. Estimates are derived by maximizing the sample log likelihood

$$LL^C(\eta, \mu, \gamma, \beta; d, X) = \sum_i \sum_k \sum_j d_{ijk} \log\left(P_{kj}(\eta, \mu, \gamma, \beta X_i)\right).$$

Finally, following Harrison & Rutström (2009), Andersen et al. (2014), Pennings and Garcia (2010), we estimate a finite mixture model that posits that a proportion π of farmers participating in the experiment are Von Neumann-Morgenstern Expected Utility maximizers $(\mu = 1)$. Estimates are derived by maximizing the mixture model sample log likelihood

$$LL^M(\eta, \mu, \gamma, \beta, \pi; d, X) =$$

$$\sum_i \sum_k \sum_j d_{ijk} \log\left(\pi P_{kj}(\eta, 1, \gamma, \beta X_i) + (1 - \pi)\, P_{kj}(\eta, \mu, \gamma, \beta X_i)\right).$$

Estimation was performed using the Stata 14 “mle” routine commands developed by Harrison & Rutström (2008). Given the strong possibility that errors among responses by the same farmer are correlated, the standard errors are adjusted for clustering.

6. Results and Discussion

We estimate the decision model under the general Rank-Dependent Utility (RDU) framework that allows farmers to subjectively weigh probabilities (equation 2) and employ a general expo-power utility function (equation 3) that allows farmers to exhibit non-constant relative risk aversion. We abbreviate this general model “RDU”. The general model nests one case of special interest. Under the restriction $\mu = 1$, farmers do not apply subjective weights to probabilities and make decisions in accordance with Von Neumann-Morgenstern Expected Utility Theory. We abbreviate this special case “EUT”.

Tables 3 presents maximum likelihood estimates, standard errors, and p-values for the parameters of the RDU and EUT models, with and without covariates. Table 4 presents the results of tests of relevant parametric restrictions.

Table 3. Maximum likelihood estimates of RDU and EUT models, with and without covariates.

	RDU			EUT		
	Coefficient	Std. Error	P-Value	Coefficient	Std. Error	P-Value
Without Covariates						
μ	1.024	0.116	0.000	-------	-------	-------
γ	-0.002	0.003	0.561	0.022	0.005	0.000
η	0.569	0.106	0.000	0.747	0.107	0.000
σ	0.835	0.035	0.000	0.727	0.015	0.000
With Covariates						
μ						
Constant	1.372	1.514	0.365	-------	-------	-------
Age in Years	0.014	0.008	0.093	-------	-------	-------
Female	0.163	0.221	0.460	-------	-------	-------
Married	0.040	0.393	0.920	-------	-------	-------
Drought Perception	-1.024	1.329	0.441	-------	-------	-------
Number of Droughts Past 5 Seasons	-0.041	0.052	0.432	-------	-------	-------
Technology Adoption Experience	0.847	0.516	0.101	-------	-------	-------
Completed Primary School	0.463	0.754	0.539	-------	-------	-------
Food Secure	-0.210	0.223	0.346	-------	-------	-------
γ						
Constant	-0.758	0.675	0.261	-1.677	0.888	0.059
Age in Years	0.000	0.000	0.385	0.006	0.004	0.101
Female	0.004	0.008	0.620	-0.037	0.120	0.758
Married	-0.008	0.011	0.481	0.526	0.551	0.340
Drought Perception	0.760	0.674	0.259	-0.169	0.178	0.342
Number of Droughts Past 5 Seasons	0.003	0.003	0.300	0.062	0.054	0.246
Technology Adoption Experience	-0.004	0.005	0.378	-0.183	0.182	0.315
Completed Primary School	-0.151	0.238	0.526	0.703	0.325	0.030
Food Secure	0.004	0.004	0.360	0.194	0.177	0.272
η						
Constant	1.809	2.228	0.417	4.331	3.327	0.193
Age in Years	0.002	0.010	0.873	-0.015	0.007	0.046
Female	0.156	0.378	0.679	-0.143	0.236	0.543
Married	-0.195	0.219	0.374	-0.848	1.764	0.631
Drought Perception	0.733	0.579	0.206	0.159	0.448	0.723
Number of Droughts Past 5 Seasons	-0.151	0.197	0.445	-0.280	0.173	0.105
Technology Adoption Experience	1.834	1.649	0.266	1.833	1.665	0.271
Completed Primary School	-0.760	0.809	0.347	-0.770	0.596	0.196
Food Secure	-0.906	1.158	0.434	-1.031	1.058	0.330
σ						
Constant	1.165	0.268	0.000	1.289	0.130	0.000
Age in Years	0.000	0.002	0.912	-0.001	0.001	0.360
Female	-0.059	0.058	0.312	0.015	0.030	0.627
Married	-0.009	0.044	0.839	-0.129	0.069	0.063
Drought Perception	-0.767	0.244	0.002	0.031	0.043	0.469
Number of Droughts Past 5 Seasons	0.017	0.033	0.608	0.004	0.015	0.806
Technology Adoption Experience	-0.147	0.090	0.104	-0.018	0.048	0.700
Completed Primary School	0.507	0.280	0.070	-0.235	0.109	0.031
Food Secure	0.098	0.075	0.189	-0.002	0.033	0.964

