Smallholder Farmer's Risk Attitudes in Northern Ghana - Expected Utility Theory or Prospect Theory: Experimental Evidence

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Abstract

We conduct controlled field experiments to elicit risk preferences and subjective probabilities among uneducated smallholder maize farmers in Northern Ghana. Motivated by Prospect Theory, we estimate a Rank-Dependent Utility Model with Power Risk Utility Function that embeds Expected Utility Theory and constant relative risk aversion as independent special cases characterized by specific parametric restrictions. We jointly estimate individual utility of money function and subjective probability weighting function parameters from experiments conducted using a multiple price list format. We initially estimate a model in which parameters are homogeneous across subjects, and then estimate a model in which parameters are allowed to vary across subjects according individual socioeconomic characteristics, including education, gender, food security status, and recent experience with losses due to drought. With both specifications, we reject the hypotheses that preferences are adequately characterized by Expected Utility Theory or constant relative risk aversion. Using a Finite-Mixture model specification, we find that 28.1% of choices made by farmers possess preferences that cannot be explained by simple Expected Utility Theory.

Keywords: Field experiment, risk aversion, Expected Utility Theory, Prospect Theory, Rank-Dependent Utility, Finite-Mixture

1. Introduction

Agriculture is the most weather dependent of all human activities and drought presents the greatest risk, given that it occurs with the greatest frequency, affects the greatest area, and causes the greatest losses to production (Hansen et al., 2004). Drought risk is especially pervasive in Sub-Sahara Africa (SSA) due to the predominance of rainfed rather than irrigated agricultural practices (Shiferaw et al., 2014)[1].

Drought risk can be a significant factor in SSA smallholder production and investment decisions due to their lack of access to efficient credit and insurance markets that allow for the transfer of drought risk to a third party. Smallholder farmers practicing rainfed agriculture in drought-prone areas are forced to adapt their production practices to reduce the adverse consequences of drought. These adaptations can be costly in terms of sacrificed income, because they generally favor the choice of safer, but low-return activities (Binici et al., 2003; Hansen et al., 2004; World Bank, 2005; Yesuf & Bluffstone, 2007; Pandey S, 2009; Hurley, 2010) As such, proper evaluation of proposed agricultural policies aimed at smallholders must take risk preferences and risk exposure into consideration.

Although risk is a pervasive factor in agricultural decision making, there exist a large gap in our understanding of risk attitudes among smallholders in SSA and, more generally, in the developing world. Part of the gap is attributable to difficulties in separating risk-related responses from other forms of behaviour (Bond & Wonder, 1980).

Over the past three decades, numerous studies has turned to experimental survey methods to elicit risk attitudes among smallholders in developing countries. Expected Utility Theory (EUT) has been the model of choice for framing these experiments (Binswanger, 1980; Miyata, 2003; Wik et al., 2004; Hill, 2009). Some studies, however, have found that EUT may not be the best model of choice under uncertainty for smallholders in developing countries, and have proposed the use of alternative theoretical frameworks based on Prospect Theory and Rank-Dependent Utility Theory (Kahneman & Tversky, 1979; Quiggin, 1993). Other recent studies posit that two (or more) latent decision-making processes may generate the same data (Mosley & Verschoor, 2005; Harrison & Rutström, 2009; Tanaka, Camerer, & Nguyen, 2010; Liu, 2013; de Brauw & Eozenou, 2014; Holden & Holden, 2014).

[1] While droughts account for only 8% of natural disasters globally, the accounted for 25% of all natural disasters in SSA between 1960 and 2006 (Gautam, 2006).

In this paper, we test competing decision-making models in the context of decision making among smallholder farmers in Northern Ghana. To this end, we estimate a general model based on Rank-Dependent Utility Theory that explicitly allows for variation in relative risk aversion and relaxation of the assumptions of Expected Utility Theory. More specifically we posit that observed individual smallholder decisions are generated by a Finite-Mixture model that embeds the conventional Expected Utility Theory as a nested, testable special case. We then correlate estimates to smallholder demographic and economic characteristics.

2. Risk preference elicitation in developing countries: previous studies

Many studies have attempted to measure risk aversion among smallholders in developing countries. Development economists and psychologists have employed a variety of experimental methodologies to elicit risk attitudes, including self-assessment (Dohmen et al., 2011; Jung & Treibich, 2014), psychometric or Likert scale household surveys (Baron, 1970; Sandmo, 1971; Antle, 1983, 1987, 1989; Villano, O'Donnell, & Battese, 2005) and experimental lotteries (Binswanger, 1980, 1981; de Brauw & Eozenou, 2014; Eckel & Grossman, 2008; Harrison, Lau, & Rutström, 2007, 2011; Harrison, Martínez-Correa, & Swarthout, 2013, 2014; Holt & Laury, 2002). The use of experimental lotteries has predominated in the last three decades.

Which risk elicitation method is best depends on the questions one wants to answer. Binswanger, (1980, 1981) provides an early test for risk aversion among Indian farmers using lottery experiments with hypothetical and real monetary payoffs. The experiments were designed to determine how wealth and financial constraints affect responses to risk. Under the assumptions of Expected Utility Theory, the author finds that most of the farmers surveyed exhibited aversion to risk, and that the apparent degree of risk aversion 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.

Following a procedure similar to Binswanger (1980), Barr (2003) conducts an experiment with Zimbabwe farmers that allows for group concertation. Like Binswanger, Barr finds that most farmers exhibit aversion toward risk, but less so if they can pool risk collectively. Wik et al. (2004) experiment with Zambian villagers closely mirrors Binswanger's, with payoffs as high as a third of an individual's annual income. They find that risk attitudes change from risk aversion to risk neutrality as lottery payoffs are reduced. In particular, 80 percent of the individuals tested exhibit extreme to moderate risk aversion when presented with lotteries with relatively high payoffs. The authors conclude that risk attitudes are consistent with decreasing absolute risk aversion and increasing partial risk aversion. Random effects interval regression model results also indicate that risk attitudes are related to a variety of other observable factors. They find for example that partial relative risk aversion decreases as wealth increases, that female respondents are more risk averse than male respondents.

Mosley and Verschoor (2005) examine risk attitudes and the ability to manage risk among Ethiopian, Ugandan, and Indian smallholders using an incentive compatible research design. In their experiments, respondents choose among seven distinct hypothetical lottery pairs. One lottery pair is randomly selected and played for real monetary payouts at the end of the experiment. Respondents are also asked to answer two hypothetical certainty equivalent questions for each of the lottery pair choices in order to estimate risk aversion. Like Binswanger, Mosley and Verschoor find that risk aversion does not vary with age, gender, education, income or wealth. They also find a significant relationship between risk attitudes and perceptions of vulnerability.

Yesuf and Bluffstone (2009) used a procedure similar to Binswanger to assess risk attitudes, except that some of the lotteries are framed in terms of gains and losses, while others are framed only in terms of gains. The authors finds that 79 to 98 percent of individuals tested exhibit risk aversion when the lottery is presented only in terms of gains. In the gain and loss lotteries, a majority of individuals exhibited extreme risk aversion (66 percent) that was insensitive to the magnitude of the payoffs. A small proportion of the respondents (4 to 11 percent depending on the magnitude of the payoffs) exhibited risk neutral or risk preferring attitudes. Using a probit model with random farmer effects, the authors find that households possessing greater wealth, larger farms, more oxen, more valuable domestic animals, and greater cash liquidity were less risk averse. Individuals with older household heads and more children, however, were more risk averse. The authors also find that risk attitudes differed between the two regions of Northern Ethiopia that were sampled.

Unlike preceding experimental studies of risk preferences in developing countries, Tanaka et al. (2010) evaluate risk attitudes employing a model based on cumulative Prospect Theory rather than Expected Utility Theory. The experiment is conducted with villagers from North and South Vietnam. Instead of having individuals chose among pairs of lotteries, the authors have individuals evaluate three distinct lists of paired lotteries. The paired lotteries are arranged in two columns and ordered from low to high payout. The lottery pairs are chosen so that switching points can be used to identify the degree of risk aversion (over gains), the degree of loss aversion, and the probability weighting based on a three parameter cumulative prospect value function. One lottery pair is selected at random and played for real money. The authors find that individual choices are consistent with CRRA (a special case of the cumulative prospect value function that was used). On average, individuals are found to be risk averse over gains (risk seeking over losses), and over-weight low probability events and under-weight high probability events. About 90 percent of the sampled individuals exhibit loss aversion. Instrumental variable regressions accounting for income endogeneity reveal that risk aversion over gains is negatively correlated with age, education, and distance to the nearest local market. Risk aversion is found to be positively correlated with fishing as an occupation, but uncorrelated with income, relative income, and average village income. Loss aversion is found to be negatively correlated with Chinese ethnicity, whether the subject is a government official, individual income, and village income, but positively correlated with being from South Vietnam.

Harrison, Humphrey, and Verschoor (2010) relax the assumptions of Expected Utility Theory. They evaluate the choices Ethiopian, Indian and Ugandan villagers made over eight binary lottery pairs (one chosen randomly and played for real money) based on Expected Utility and Prospect Theory. The lotteries used in the experiment are for gains only, so the difference between Expected Utility and Prospect Theory reduced to whether and to what degree individuals weight the probabilities of outcomes. A novel feature of their analysis is that it allows choices to be described either by Expected Utility Theory or Prospect Theory within the context of a Finite-Mixture model. Under the assumptions of both Expected Utility Theory and Prospect Theory, the authors find that individuals are risk averse on average, that Ugandans are more risk averse, and older individuals and women are less risk averse. Contrary to Tanaka et al. (2010), they find that individuals tend to under-weight low and over-weight high probability events, a tendency that intensifies households increase in size. When considering Expected Utility and Prospect Theory jointly, the authors find that just under half of the choices are best explained by Expected Utility Theory, and just over half are best explained by Prospect Theory. Choices best explained by Expected Utility Theory indicated risk aversion on average, while choices best explained by Prospect Theory indicated risk preferring on average and over-weighing low and under-weighing high probability events, respectively. One interpretation of these results is that about half of the individuals understood the prospect of a favorable outcome and did not like to take chances, while the other half were pessimistic about the prospects of a favorable outcome and liked to take chances. Another interpretation is that the experimental design was not rich enough to adequately discern mixtures of behavior in the population.

In an attempt to understand the sensitivity of experimental results to framing, (Holden (2014) studies the risk preferences of poor rural households in Malawi, comparing the Holt and Laury (2002) approach based on EUT with the Tanaka et al. (2010) approach based on Prospect Theory. Holden finds that risk aversion estimates based on the Holt and Laury framework correlate closely with those obtained with the Tanaka, Camerer and Nguyen framework and that risk aversion may be upwardly biased due to measurement error arising from inconsistent responses across the Holt and Laury framework. The author also finds that recent exposure to a drought is associated with greater risk aversion in the hypothetical Holt and Laury framework, regardless of whether subjective probability weighting is used, whereas exposure to drought did not affect risk aversion in the monetary Holt and Laury and Tanaka, Camerer and Nguyen framework. The author concludes that experimental results are sensitive to framing.

de Brauw and Eozenou (2014) use a lab-in-the-field experiment to explore risk preferences among sweet potato producers in northern Mozambique, with a focus on differences between husbands and wives. They also test whether preferences are consistent with constant relative risk aversion (CRRA), and whether preferences are consistent with 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% of choices made by the farmers in their sample were consistent with Expected Utility Theory and more than 70% were consistent with the general Rank-Dependent Utility Theory. These results differed markedly from Mosley and Verschoor (2005), who find that 32, 37, and 40 percent of Ugandan, Ethiopian and Indian farmers exhibit preferences inconsistent with Expected Utility Theory.

3. Context of the Experiment and the Data Collection

3.1. Context of the Experiment

In this study, we use the Holt and Laury experimental approach to investigate risk preferences among smallholders in Northern Ghana. Unlike previous studies, we pay a particular attention to the correlation between risk preferences and household food insecurity status and drought exposure.

The experiment was conducted as part of an ongoing impact evaluation study of the effects of index insurance-backed contingent credit on production technology adoption among smallholders in Ghana. The study, which is funded by the US Agency for International Development, is a three-year randomized controlled trial (RCT) that begun in January 2014 in Northern Ghana. The study, which is being conducted in collaboration with 14 Rural and Community Banks (RCBs) and the Ghana Agricultural Insurance Pool, offered index-insured loans to 279 randomly-selected smallholder lending groups, comprising 89 groups from five districts of Northern region, 33 groups from six districts of the Upper West region, and 157 group from ten districts of the Upper East region[2].

In the RCT study, smallholder lending groups were randomly assigned to one of three treatment arms: 1) groups that were offered conventional loans, with no index insurance; 2) groups that were offered insured loans in which farmers where the beneficiaries of any payouts made by the index insurance contract; and 3) groups that were offered index-insurance backed contingent credit loans in which any insurance payouts are made directly to the lender, rather than the farmers, but for the expressed purpose of retiring the group's loan obligations. Randomization was conducted within two strata: the region and the loan status of the farmer group.

In order to elicit farmers' risk attitudes, we interviewed a random subsample of 333 farmers included in the RCT: 57 farmers from 16 communities in Bawku West district, 42 farmers from 7 communities in Bawku Municipal district, 42 farmers from 7 communities in Binduri district, and 192 farmers from 36 communities in Garu Tempane district. Farmers selected for the risk elicitation study were contacted by local extension workers and given the option to participate in the risk elicitation field experiments. We conducted one training session for ten enumerators (six Ghana Ministry of Food and Agriculture extension specialists and four national services personnel

[2] The lending groups participating in the study were selected randomly from 791 groups serviced by lenders in the Association of Rural Banks – Northern Chapter. Selection was based on five criteria: 1- Farmer groups that have been in good standing with the bank in terms of borrowing, potential groups that are qualified to receive loans and groups that have been denied loan due to low regional rainfall; 2- Farmers that belong to districts that belong to low rainfall areas (between 800-1100mm annually) since the impact of insured loan is more likely to be seen when rainfall is low; 3- Farmer groups whose primary or secondary crop is maize since maize is the primary crop grown in the northern regions; 4- Farmers groups with 7-15 members due to budget constraints and logistics of maintaining smoother field work; 5- Farmers that take out a loan of less than 10,000 GHC because farmers above this range are outliers and are beyond the definition of smallholder farmers.

from the Tamale University of Development Studies) and five training sessions for farmers (one session in Bwaku, one session in Bwaku West, one session in Binduri, and two sessions for Garu Tempane). Two farmers were dropped for failing to complete the training sessions.