As seen in table 3, the estimate of the probability weighting function parameter μ for the RDU model without covariates, 1.024, is slightly greater but essentially indistinguishable from one, indicating no significant systematic subjective weighting of outcome probabilities. The average estimate of μ for the RDU model with covariates, 1.156, is greater than one, indicating that farmers underweight low probability outcomes and overweight high probability outcomes or events.

Table 4. Tests of parametric restrictions of RDU and EUT models, with and without covariates.

	RDU		EUT	
	Chi-Sq(1)	P-Value	Chi-Sq(1)	P-Value
Without Covariates				
H0: $\mu = 1$	0.04	0.837	-------	-------
H0: $\gamma = 0$	0.34	0.561	21.66	0.000
With Covariates				
H0: $\mu = 1$	0.06	0.806	-------	-------
H0: $\gamma = 0$	1.25	0.262	3.56	0.059

The weighting function for the latter is illustrated in figure 3. However, as seen in table 4, the hypothesis that the weighting function parameter equals 1 cannot be rejected at the 5 per cent level of significance for either model, based on a chi-squared (1) test of a single parametric restriction. This indicates that the standard Von Neumann-Morgenstern expected utility model can reasonably explain the decisions rendered by farmers in our experiment as a whole.

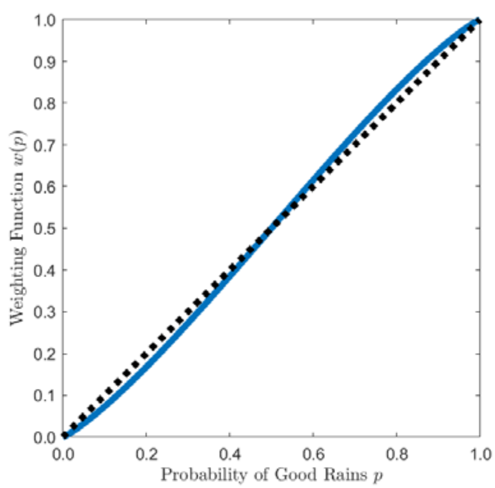

Figure 3. Probability weighting function for RDU model with covariates.

As seen in table 3, the estimate of the expo-power utility function parameter γ is not significantly different from zero for the RDU model without covariates, based on a standard t-test. However, as seen in table 4, a stronger test based on a chi-squared (1) test indicates that γ is significantly different from zero, soundly rejecting the hypothesis that farmers exhibit constant relative risk aversion. The estimate of γ for the RDU model with covariates is found to be significantly different from zero under both tests, also rejecting the hypothesis of constant relative risk aversion. Estimates of the expo-power utility function parameter σ for the RDU model, with and without covariates, are also found to be significantly different from zero, further rejecting the hypothesis that farmers are risk neutral.

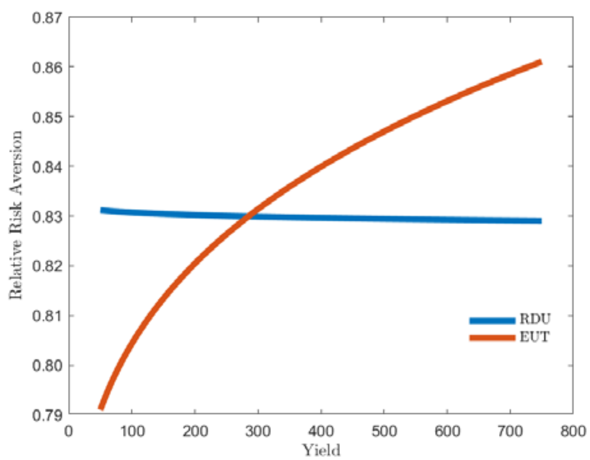

Figure 4. Relative risk aversion for the RDU and EUT models without covariates.

Figure 4 maps relative risk aversion over the range of yield outcomes considered in the experiment for the RDU and EUT models without covariates. Our estimates based on the RDU model indicate that relative risk aversion is on the order of 0.91 (equation 4), a value that is lower than many estimates reported in the literature. Our estimates further indicate that preferences exhibit increasing relative risk aversion, a result that is often, though not universally, reported in the literature.

Given that expected utility maximization by all farmers cannot be rejected, it is worthwhile to examine estimates for the EUT model, in which the restriction = 1, indicating no subjective weighting of probabilities, is maintained. As seen in tables 3 and 4, estimates of the expo-power utility function parameter γ for the EUT model, with and without covariates, are significantly different from zero, based on both a standard t-test and the stronger chi-squared (1) test. As such, the hypothesis that farmers exhibit constant relative risk aversion is soundly rejected. Estimates of the expo-power utility function parameter σ for the RDU model, with and without covariates, are also found to be significantly different from zero, further rejecting the hypothesis that farmers are risk neutral. As seen in figure 4, the estimates of the EUT model without covariates imply a level of relative risk aversion on the order of 0.95, which is slightly greater than that obtained with the RDU model, but still lower than many estimates reported in the literature. Estimates based on the EUT model also indicate modestly increasing relative risk aversion, as with the more general RDU model.

As seen in table 3, the parameter estimates of most covariates fail to achieve significance at the 10 per cent level in both the RDU and EUT models. More specifically, we find that risk attitudes are not significantly affected by the age and gender of the farmer, recent experience with drought, experience adopting new technologies, drought perception, and food security status. Only completed primary school achieves significance at the 10 per cent level for the risk aversion parameter σ in both RDU and EUT models.

Although the hypothesis that all farmers are expected utility maximizers is not rejected, it is of interest to see if at least some are not. To this end, we estimate a finite mixture model that allows us to estimate the proportion of farmers who are and are not expected utility maximizers (Harrison & Rutström, 2009). Table 5 presents the maximum likelihood estimates for the finite mixture model, without covariates. The proportion of farmers who are expected utility maximizers is indicated by π. As seen in table 5, this parameter is estimated to be 76 per cent. The hypothesis that $\pi = 0$, indicating that no farmer is an expected utility maximizer, is soundly rejected based on simple t-test, a result that is expected, given our findings above. The hypothesis that $\pi = 1$, indicating that all farmers are expected utility maximizers, cannot be rejected, based on a chi-squared (1) test of the restriction, which yielded a statistic of 1.82.

Table 5. Maximum likelihood estimates of finite mixture model.