Enumerators initiated the experiment two days after training. Because farmers were already in the general baseline survey, we had data regarding the respondent's household demographic and socio-economic characteristics, including agricultural production practices, landholdings, experience growing maize, non-agricultural income, credit and saving, drought perceptions, social networks, drought adaptation and mitigation strategies etc.

3.2.Experimental design

The experiment to elicit risk preferences is framed around the adoption of high yield variety of maize (HYV) and consisted of offering a menu of ordered lottery choices over hypothetical gains to the farmers. The first option (the safer option, option A) provides traditional maize that yields 350kg of maize per hectare with good rains, but yields a slightly lower 250kg of maize per hectare with bad rains. The second option (the risky option, option B) provides "high yield" maize (HYV) that yields 750kg of maize per hectare with good rains, but only 50kg of maize per hectare with bad rains. Farmers were asked to choose between these two options under 10 different scenarios, in which the probability of good rains were gradually increased from 10% to 100%[3].

The payoff matrix for the experimental lottery is presented in table 1 below. Each line of the table represents a situation in which farmers was asked to choose between the safer option (A) and the riskier option (B) assuming a particular probability of good rains. The net expected value of each choice (not shown to the respondent) is computed as:

$$E(A) - E(B) = \sum_{s=1}^{2} p(A_s)A_s - \sum_{s=1}^{2} p(B_s)B_s$$

where for each option (A or B), s = 1 good rains, and s = 2 poor rains. As shown in table 1, the expected yield is always higher for option B than option A for probabilities of good rains of 40% and above.

[3] Note that in this context risk preferences are being asked in a narrow, hypothetical context, and that farmers' previous experience with actual rainfall might affect the subjective beliefs that farmers have about rainfall in the experiment (de Brauw & Eozenou, 2014).

Table1. Payoff matrix, hypothetical experiment.

Variety A				Variety B				E(A)	E(B)	E(A)-E(B)
$P(A_1)$	A_1	$P(A_2)$	A_2	$P(B_1)$	B_1	$P(B_2)$	B_2			
0.1	350	0.9	250	0.1	750	0.9	50	260	120	140
0.2	350	0.8	250	0.2	750	0.8	50	270	190	80
0.3	350	0.7	250	0.3	750	0.7	50	280	260	20
0.4	350	0.6	250	0.4	750	0.6	50	290	330	-40
0.5	350	0.5	250	0.5	750	0.5	50	300	400	-50
0.6	350	0.4	250	0.6	750	0.4	50	310	470	-160
0.7	350	0.3	250	0.7	750	0.3	50	320	540	-220
0.8	350	0.2	250	0.8	750	0.2	50	330	610	-280
0.9	350	0.1	250	0.9	750	0.1	50	340	680	-340
1.0	350	0	250	1	750	0	50	350	750	-400

The proportion of farmers that chose one or the other option for different probabilities of experiencing good rains is also reported in figure 1. As seen in figure 1, the proportion of farmers that chose the risky (safer) option increases (decreases) monotonically as the probability of good rains increases. However, the rates of change are substantially slower rate than would be expected if all respondents were risk neutral, implying that the average farmer in our sample is risk averse.

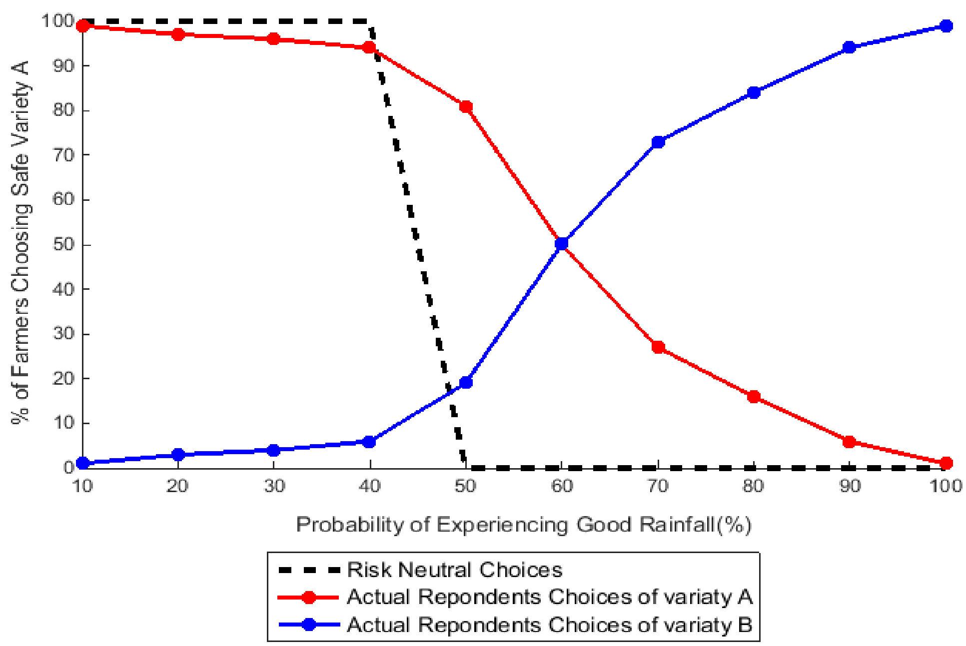

Figure 1. Risk experiment responses to safer choices.

4. Descriptive Statistics

4.1.Food Insecurity Status of Farmers

The farmers that participated in our risk elicitation experiment are smallholders in Northern Ghana, most of whom rely on rain-fed agriculture as their main source of income. Maize constitutes their main staple food crop. Most of farmers in the sample are food insecure. We find interesting to investigate how farmer's food insecurity status is associated with their risk preferences.

There is a new direction in measuring food insecurity based on people's experience of access to quantity and quality food. This method is derived from the US Household Food Security Survey Module (HFSSM) and the Latin American and Caribbean Food Security Scale and it is being vulgarized worldwide by the FAO Voices of the Hungry (VOH) project in the form of Food Insecurity Experience Scale (FIES). The FIES questions, ask people directly about having to compromise the quality and quantity of the food they eat due to limited money or other resources to obtain food. It is composed of 8 items, each item refers to a different situation and is associated with a level of severity according to the theoretical construct of food insecurity underlying the scale. The analysis of the FIES is based on the Item Response Theory (IRT) commonly used in the educational and psychological tests. Among the models based on the IRT, the VoH uses the One Parameter Logistics Model (*Rasch Model*), which represents the probability that an individual with food insecurity *bh* responds positively to an item characterized by severity level *ai* is modelled as a logistic function of the distance between *bh* and *ai* (Rash, 1960):

$$\Pr ob\left(x_{h,i} = 1 | b_h, a_i\right) = F\left(b_h - a_i\right) = \frac{e^{b_h - a_i}}{1 + e^{b_h - a_i}}$$

This study is the first to study the correlation between food insecure status and risk aversion behavior. de Brauw and Eozenou (2014) find a negative correlation with risk aversion behaviour using food expenditure per capital, we anticipate the same result in this study.

4.2.Drought Shocks Experience

Do weather shocks such as drought or flood increase risk aversion? Rainfall risk is the most dominant and relevant weather-related risks to rain-fed crop production. We pay particular attention to drought. We therefore depend on information from the farmers themselves regarding the occurrence of drought. We have asked farmers to recall whether they experienced drought that affected their crops last growing season and the number of time they experience drought in the last five growing seasons. As in most studies, farmers had no difficulties recalling such events and their answers are consistent across farms in given neighbourhoods. We therefore used these two variables as good indicators of drought exposure. We expect these variables to be positively corrected with risk aversion. de Brauw & Eozenou (2014) find severe drought shock to income and to assets to be positively correlated with risk aversion even though not significant, Holden (2014) and Nielsen, Keil, and Zeller (2013) find the same results using drought dummy variable. Drought perception is also an important variable that can affect farmer's choice of different gambling. In the baseline household survey, we asked farmers this following question: "*In your view what is the likelihood that there will be drought next growing season*", we thought farmers who strongly believe that there will be drought next season can be skeptical about risky technologies even though highly productive. Farmers then form their choice based on certain subjective probability[4].

4.3.Livestock endowment

Livestock in most Smallholder's household serve as back up strategies to shock, even though we may think that weather shock may affect them as well. The Tropical Livestock Units (TLU)[5] methodology was adopted to evaluate the livestock endowment of each farmer. We expect this variable to be negatively correlated with risk aversion behaviour. The literature is not clear on this subject, some studies find a positive relationship between livestock endowment and risk aversion behaviour (Kouame & Komenan, 2012) and others find a negative relationship (Yesuf & Bluffstone, 2009).

Table 2 below presents descriptive statistics for the sample households. These variables are also the regressors included in the maximum likelihood estimation presented later. Households in northern Ghana typically hold livestock, including chickens, bulls, cows, sheep and goats.

[4] This is another reason why the literature is pushing the idea of replacing Expected Utility Theory with Prospect Theory in developing countries.

[5] For a number of applications there is a need to use a common unit to describe livestock numbers of various species as a single figure that expresses the total amount of livestock present – irrespective of the specific composition. In order to do this, the concept of an "Exchange Ratio" has been developed, whereby different species of different average size can be compared and described in relation to a common unit.

Livestock are significant assets sold to finance consumption needs especially during drought. Most farmers in our sample have at least one livestock. The average livestock endowment measured in term of tropical livestock unit (TLU) is 5.59. Women are mostly Smallholders. Indeed, 60 % of our sample are female. More than 80 % of farmers in our sample have never attended school and fewer than 7% had attended at least middle school. Food insecurity is a big challenge for many households, more than 42% of our sample are severe food insecure with only 16% food secure.

Table 2. Descriptive statistic and regressors used in maximum likelihood model.

Variable	Obs	Mean	Std. Dev.
Age in year	331	46.810	13.473
Sex (1.male, 0.female)	331	0.404	0.492
Married (1 Married, 0=others)	331	0.849	0.359
Level of Education			
Primary	331	0.039	0.194
Middle School/JSS	331	0.039	0.194
High Schools/SSS/Secondary	331	0.027	0.163
College or University	331	0.015	0.122
Dependency Ratio	331	1.145	0.896
Drought 2014, Dummy	331	0.637	0.481
Number of Drought Last 5 Seasons	331	2.520	0.832
Idiosyncratic Shocks			
Medical Emergencies	331	0.323	0.468
Death of the Household Member	331	0.148	0.356
Festival in the Household	331	0.314	0.465
Drought perception	331	0.828	0.378
Peers consultations	331	4.933	2.364
Aspiration Index	331	0.012	0.571
Expectation Index	331	0.005	0.609
Adoption Experiences	331	0.130	0.337
Belief God decide for rain	331	0.828	0.378
Time preferences	331	0.069	0.054
Log farm size	331	1.614	0.561
Distance to nearest market (h)	331	1.071	0.794
Food security status			
Middle food insecure	331	0.250	0.434
Moderate food insecure	331	0.169	0.375
Severe food insecure	331	0.420	0.494
Household saving (100)	331	2.963	4.109
Household Loan Received (100)	331	2.788	2.240
Remittances	331	123.511	217.762
Log agri income	331	7.046	0.812
Log income	331	7.592	0.786
Livestock endowment (TLU)	331	5.587	15.993
Non Agric Business	331	0.580	0.494
District			
Binduri	331	0.123	0.330
Bawku West	331	0.172	0.378
Garu Tempane	331	0.580	0.494

Drought impedes farming practices and very few households have access to irrigation. More than 36% of farmers in our sample claimed having experienced drought last growing season and more than 90% had at least experienced drought in the past 5 growing seasons with more than 60% experienced at least 3 times. Average household size is about 7.5, with more inactive members than active members, the average dependency ratio is 1.15. Farms tend to be small, with a mean of less than 6 acres spread over an average of 3 plots. In Ghana land is state property and farm households are granted user rights. As a result, there is no land market. This makes land a very constrained resource and a key to various farming decisions.

5. Methods

We considered a combination of two competing theories of choice under uncertainty to explain these data: Expected Utility Theory (EUT) and Prospect Theory (PT). The Expected Utility Theory is the predominant theory in economics for analyzing risky behaviors. Introduced by von Neumann & Morgenstern (1944), the Expected Utility Theory is mainly based on the assumption that people make choices to maximize Expected Utility. There are three features to Expected Utility: the possible outcomes, the likelihood of possible outcomes, and the utility of possible outcomes. The utility derived from a particular outcome serves as a device for capturing individual attitudes toward risk(Hurley, 2010). While Expected Utility Theory has been the predominant theory for explaining risky choices in the development economics literature, it is not without critics because there are numerous examples of its failure to adequately organize observed behavior in developed countries (Tversky & Kahneman, 1992; Davis & Holt, 1993; Camerer, 1998; Mosley & Verschoor, 2005). While the failures of Expected Utility Theory have led to a large variety of proposed alternatives, Prospect Theory has been identified as the preferred alternatives for evaluating risk attitudes especially in developing countries. Prospect Theory generalize Expected Utility Theory to account for four observed regularities: (i) risk averse behavior for likely gains, (ii) risk preferring behavior for unlikely gains, (iii) risk averse behavior for unlikely losses, and (iv) risk preferring behavior for likely losses (Tversky & Kahneman, 1992). To account for these regularities, Prospect and Cumulative Prospect Theory embellish Expected Utility Theory in four ways. First, the shape of the utility function is assumed to depend on some reference points (e.g. (Pennings & Smidts, 2003; Pennings & Garcia, 2009)). Second, marginal utility is assumed to be increasing at a decreasing rate above and at an increasing rate below this reference point, such that individuals display risk averse attitudes above and risk preferring attitudes below this reference point (Tversky & Kahneman, 1992). This assumption implies that preferences depend on whether an individual frames the risk in terms of a gain or loss. Third, marginal utility is assumed to be increasing at an increasing rate faster below the reference point than it is increasing at a decreasing rate above the reference point, which implies losses are more salient than gains and is commonly referred to as loss aversion. Fourth, the probability of an outcome is weighted before it is summed with the utility of the outcome (Hurley, 2010). These weighting functions capture the common observation that individuals seem to perceive that unlikely outcomes are more common and likely outcomes are less common than actuality.