	Coefficient	Std. Error	P-Value
π	0.762	0.176	0.000
μ	1.737	0.225	0.000
γ	0.018	0.006	0.005
η	0.571	0.140	0.000
σ	0.802	0.036	0.000

7. Conclusion

This paper reports findings from a field experiment conducted with smallholder maize farmers in Northern Ghana to elicit their attitudes toward risk. In the experiment, 331 farmers were presented with multiple price list lotteries representing a choice between a safe hypothetical traditional maize seed and a risky hypothetical high-yield variety. By positing a rank-dependent utility framework with an expo-power utility function, we were able to test whether farmer decisions conform to the tenets of von Neumann-Morgenstern expected utility maximization and whether farmers exhibit constant relative risk aversion, two assumptions that are commonly made in applied work on decision making under uncertainty, risk management and insurance. We also examined whether risk preferences are affected by the farmer's demographic characteristics, production practices, and past experience with drought and technology adoption.

Our findings generally support the hypothesis that farmers are mostly expected utility maximizers, but do not exhibit constant relative risk aversion. Using a finite mixture model, we found that only 25-30 per cent of farmers deviate from expected utility maximization, and those that do tend to slightly underweight low probability outcomes and overweight high probability outcomes.

Our findings contribute to a growing but mixed literature on the risk preferences of farmers in the developing world. In particular, our findings support those of Binswanger (1980, 1981), Barr & Genicot (2008), de Brauw and Eozenou (2014), and Wik et al. (2004) that farmers exhibit non-constant increasing relative risk aversion. Our findings, however, provide stronger support for the von Neumann-Morgenstern expected utility model than numerous other recent studies, including Tversky & Kahneman (1992), Davis & Holt (1993), Camerer (1998), Mosley & Verschoor (2005) and Harrison & Rutström (2009). Our findings support the hypothesis that farmers possess heterogeneous preferences, with some conforming to expected utility maximization and other not, as in Harrison & Rutström (2009). As regards to farmers who do not conform to expected utility maximization, our findings are consistent with those of Harrison, Humphrey, & Verschoor (2010), who find that their experimental subjects tend to underweight low and overweight high probability events.

The need for a better understanding of the risk preferences of farmers in the developing world have never been greater, given the growing interest in developing effective insurance products designed to expand access to agricultural credit and promote adoption of advanced production practices among the rural poor. Experimental field studies that employ more varied theoretical frameworks and more innovative experimental designs can help address many of the pressing unanswered questions regarding decision making under uncertainty by farmers in the developing world. Applications of prospect theory remain scant. And much remains unknown regarding how informal and formal communal risks-sharing arrangements, including group credit, impact the risky decisions made by the poor, despite the fact that such arrangements are commonplace in much of the developing world.

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Notes

1. While droughts account for only 8 per cent of natural disasters globally, they account for 25 per cent of natural disasters in Sub-Saharan Africa (Gautam, 2006).
2. The Tropical Livestock Unit (TLU) measures the livestock endowment of each farmer, without regard to species composition, using factors that are proportionate to animal weight (Chilonda & Otte, 2016).
3. The FIES scale measures people's perceptions regarding access to quality food in adequate quantities based on how frequently they have had to compromise the quality and quantity of the food they eat due to limited financial resources. The FIES is based on the Item Response Theory (IRT) commonly used in educational and psychological tests.
4. There are more flexible probability weighting functions than the Tversky and Kahneman (1992) probability weighting function. See for example Prelec

(1998) $w(p) = \exp\{-\eta(-\ln p^{\phi})\}$ and Rieger and Wang (2006) $w(p) = p + [(3 - 3b)/(a^2 - a + 1][p^3 - (a-1)p^2 + ap]$ probability weighting functions in Harrison et al. (2008)). Particularly, the Tversky and Kahneman probability weighting function does not allow independent specification of location and curvature and it has a fixed point where $p = w(p)$. The Prelec and Rieger and Wang probability weighting functions offer a two-parameter probability weighting functions that exhibit more flexibility than the Tversky and Kahneman (1992). As requested by one of the reviewers, we computed the Prelec probability weighting function, but *we could not get it to solve and we ended up using* Tversky and Kahneman probability weighting function.