Our experiment is designed around the gain domain of the Prospect Theory, we do not have any losses in the lotteries, so we drop the form of the utility function in PT that is defined for losses. The only different with Expected Utility Theory is the probability weighting function proposal by Tversky & Kahneman (1992). In this form the PT is resumed to a Rank-Dependent Utility (RDU) proposed by (Quiggin, 1982, 1993). Under RDU, subjective probabilities are not constrained to be equal to objective probabilities, as in Expected Utility Theory. Instead, agents are allowed to make their choices under uncertainty according to a nonlinear probability weighting function.

5.1.Theoretical Framework

Following de Brauw & Eozenou (2014) and Holden (2014), we assume that utility $U\left(\sum_j w(p_j)y_j\right)=\sum_j w(p_j)U(y_j)$ is formed over risky lottery outcomes y_j, $j \in \{1,2\}$ weighted by their subjective probability of occurrence $w(p_j)$ with $p_j \geq 0$ and $0 \leq \sum w(p_j) \leq 1$ [6]. We restrict our attention to the gain domain, i.e. $y_j > 0$.

5.1.1. Utility Function Specification

We consider the power risk aversion function which is a general parameterization of the utility function proposed by Xie (2000) and used to elicit the risk attitude of smallholders in Northern Mozambique by de Brauw & Eozenou (2014). This general utility function has the advantage over

[6] It is not required that the sum of weighted probabilities is equal to 1. If it is less than one, it is said that there is sub certainty overall (Gonzalez & Wu, 1999; Tversky & Kahneman, 1992).

other general form of utility function because it can be used to test the assumption of constant relative risk aversion (CRRA), we also used the case of the expo-power (EP) utility function[7] proposed by Saha (1993).

The power risk aversion is expressed as follow:

$$U^{PRA}(y)=\frac{1}{\gamma}\left[1-\exp\left(-\gamma\left(\frac{y^{1-\sigma}-1}{1-\sigma}\right)\right)\right] \tag{1}$$

Where y is income or outcome in our case and γ and σ are parameters to be estimated.

The coefficient of absolute risk aversion is now non-increasing in y and given by

$$ARA^{PRA}(y)=\frac{\sigma}{y}+\frac{\gamma}{y^{\sigma}} \tag{2}$$

While the coefficient of relative risk aversion can be written as

$$RRA^{PRA}(y)=\sigma+\gamma y^{1-\sigma} \tag{3}$$

The PRA reduces to the constant relative risk aversion (CRRA) utility function when $\gamma \to 0$ which is the most commonly assumed specification in studies of risk aversion. It can be written as:

$$U^{CRRA}(y)=\frac{y^{1-\sigma}-1}{1-\sigma} \tag{4}$$

Under this parameterization, the coefficient of relative risk aversion is $RRA^{CRRA}=\sigma$), and the coefficient of absolute risk aversion is assumed to be decreasing ($ARA^{CRRA}(y)=\sigma/y$). The γ parameter is simply an additive constant used to alter the magnitude of utility.

5.1.2. Expected Utility Theory

If we assume that Expected Utility Theory holds for the choices over risky alternatives, then the Expected Utility for each lottery *i* can be written as:

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[7] An alternative utility function is the expo-power (EP) utility function (Saha, 1993), and it is used by Holt and Laury (2002) in their assessment of risk preferences using MPL: $U(y)=\frac{1-\exp\left(-\alpha y^{1-\sigma}\right)}{\gamma}$ This function also allow relative risk aversion to vary with income as long as $\gamma \neq 0$ $\sigma = CRRA$ if $\gamma = 0$, and $\gamma = CARA$ if $\sigma = 0$.

$$EU_i = \sum_j p_j(y_j)U(y_j) \tag{5}$$

where p_j are the objective probabilities for each outcomes y_j that are induced by the experimenter.

Despite the simplicity and the popularity of EUT, a number of experiments suggest that EUT often fails as a descriptive model of individual behavior, especially in poor non educated households in developing countries.

5.1.3. Rank-Dependent Utility Theory

Although there are many proposed alternatives to EUT, we consider RDU, which was incorporated into cumulative Prospect Theory. RDU extends the EUT model by allowing for non-linear probability weighting associated with lottery outcomes. To calculate decision weights under RDU, one replaces Expected Utility with:

$$RDU_i = \sum_j w_i(p(y_j))U(y_j) \tag{6}$$

Where $w_{i2} = w_i(p_2 + p_1) - w_i(p_1) = 1 - w_i(p_1)$ and $w_{i1} = w_i(p_1)$ and $w(\cdot)$ is the weighting function. We consider the weighting function form proposed by Tversky & Kahneman (1992):

$$w(\rho) = p^{\mu} / \left[p^{\mu} + (1-p)^{\mu}\right]^{1/\mu} \tag{7}$$

This weighting function has been widely used and it is assumed to have well-behaved endpoints such that $w(0) = 0$ and $w(1) = 1$ and to imply weights $w(\rho) = p^{\mu} / \left[p^{\mu} + (1-p)^{\mu}\right]^{1/\mu}$ for $0 < p < 1$. The normal assumption, backed by a substantial amount of evidence reviewed by Gonzalez and Wu (1999), is that $0 < \mu < 1$. This gives the weighting function an inverse S-shape, characterized by a concave section signifying the overweighting of small probabilities up to a crossover-point where $w(p) = p$, beyond which there is then a convex section signifying underweighting. If $\mu > 1$ the function takes the less conventional S-shape, with convexity for smaller probabilities and concavity for larger probabilities. When $\mu = 1$, it implies that $w(p) = p$ and this serves as a formal test of the hypothesis of no probability weighting therefore may be used to test whether decision making follows EUT or RDU.

5.1.4. Stochastic Error Specifications

Choice under uncertainty is often made with stochastic error. Stochastic error in decision making was first introduced by Fechner (1860) and now on popularized by studies such as Luce (1959); Luce and Suppes (1965); Hey and Orme (1994); McFadden (1974); Camerer and Hua Ho (1999); Holt and Laury (2002); Drichoutis and Lusk (2014); Holden (2014). Such error may arise from a variety of sources: the subjects could misunderstand the nature of the experiment; they could choose by accident; they could be in a hurry to complete the experiment; they could be motivated by something other than maximizing their welfare from participating in the experiment (Hey & Orme, 1994). There are various specifications in use: some place the error at the stage at which the subject forms the Expected Utility, some at the stage when the respondent compares the expected utilities, and some at the stage when the subject makes a choice.

This analysis considers the second stage of stochastic error initially developed by Luce (1959) and have been popularized by Holt and Laury (2002)[8]. In this case the probabilistic model can be written as:

$$\nabla EU = \frac{EU_A^{1/\eta}}{EU_A^{1/\eta} + EU_B^{1/\eta}}, \tag{8}$$

where η is a structural noise parameter that captures decisions making errors, EU_A and EU_B refer to expected utilities (or Rank-Dependent expected utilities) of options A and B (the left and right lottery respectively, as presented to subjects). The latent index is linked to the observed choices using a standard cumulative normal distribution function $\Phi(\nabla EU)$. The standard cumulative normal distribution function is a logit function that takes any argument between $\pm\infty$ and transforms it into a number between 0 and 1.

$$\Pr\left(\frac{EU_A^{1/\eta}}{EU_A^{1/\eta} + EU_B^{1/\eta}} > 0\right) = \Phi(\nabla EU). \tag{9}$$

[8] One may also use a Fechner error parameter $\left(\nabla EU = \frac{EU_A - EU_B}{\eta}\right)$.

5.2.Estimation

We assumed that farmers in our sample choose the maize varieties that deliver the highest Expected Utility under each rainfall scenario. This can be compared to a Random Utility model where EU_A and EU_B are unobserved single period utility levels associated with the choice of variety A and B. For any given rainfall scenario, we assume in equation (8) that the difference $\nabla EU = \frac{EU_A^{1/\eta}}{EU_A^{1/\eta} + EU_B^{1/\eta}}$ is a latent variable or index that is based on latent preferences.

With the Expected Utility function specification, it is possible to construct a log-likelihood function that is used for the maximum likelihood estimation of relevant parameters such as σ, γ and η as follow:

$$\ln L^{EUT}(\sigma,\gamma,\eta \mid X,y) = \sum_i \ln l_i^{EUT} = \sum_i \left[y_i = 1 \mid \ln\left(\Phi\left(\nabla EU(\sigma,\gamma,\eta \mid X)\right)\right) + y_i = 0 \mid \ln\left(1-\Phi\left(\nabla EU(\sigma,\gamma,\eta \mid X)\right)\right)\right] \quad (10)$$

With the Rank-Dependent Utility function specification, RDU utility function is used instead of the EUT utility function and $w(p)$ is used instead of p but the steps are otherwise essentially identical. Thus the likelihood, conditional on the RDU model being true, depends on the estimates of σ,γ,η and μ given the above specification and the observed choices. The conditional log-likelihood is:

$$\ln L^{RDU}(\sigma,\gamma,\eta,\mu \mid X,y) = \sum_i \ln l_i^{RDU} = \sum_i \left[y_i = 1 \mid \ln\left(\Phi\left(\nabla EU(\sigma,\gamma,\eta,\mu \mid X)\right)\right) + y_i = 0 \mid \ln\left(1-\Phi\left(\nabla EU(\sigma,\gamma,\eta,\mu \mid X)\right)\right)\right] \quad (11)$$

where $y_i = 1(0)$ denotes the choice of lottery A (lottery B) in task i, and X is a vector of individual characteristics that implicitly conditions ∇EU.

We include individual characteristics X in the model to control for observable heterogeneity in σ; the coefficient of relative risk aversion under CRRA utility. The parameter σ_i is estimated as a linear function of the explanatory variables; $\hat{\sigma}_i = \hat{\sigma}_0 + \hat{\sigma}(X_i) + \varepsilon_i$ using maximum likelihood estimates of the necessary parameters. By excluding individual characteristics, we are assuming homogenous preferences across subjects and estimating the risk attitude of a representative individual (Andersen et al., 2010; Harrison, 2008).

5.3. Finite-Mixture model

Following Harrison and Rutström (2009), Andersen et al. (2010), Pennings and Garcia (2010) we also estimate a Finite-Mixture model where we allow both EUT and RDU to explain observed choices under uncertainty. If we let π^{EUT} denotes the probability that the EUT model is correct, and $\pi^{RDU} = \left(1 - \pi^{EUT}\right)$ denotes the probability that the RDU model is correct, the Rank-likelihood can be written as the probability weighted average of the conditional likelihoods. Thus the likelihood for the overall model estimated is defined by

$$\ln L\left(\sigma, \gamma, \eta, \mu, \pi^{EUT}; y, X\right) = \sum_i \ln\left[\left(\pi^{EUT} \times l_i^{EUT}\right) + \left(\pi^{RDU} \times l_i^{RDU}\right)\right] \quad (12)$$

This log-likelihood can be maximized to find estimates of the parameters.

These models are estimated using the maximum likelihood method. The estimation is done using Stata 14 (Harrison (2008) Appendix F). Given the possibility of correlation between responses by the same subject, the standard errors are adjusted for clustering (Harrison et al., 2010).

6. Results and Discussions

We construct a structural models based on maximum likelihood estimation of two utility functions; Power Risk Aversion utility function (Xie, 2000) and the commonly used Constant Relative Risk Aversion utility function (von Neumann & Morgenstern, 1953). We then run each of these models without and with the subjective probability weights to illustrate the effect of the assumption of EUT or RDU on the estimated parameters. Because the EUT is nested under the RDU, we also test which risk preferences utility theory best characterizes the preferences of farmers in our sample. We proceed by allowing EUT and RDU to simultaneously explain the observed choices in our sample using the Finite-Mixture model specification. We further look at their interaction with household characteristics.

6.1. Homogenous Preferences

Tables 3 presents maximum likelihood estimates of the EUT and RDU under PRA and CRRA. First, we look at the parameters of the utility functions. Under CRRA utility function, the coefficient of relative risk aversion (curvature of the utility function) is summarized in only one parameter (σ). σ is positive and significantly different from zero at 1% level in both models specification(EUT and RDU). Under PRA utility however, the coefficient of relative risk aversion is determined by two parameters, σ and γ, each of which influences the curvature of the utility function. Although both σ and γ increase the curvature of the utility function, the effect of these two parameters on the coefficient of relative risk aversion (RRA) is different. Relative risk aversion always increases with γ, but changes in σ have an ambiguous effect on RRA(x) when γ ≠ 0, see equation (3) for the illustration. Figure 2 shows the relative effect of σ and γ parameters on the curvature of the utility function.

Table 3. Maximum likelihood estimates, CRRA and PRA models in respect to EUT and RDU.

	CRRA	**PRA**
	(1)	(2)
EUT		
σ	0.814***	0.906***
	(0.029)	(0.013)
γ	-	0.064***
		(0.005)
η	0.040***	0.062***
	(0.006)	(0.005)
Log likelihood	-1037	-1041
RDU		
σ	0.785***	0.881***
	(0.056)	(0.019)
γ	-	0.072***
		(0.006)
η	0.043***	0.056***
	(0.007)	(0.004)
μ	0.895***	0.759***
	(0.163)	(0.123)
F-stat (H0: $\mu = 1$)	0.41	3.81**
p-Value	(0.520)	(0.05)
Log likelihood	-1037	-1039
Observations	3,310	3,310

Note: ***, ** and * denote statistical significance levels at 1%, 5% and 10%, respectively.