5. In many applications of random utility theory, the utility function is linear in a subset of its parameters. The parameters are not distinguishable identified from the error scale parameter, allowing us to set the latter to 1 without loss of generality, leading to the more familiar form of the choice probability function in which the scale parameter does not appear. However, the expo-power utility function is not linear in any of its parameters. As such, one may not arbitrarily set the error scale parameter to 1.

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Appendix: Instructions to Experimental Subjects

Enumerator: Read the introduction to all participants in a group, but take each respondent aside to ask them individually what their choices are. Please try to ensure that respondents do not observe others' responses.

Introduction: The following choices are hypothetical, but can help provide some input to the farm risk preference research. Assume there are two varieties of maize (local variety called Obatanpa "variety A" and HYV called Pan 53, "variety B") being planted that have different yield potential depending on the weather conditions. Below you would make 10 choices between the two varieties, Variety A and Variety B, under different situations about possible rainfall. When making your choices, assume you have access to one acre of land on which to plant one of these two varieties. Both varieties would fetch the same price in the market, so they only differ in the possible yields. For each of the following 10 cases, please tell us whether you would prefer variety A or variety B in each case. All yields are measured in units of 100 kg bags. Once again, the two varieties only differ in how they perform under different rainfall conditions. Variety B performs extremely well under good rainfall conditions, yielding 1500kg (15 bags). However, it does not perform that well if rainfall is bad; with bad rainfall Variety B yields only 100kg (1 bags). On the other hand, Variety A gives more consistent yields: if there is good rainfall, it yields 700kg (7 bags), and if there is bad rainfall it will yield 500kg (5 bags). Therefore, Variety B is riskier than Variety A. Again if there is very good rainfall, Variety B will yield 1500kg while Variety A will yield 700kg. If there is bad rainfall, Variety B will yield only 100kg, while Variety A will yield 500kg. Variety B is good as long as rainfall is good, but it is risky. Variety A gives more moderate yields irrespective of the rain received. Do you understand?.

We will ask you now, individually, to please tell us which variety you would prefer under different situations where the chance of very good rainfall is increasing from 10 per cent to 100 per cent. So we will ask you: if the chance of very good rainfall is 1 out of 10 and that of bad rainfall is 9 out of 10, which variety would you choose? And we will keep changing the chance of very good rainfall. So then we will ask you if the chance of good rainfall is now two out of ten and the chance of bad rainfall is 8 of 10, what would you choose? And so on. . . we will ask you ten questions changing the chance of good rainfall from 1 out of 10 to 10 out of 10 and ask your preference in each case. These are all hypothetical choices, and there are no right or wrong answers. One way to understand what is meant by the chance of very good rainfall is to think of weather forecasts. When the weather forecasters make a prediction, they are not certain of the prediction and say that there is such and such percent chance of rain. This is what we mean by chance of good and bad rainfall. For example, over the next ten-year period, the chance of very bad rainfall being 2 out of 10 means over the next ten year period there is likely to be very bad rainfall in 2 years. And so on. . . .. Please note once again that both varieties would command the same price in the market." To explain the among of chance, draw two circles on the ground and use 10 grains of maize, name the circles "good rainfall" and "bad rainfall. For example, when the chance of very bad rainfall is 2 out of 10, put 2 grains of maize in a circle "good rainfall" and 8 grains of maize in circle "bad rainfall".

Enumerator: Please ensure that the respondent understands what is meant by asking them to repeat back to you the structure of the choices. Please do not translate this to say "there will be good/moderate rainfall;" please use "likely to be". You may ask one or two questions to make sure they have understood. Writing out the yields for the two varieties (on the ground) may be useful. You may want to use sticks to represent bags and thus demonstrate the 15, 7, 5 and 1 bags for those who are not literate. Once you are convinced they have understood the set up, you can proceed to the choices. A common misunderstanding is to interpret higher chance of rain as a higher quantity of rain—this is not what is meant here. You can also ask them when they switch, why they switched. Key messages: There will be 10 choices. One variety is risky; the other is stable—as demonstrated by the yields written out. Ask the respondent to explain the question back to you and make sure s/he understands. Then start asking the questions and again.