We further test the hypothesis that γ parameter which represents the difference between the PRA and the CRRA utility functions is equal to zero. We found γ significantly different from zero at 1% level in both models specification (RDU and EUT). As we can reject the null hypothesis that γ is equal to zero at 1% significance level, we conclude that farmer’s choices on average are not best characterized by CRRA utility function in favor of PRA utility function.

Second, we look at the parameter of the subjective probability function (μ), which describes the shape of the relationship between the objective probabilities of the two states A and B, and the subjective probabilities assigned to those states by the respondent (see equation (7)). The parameter of the subjective probability function reported in table 3 is less than one ($\hat{\mu} < 1$) in all specifications (CRRA and PRA), which means that farmers' probability weighting function in our sample is an inverse S-shaped, evidence of the overweighting of small probabilities and the underweighting of large probabilities relative to the objective probabilities. Figure 2 illustrates the plotting of the weighting probability function at the estimated parameter value of u against the identity function that is impose if we assume EUT. We observe in figure 3 that it is only around a probability of a good rainfall state of 0.4 that farmers begin to underweight objective probabilities. The F statistic of the hypothesis test that $\mu = 1$ is reported in table 3. We reject EUT in favor of RDU at 5% level of significance in PRA specification.

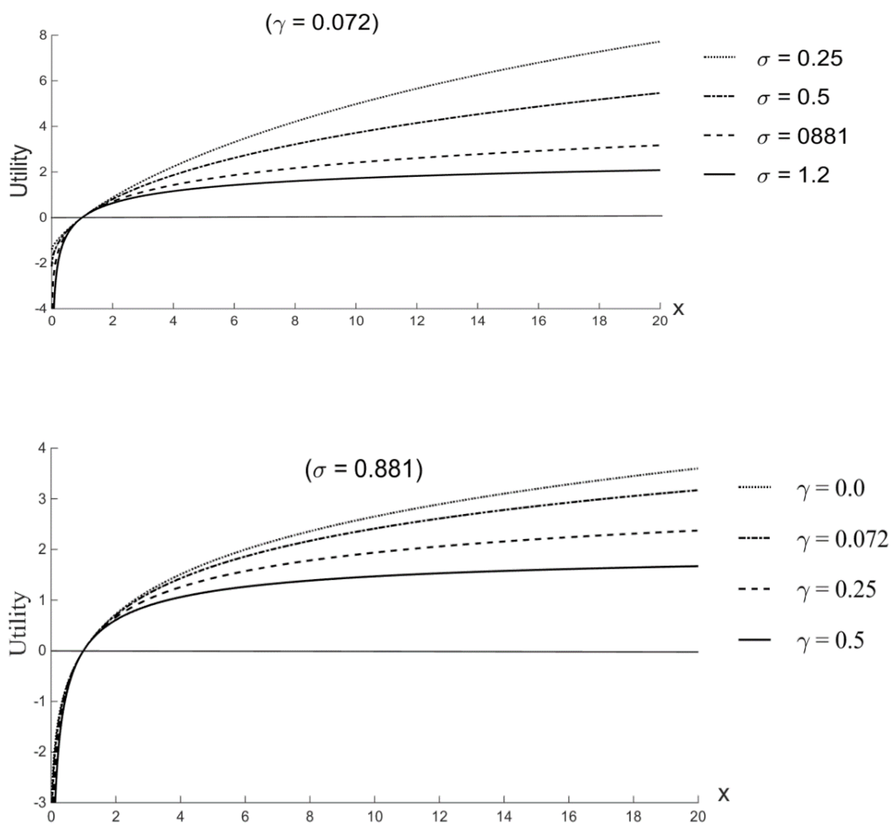

Figure 2. Power risk aversion utility function.

Last, we look at the structural noise parameter (η), which captures decision making errors. Thus as $\eta \to 0$ the decision making collapses to the deterministic choice model, where the choice is strictly determined by the Expected Utility of the two lotteries; but as η gets larger and larger the choice essentially becomes random. The result reported in table 3 shows that η is significantly different from zero in all utility function specifications. Therefore, farmers in our sample did make errors that impinge their decisions.

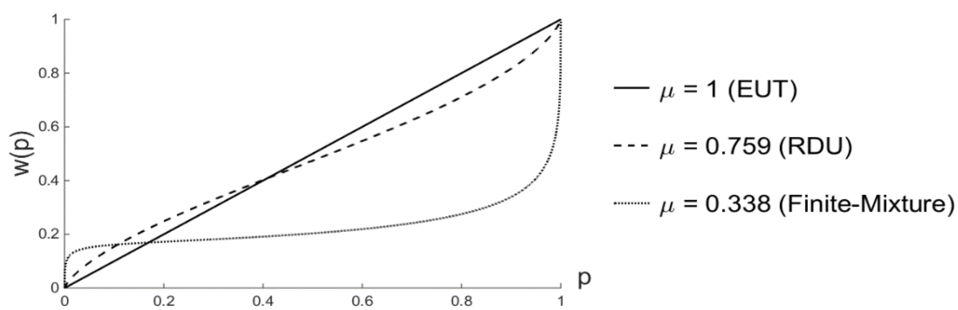

Figure 3. Weighting function for the PRA utility.

6.2.Preference Heterogeneity

In the precedent analysis, we considered that our data is either explained by EUT or RDU. This consideration does not allow the two utility frameworks to simultaneous explain farmers' choices in our sample. Some farmers may choose according to EUT and some according to RDU (Harrison & Rutström, 2009; de Brauw & Eozenou, 2014). We thus proceed with the estimation of the Finite-Mixture model, which allow each theory to have positive probability of explaining the observations, and therefore recognizing heterogeneity in decision making. We found that neither EUT nor RDU fully explains the observed attitudes toward risk behavior related to maize yield in Northern Ghana.

Table 4 presents the maximum likelihood estimates of the Finite-Mixture model. First, we observe that the estimated probabilities for EUT (π^{EUT}) and RDU (π^{RDU}) are both significantly different from zero at 1% level. However, when we assume no individual covariates (column 1, table 4), the probability of the EUT model explaining choices is 0.719 compared to the probability of the RDU model which is 1-0.7190=0.281. We reject the hypothesis that each model contributes equally at 5% level of significance. This tells that there are more choices being made with EUT logic than choices being made with RDU logic. But when we allow the interaction with the individual characteristics (columns 2 and 3, table 4), we cannot reject the hypothesis that each model contributes equally. The data is grossly evenly split between choices that are best characterized by EUT and choices that are best characterized by RDU. Harrison and Rutström (2009) found similar result. Indeed, the probability of the EUT model explaining choices is 0.601 in the case of no district effect (column 2, table 4) and 0.548 when we consider district effect (column 3, table 4) compared to 0.399 and 0.452 probability of RDU.

Second, the estimates of the RDU parameter μ when the specification is only assumed to fit some of the subjects, as in the Finite-Mixture model is clearly lesser than 1 compared to when the specification is assumed to fit every subject, as in the case of RDU homogenous preferences previously analyze. When estimated in the homogenous preference specification, $\hat{\mu}$ is 0.759 significantly different from 1 at the 5% significance level only on the PRA specification. However, when μ is estimated in the Finite-Mixture model, where it is only assumed to account for the behavior of some of the subjects, the estimated value falls to 0.338, clearly lesser than 1 at 1% significance level.

Table 4. Maximum likelihood estimates, Finite-Mixture model.

	Finite-Mixture		
	(1)	(2)	(3)
σ	0.744***	0.653***	0.658***
	(0.023)	(0.140)	(0.112)
Age in year		0.001	0.002
		(0.002)	(0.001)
Sex (1.male, 0.female)		0.013	0.020
		(0.027)	(0.027)
Married (1 Married, 0=others)		-0.106**	-0.088**
		(0.044)	(0.042)
Level of Education			
Primary		0.107**	0.124***
		(0.049)	(0.047)
Middle School/JSS		0.001	-0.001
		(0.051)	(0.046)
High Schools/SSS/Secondary		-0.123	-0.091
		(0.076)	(0.093)
College or University		-0.132*	-0.093*
		(0.069)	(0.055)
Drought 2014, Dummy		0.063**	0.035
		(0.029)	(0.031)
Number of Drought Last 5 Seasons		0.013	0.023*
		(0.014)	(0.014)
Drought perception		0.093***	0.088***
		(0.030)	(0.031)
Peers consultations		-0.024***	-0.034***
		(0.007)	(0.008)
Aspiration Index		-0.051**	-0.047***
		(0.024)	(0.013)
Food security status			
Middle Food Insecure		0.033	0.046
		(0.043)	(0.040)
Moderate Food Insecure		0.060	0.064
		(0.051)	(0.045)
Severe Food Insecure		0.060	0.077**
		(0.040)	(0.037)
Livestock Endowment (TLU)		-0.001***	-0.001*
		(0.000)	(0.000)
Non Agric Business		-0.024	-0.004
		(0.035)	(0.033)
District Effect	No	No	Yes
μ	0.338***	0.323***	0.327***
	(0.062)	(0.067)	(0.074)
F-stat (H0: $\mu=1$)	115.52***	103.01***	82.46***
p-Value	(0.000)	(0.000)	(0.000)
η	0.049***	0.031***	0.030***
	(0.009)	(0.006)	(0.006)
π^{EUT}	0.719***	0.601***	0.548***
	(0.095)	(0.144)	(0.124)
π^{RDU}	0.281***	0.399***	0.452***
	(0.095)	(0.144)	(0.144)
F Stat ($H_0 : \pi^{EUT} = \pi^{RDU}$)	5.290**	0.490	0.150
p-Value	(0.021)	(0.484)	(0.700)
Observations	3,310	3,310	3,310
Log likelihood	-1025	-947.7	-940.2

Note: maximum likelihood estimates. ***, ** and * denote statistical significance levels at 1%, 5% and 10%, respectively.

6.3. Risk Aversion and Individual Characteristics

Table 4 columns 2 and 3 present estimates from the Finite-Mixture model with individual characteristics. Each respondent has a different implied coefficient of risk aversion, given by the set of estimates and their individual characteristics. There is not a strong difference between estimates without district effect (table 4, column 2) and estimates with district effect (table 4, column 3). Thus, the following analysis is based on estimates with district effect. We include variables measured in the baseline survey, such as age, gender, level of education, marital status, household dependency ration, drought experience, idiosyncratic shocks, drought perception, peer consultations, aspiration, livestock endowment, participation in non-agricultural business and most importantly farmers food security status.

First, we look at food security status of the respondent. We observe that severe food insecurity is positive and significant at 5% level. Severe food insecure farmers therefore appear to be more averse to risk related to maize yields compared to food secure farmers. This is consistent with the fact that maize constitutes the main staple food for food insecure' farmers and any large variability in maize yield threatens their maize related food intake.

Second, we look at livestock endowment of the respondent, we observe that livestock endowment measured in Tropical Livestock Units (TLU) is significantly negatively correlated with σ parameter at the 10% significance level. It is not surprising that farmers who are engaged in livestock businesses are less risk averse. Livestock may serve as insurance for farmers in cases of maize yield shocks. We found similar result with farmer's participation to nonagricultural business even though non-significant.

Third, peer consultation measured by the number of peer farmers the respondent farmer consults before taking important agricultural decisions and aspiration level of the respondent are both significantly negatively correlated with the coefficient of risk aversion at 1 % significance level.

Fourth, lagged drought experience is positively correlated with σ. This implies that farmers who experienced drought in the past are more likely to be high risk averse than farmers who did not. Drought perception is also significantly positively associated with risk aversion at 1% significance level. Farmers who perceive there will be a drought in the coming season are highly averse to any technology that can be hurt by drought.

Fifth, High education is significantly negatively correlated with the coefficient of risk aversion at the 10% significance level compared to primary education which is significantly positively associated with the coefficient of risk aversion at 1% level of significance. This implies that farmers who are high educated are less risk averse compared to non-educated farmers. The similar result is found with the marital status variable. We found farmers who are married to be less risk averse compared to otherwise.

7. Conclusion

This paper used field experiment among poor rural smallholder maize growers with limited education in Northern Ghana. The paper presents the results of multiple prices list lottery choice experiment that allows us to measure the degree of risk aversion, subjective probability weighting parameter and to investigate how farmers' characteristics and other demographic variables are correlated with risk preference.

The experiment was designed around the adoption of high yield variety of maize (HYV) and consisted of offering farmers a menu of ordered lottery choices over hypothetical gains. The first option (safer option), designed around the adoption of traditional maize offers 350kg of maize per hectare for good weather and 250kg of maize per hectare for bad weather. The second option (risky option) designed around the adoption of high yield variety of maize, offers 750kg of maize per hectare for good weather and 50kg of maize per hectare for bad weather. The chance of good weather was designed to change from 10% to 100% in an ordering manner. And farmers were to make their choice between the two options.

Instead of imposing a specific utility function, or a specific process generating the data, a general class of value functions that explicitly allows for variation in relative risk aversion, relaxing the assumption of constant relative risk aversion (CRRA) that is often made in the literature was used and two popular contending models of choice under uncertainty; Expected Utility Theory (EUT) and Rank-Dependent Utility (RDU) were used as potential latent decision-making processes generating our data either separately or combined using a Finite-Mixture model. Structural models with a flexible PRA utility function with Luce error were estimated using maximum likelihood.

With both specifications, we reject the hypotheses that preferences are adequately characterized by Expected Utility Theory or constant relative risk aversion. We find that farmers on average tend to overweight small probabilities relative to objective probability and underweight large probabilities. From the estimation of the Finite-Mixture model which determines the proportion of farmers whose preferences are adequately characterized by Expected Utility Theory and the proportion of farmers whose preferences are adequately characterized by Rank-Dependent Utility Theory, we find that 28.1% of choices made by farmers possess preferences that cannot be explained by simple Expected Utility Theory.

The individual's characteristics results show that severe food insecurity, drought experience, and drought perception are associated with high risk aversion while livestock endowment, peer consultation, aspiration, high education and marriage are associated with less risk aversion.

It appears therefore that our results are sensitive to the utility function specification, the assumption of the model of choices under uncertainty and the individual characteristics of the respondent.

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